

1(a)

(i) Since the classes are equiprobable we have that:

$$P(w_1) = P(w_2) = P(w_3) = \frac{1}{3}$$

$$\text{For } w_1: P(x|w_1) \cdot P(w_1) = \frac{1}{3} \cdot \frac{1}{3} = \frac{1}{9} = 0.1, x \in \{3, 4\} \cup \{6, 8\}$$

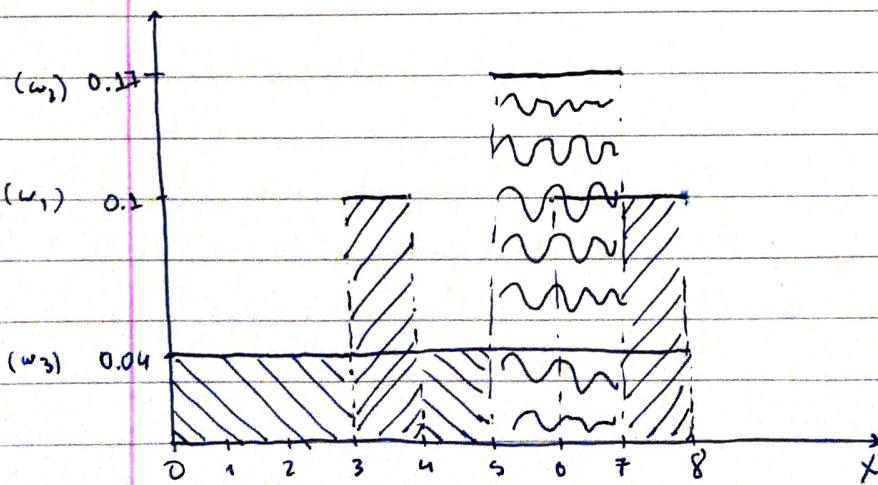
$$\text{For } w_2: P(x|w_2) \cdot P(w_2) = \frac{1}{2} \cdot \frac{1}{3} = \frac{1}{6} = 0.17, x \in \{5, 7\}$$

$$\text{For } w_3: P(x|w_3) \cdot P(w_3) = \frac{1}{8} \cdot \frac{1}{3} = \frac{1}{24} = 0.04, x \in \{0, 8\}$$

In order to decide in favour of 1 class over another we will use the Bayes rule. For classes i, j if $P(x|w_i) \cdot P(w_i) > P(x|w_j) \cdot P(w_j)$, the classification is in favour of class i . Therefore:

- (0, 3): classification in favour of w_3
- (3, 4): classification in favour of w_1
- (4, 5): $\xrightarrow{\quad || \quad} w_3$
- (5, 7): $\xrightarrow{\quad || \quad} w_2$
- (7, 8): $\xrightarrow{\quad || \quad} w_1$

In the following diagram the horizontal lines are the $P(x|w_i)P(w_i)$ and the drawn areas the decision regions for the classes.



Decision regions for w_1, w_2, w_3 :

$$R_1 = \{3, 4\} \cup \{7, 8\} : \text{|||}$$

$$R_2 = \{5, 7\} : \text{~~~}$$

$$R_3 = \{0, 3\} \cup \{4, 5\} : \text{///}$$

(ii) having in mind that the classes are equiprobable the probability of error is:

$$\begin{aligned}
 P_e &= \frac{1}{3} \left(\int_{R_1} (\rho(x|w_2) + \rho(x|w_3)) dx + \int_{R_2} (\rho(x|w_1) + \rho(x|w_3)) dx + \int_{R_3} (\rho(x|w_1) + \rho(x|w_2)) dx \right) \\
 &= \frac{1}{3} \left(\int_3^4 (\rho(x|w_2) + \rho(x|w_3)) dx + \int_7^8 (\rho(x|w_2) + \rho(x|w_3)) dx + \int_5^7 (\rho(x|w_1) + \rho(x|w_3)) dx + \right. \\
 &\quad \left. \int_0^3 (\rho(x|w_1) + \rho(x|w_2)) dx + \int_4^5 (\rho(x|w_1) + \rho(x|w_2)) dx \right) = \\
 &= \frac{1}{3} \left(\int_3^4 \frac{3}{8}(0 + \frac{1}{8}) dx + \int_7^8 (0 + \frac{1}{8}) dx + \int_5^6 (0 + \frac{1}{8}) dx + \int_6^7 (\frac{1}{8} + \frac{1}{8}) dx + \right. \\
 &\quad \left. \int_3^4 (0+0) dx + \int_4^5 (0+0) dx \right) = \frac{1}{3} \left(\frac{1}{8} \right) = \\
 &= \frac{1}{3} \left(\frac{1}{8} [x]_3^4 + \frac{1}{8} [x]_7^8 + \frac{1}{8} [x]_5^6 + \frac{11}{24} [x]_6^7 + 0 + 0 \right) = \\
 &= \frac{1}{3} \left(\frac{1}{8} + \frac{1}{8} + \frac{1}{8} + \frac{11}{24} \right) = \frac{1}{3} \cdot \frac{20}{24} = 0,27
 \end{aligned}$$

Probability of error is 0,27.

(iii) $x_1=2$ is classified to w_3 , $2 \in R_3$

$x_2=4.5$ is classified to w_3 , $4.5 \in R_3$

$x_3=5.5$ is classified to w_2 , $5.5 \in R_2$

$$1(b) (i) P(x) = 2\theta \times e^{-\theta x^2} u(x) \quad (1)$$

Assuming statistical independence among the elements of X , the log-likelihood function of θ is:

$$L(\theta) = \ln p(X; \theta) = \ln \left(\prod_{i=1}^n p(x_i; \theta) \right) = \sum_{i=1}^n \ln(p(x_i; \theta))$$

Utilizing (1) we have that:

$$\begin{aligned} L(\theta) &= \sum_{i=1}^n \ln(2\theta \times e^{-\theta x_i^2}) = \sum_{i=1}^n [\ln(2\theta) + \ln(e^{-\theta x_i^2})] = \\ &= \sum_{i=1}^n [\ln(2\theta) + \ln(x_i) - \theta x_i^2] = \cancel{n \ln(2\theta)} + \sum_{i=1}^n \ln(x_i) - \theta \sum_{i=1}^n x_i^2 \end{aligned}$$

Maximum-likelihood estimate of θ is obtained by taking the gradient of the L and equating to 0,

$$\frac{\partial L(\theta)}{\partial \theta} = 0 \Rightarrow \frac{N}{\theta \theta_{ML}} - \sum_{i=1}^n x_i^2 = 0 \Rightarrow \theta_{ML} = \frac{N}{\sum_{i=1}^n x_i^2}$$

$$(ii) X_1 = \{0, 0.5, 1, 1.5, 2\}, N_1 = 5$$

$$X_2 = \{3, 3.5, 4, 4.5, 5\}, N_2 = 5$$

$$I \quad \theta_{ML}^1 = \frac{5}{0+0.25+1+2.25+4} = 0.67, \quad P_1(x; \theta) = 1.34 \times e^{-0.67x^2}$$

$$\theta_{ML}^2 = \frac{5}{9+12.25+16+20.25+25} = 0.06, \quad P_2(x; \theta) = 0.12 \times e^{-0.06x^2}$$

$$II \text{ For the a-priori } P(w_i) = \frac{N_i}{N}, \quad N=10, i=1, 2$$

$$P(w_1) = \frac{1}{2}, \quad P(w_2) = \frac{1}{2}$$

According to Bayes rule, we decide in favour of w_1 when

$$P(w_1) \cdot P(x|w_1) > P(w_2) \cdot P(x|w_2) \quad \Rightarrow \quad P(w_1) = P(w_2)$$

$$\Rightarrow 1.34x \cdot e^{-0.67x^2} > 0.12e^{-0.06x^2} \xrightarrow{x>0} \\ \cancel{1.34e^{-0.67x^2}} 1.34e^{-0.67x^2} > 0.12e^{-0.06x^2} \Rightarrow \\ \ln(1.34) - 0.67x^2 > \ln(0.12) - 0.06x^2 \Rightarrow \\ 0.29 - 0.67x^2 > -2.12 - 0.06x^2 \Rightarrow \\ 2.41 > 0.61x^2 \Rightarrow \\ x^2 < 3.95 \Rightarrow \\ -1.99 < x < 1.99$$

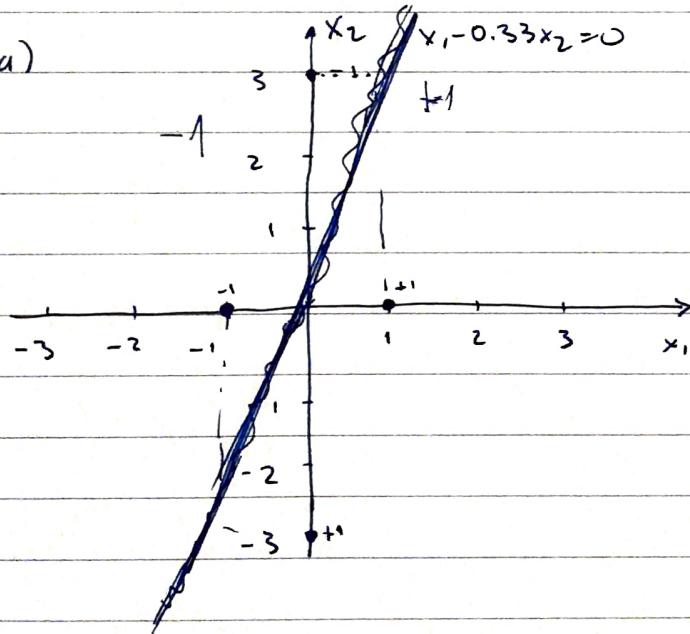
Thus, we classify to ω_1 when $x \in (-1.99, 1.99)$ and to ω_2 otherwise

We have made the assumption that $x > 0$ thus the regions become: $\omega_1: x \in (0, 1.99)$

$$\omega_2: x \in (1.99, \infty)$$

$$\omega_1 \text{ or } \omega_2 \text{ if } x = 1.99$$

2(a)



We will utilize the LS criterion where $\theta = (X^T X)^{-1} X^T y$

θ is the parameter vector of the line that separates the classes

$$X = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & -3 \\ 1 & -1 & 0 \\ 1 & 0 & 3 \end{bmatrix} \quad Y = \begin{bmatrix} 1 \\ 1 \\ -1 \\ -1 \end{bmatrix}$$

$$\bullet X^T X = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 0 & -1 & 0 \\ 0 & -3 & 0 & 3 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & -3 \\ 1 & -1 & 0 \\ 1 & 0 & 3 \end{bmatrix} =$$

$$= \begin{bmatrix} 4 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 18 \end{bmatrix}$$

$$\bullet (X^T X)^{-1} = \frac{1}{\det(X^T X)} \cdot \text{adj}(X^T X)$$

$$\det(X^T X) = 4 \begin{vmatrix} 4 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 18 \end{vmatrix} = 144$$

$$\text{adj}(X^T X) = \begin{bmatrix} 44 & 0 & 0 \\ 0 & 72 & 0 \\ 0 & 0 & 8 \end{bmatrix}$$

$$X^T X^{-1} = \begin{bmatrix} 0.25 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.056 \end{bmatrix}$$

$$\bullet (X^T X)^{-1} \cdot X^T = \begin{bmatrix} 0.25 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.056 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 0 & -1 & 0 \\ 0 & -3 & 0 & 3 \end{bmatrix} = \begin{bmatrix} 0.25 & 0.25 & 0.25 & 0.25 \\ 0.5 & 0 & -0.5 & 0 \\ 0 & -0.17 & 0 & 0.17 \end{bmatrix}$$

$$\bullet (X^T X)^{-1} X^T y = \begin{bmatrix} 0.25 & 0.25 & 0.25 & 0.25 \\ 0.5 & 0 & -0.5 & 0 \\ 0 & -0.17 & 0 & 0.17 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ -0.33 \end{bmatrix}$$

$$\theta = [0, 1, -0.33]^T$$

The line that separates the two classes is :

$$0 + y_1 - 0.33x_2 = 0 \Rightarrow x_1 - 0.33x_2 = 0$$

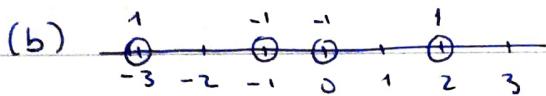
$$(ii) [5, 1]^T : 5 - 0.33 > 0 \Rightarrow \text{class } +1$$

$$[1, 5]^T : 1 - 5 \cdot 0.33 < 0 \Rightarrow \text{class } -1$$

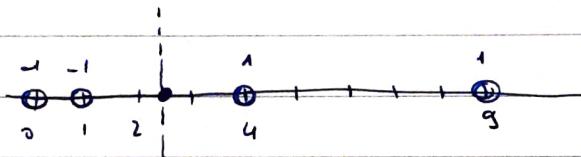
(iii) SVM would give the exact same line.

This line is parallel to the two lines that pass from the two points of each class and ~~is at the distance~~ ~~at~~ passes in the middle of these two lines.

~~Therefore,~~



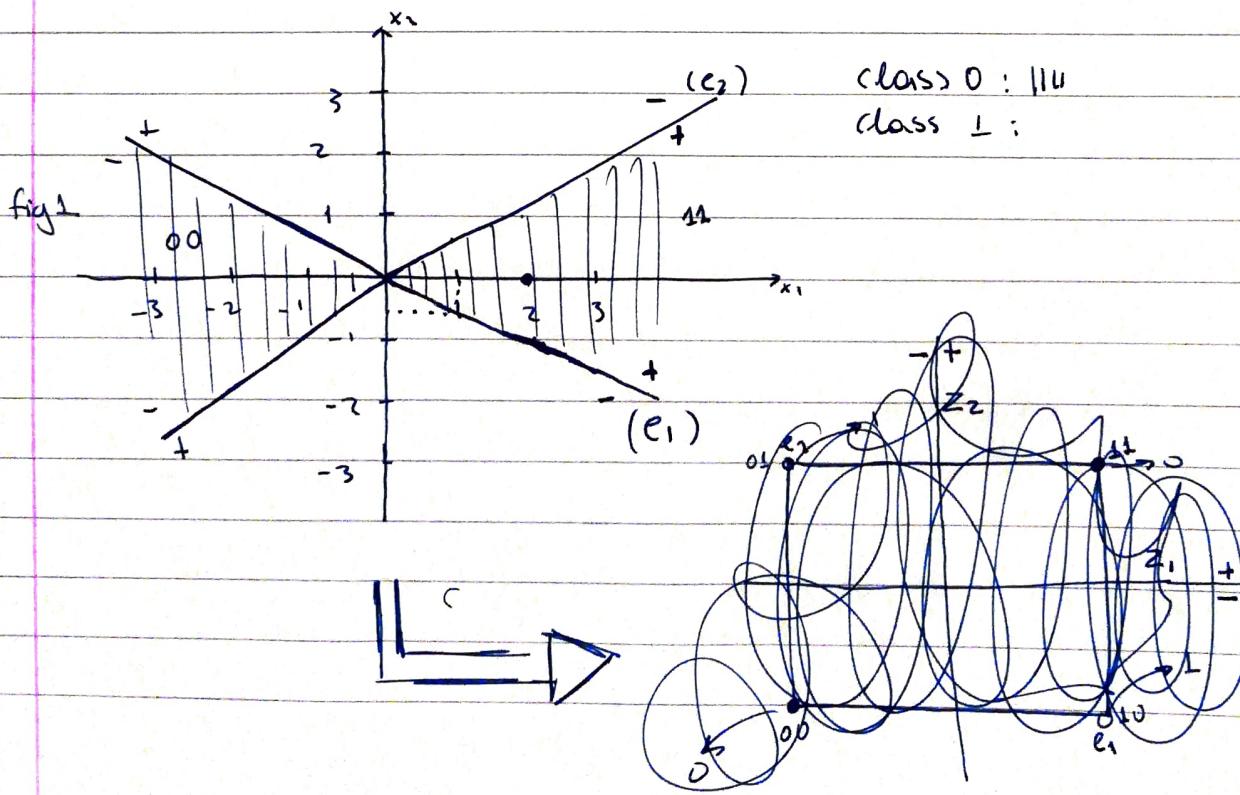
with $\phi(x) = x^2$ the points become

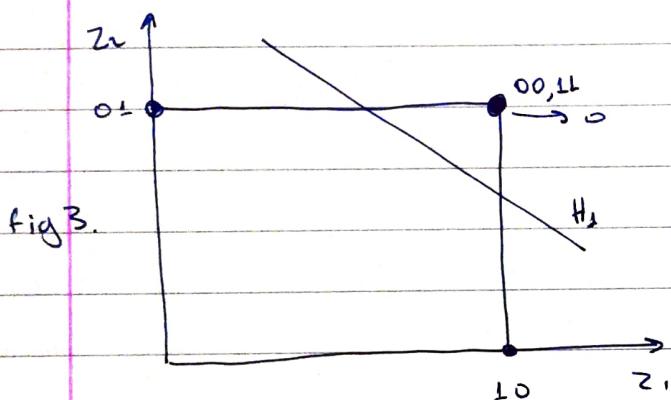
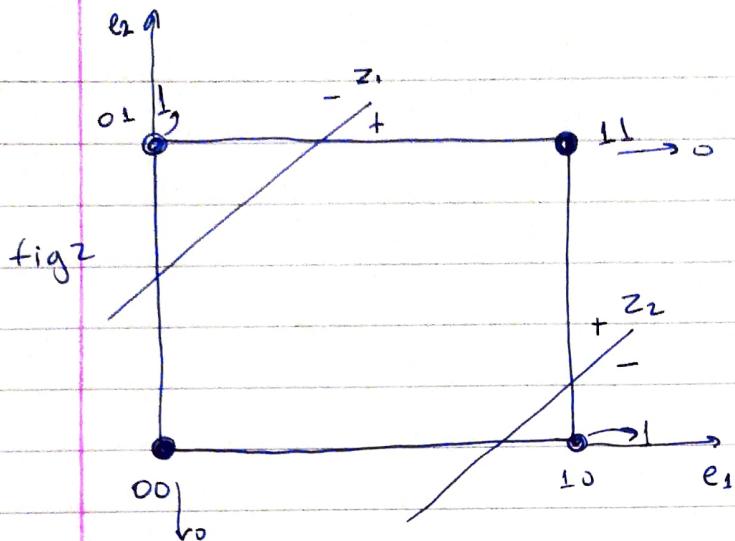


Therefore, it is linearly separable. The ~~line~~ point $x=2.5$ separates the two classes.

$$3(a) \quad x_1 + 2x_2 = 0 \quad (e_1)$$

$$x_1 - 2x_2 = 0 \quad (e_2)$$





- As we can see on (fig 1) the two classes are not linearly separable. Since they are separated with two lines, the 1st layer of the Neural Network will have two nodes with weights $(1, 2)$ and $(1, -2)$ respectively and biases equal to 0.

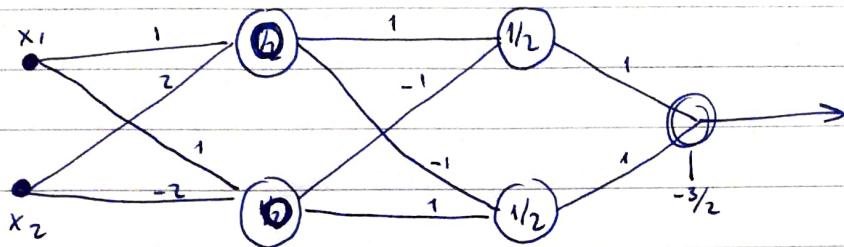
- Moving to the second layer, (fig 2) the classes are still non-linearly separable. Therefore, we need another layer of two nodes (since the two classes are again separated by two lines).
~~The lines, that I drew are ok~~

z_1 : passes through the points $(0, \frac{1}{2})$, $(\frac{1}{2}, 1)$ therefore
 $x_1 - x_2 + \frac{1}{2} = 0$: weights $(1, -1)$ bias $\frac{1}{2}$

z_2 : passes through the points $(\frac{1}{2}, 0)$, $(1, \frac{1}{2})$ therefore
 $-x_1 + x_2 + \frac{1}{2} = 0$: weights $(-1, 1)$ bias $\frac{1}{2}$

- Finally, the classes are linearly separable, by the line that passes through the points $(1, \frac{1}{2})$, $(\frac{1}{2}, 1)$

$$H_1: x_1 + x_2 - \frac{3}{2} = 0 : \text{weights } (1, 1) \text{ bias } -\frac{3}{2}$$



(b) (i) From the 5 nearest neighbors, 3 belong to class w_1 and 2 to class w_2 . Therefore, we classify the point to class 1.

(ii) For the probabilities $P(w_1)$, $P(w_2)$: They are equal

$$P(w_1) = \frac{N_{w_1}}{N} = \frac{18}{27} \quad \text{since classes are equiprobable}$$

$$P(w_1) = P(w_2) = \frac{1}{2}$$

$$P(w_2) = \frac{N_{w_2}}{N} = \frac{9}{27} \quad N_1 = 18, N_2 = 9$$

For w_1 the circle that has the smallest radius and contains 3 neighbors has radius $r_1 = 1$ and $V_1 = \pi (r_1^2)$

for w_2 the circle that has the smallest radius and contains 3 neighbors has radius $r_2 = \sqrt{5}$ and $V_2 = 5\pi (r_2^2)$

$$P(x|w_1) = \frac{k}{N_1 V_1} = \frac{3}{18 \cdot \pi} = 0.053$$

$$P(x|w_2) = \frac{k}{N_2 V_2} = \frac{3}{9 \cdot 5\pi} = 0.021$$

Since $P(x|w_1) \cdot P(w_1) > P(x|w_2) \cdot P(w_2)$ and based on Bayes classification rule we classify the point to class w_1

4(a) feature space is separated by line $x_1 = 1/2$, thus the root of the tree will have the condition $x_1 \leq 1/2$.

$x_1 \leq 1/2$: YES

The given feature space is separated by line $x_2 = 1/4$, thus the condition will be $x_2 \leq 1/4$.

$x_2 \leq 1/4$: YES classify to class w_3

$x_2 \geq 1/4$: NO classify to class w_1

Splitting process stops here for this branch, since classes are perfectly separated.

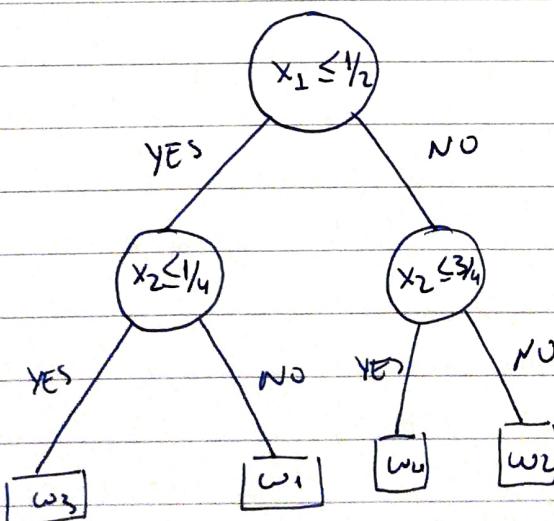
$x_1 \leq 1/2$: NO

The given feature space is separated by line $x_2 = 3/4$, thus the condition will be $x_2 \leq 3/4$.

$x_2 \leq 3/4$: YES classify to w_4

$x_2 \geq 3/4$: NO classify to w_2

Process stops here for this branch, since classes are perfectly separated.



(b) Since θ is unbiased estimator of θ we have that :

$$E[\theta] = \theta_0$$

We need θ' to be unbiased too, therefore $E[\theta'] = \theta_0 \Rightarrow$

$$\Rightarrow E[(a^2 - 3)\theta] = (a^2 - 3)E[\theta] = (a^2 - 3)\theta_0$$

$$E[\theta'] = \theta_0 \Rightarrow (a^2 - 3)\theta_0 = \theta_0 \Rightarrow a^2 - 3 = 1 \Rightarrow \\ \Rightarrow a^2 = 4 \Rightarrow a = \pm 2$$

for $a = \pm 2$ θ' is unbiased estimator of θ .

(c) $f(x) = x_1^2 + 4x_2 + 6$

$$y_1 = \cancel{4} + \cancel{4} \cdot 3 + 6 \Rightarrow y_1 = 22$$

$$y_2 = \cancel{1} + \cancel{4} \cdot 1 + 6 \Rightarrow y_2 = 11$$

$$y_1 = 4 + 4 \cdot 3 + 6 \Rightarrow y_1 = 22$$

$$y_2 = 1 + 4 \cdot 1 + 6 \Rightarrow y_2 = 11$$

(d) (g) both x_1 and x_2

None of the x_1, x_2 alone discriminate the classes, since the projection on the axes is the same for the two classes (no matter which axis you choose to project on)

Therefore, we need both axes x_1, x_2 to separate the classes.

(f) $x_1 = [1, 0]^T, x_2 = [-3, 0]^T, x_3 = [1, 10]^T, x_4 = [3, 10]^T$

1st fit $\theta_1(0) = [4, 10]^T \quad \theta_2(0) = [4, 0]^T$

x_1	$\log((4-1)^2 + (10-0)^2)$	9	class w_2
x_2	101	1	class w_2
x_3	9	109	class w_1
x_4	1	101	class w_1

We computed the squared Euclidean distances and classified each point to a class by the rule $\min_{j=1,2} \|x_i - \theta_j(0)\|^2 \quad i=1, \dots, 4$

For the new θ :

$$\theta_1(1) = \frac{1}{2} \left(\begin{bmatrix} 1 \\ 10 \end{bmatrix} + \begin{bmatrix} 3 \\ 10 \end{bmatrix} \right) = \frac{1}{2} \begin{bmatrix} 4 \\ 20 \end{bmatrix} = \begin{bmatrix} 2 \\ 10 \end{bmatrix}$$

$$\theta_2(1) = \frac{1}{2} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 3 \\ 0 \end{bmatrix} \right) = \frac{1}{2} \begin{bmatrix} 4 \\ 0 \end{bmatrix} = \begin{bmatrix} ? \\ 0 \end{bmatrix}$$

and it) $\theta_1(1) = [2 \ 10]^\top$

$$\theta_2(2) = [2 \ 0]^\top$$

$x_1 \quad 201$

1 class w_2

$x_2 \quad 101$

1 class w_2

$x_3 \quad 1$

101 class w_1

$x_4 \quad 1$

201 class w_1

$$\theta_2(2) = \frac{1}{2} \left(\begin{bmatrix} 4 \\ 20 \end{bmatrix} \right) = \begin{bmatrix} ? \\ 0 \end{bmatrix}$$

$$\theta_2(2) = \frac{1}{2} \left(\begin{bmatrix} 4 \\ 0 \end{bmatrix} \right) = \begin{bmatrix} ? \\ 0 \end{bmatrix}$$

Since for two iterations in a row the representatives do not change (classification does not change either for the x 's) we stop the process.

In conclusion, x_1, x_2 are classified to w_2 with $\theta_2 = [2 \ 0]^\top$ and x_3, x_4 are classified to w_1 with $\theta_1 = [2 \ 10]^\top$

(e) PCA does not necessarily retain class separability because it is possible that ~~by eliminating projection~~ projection on an ~~the first~~ axis does not separate the classes e.g.

