Problem Solutions

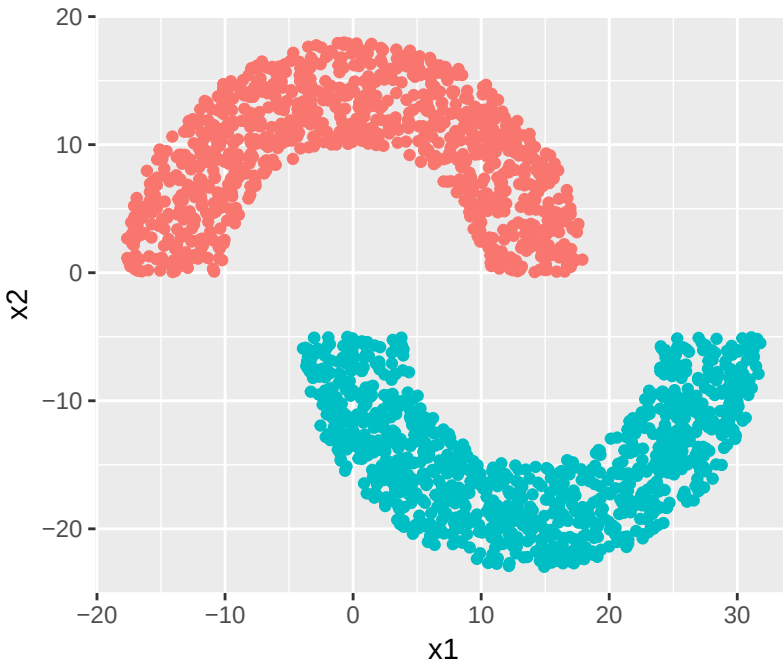
Chapter 3

Pierre Paquay

Problem 3.1

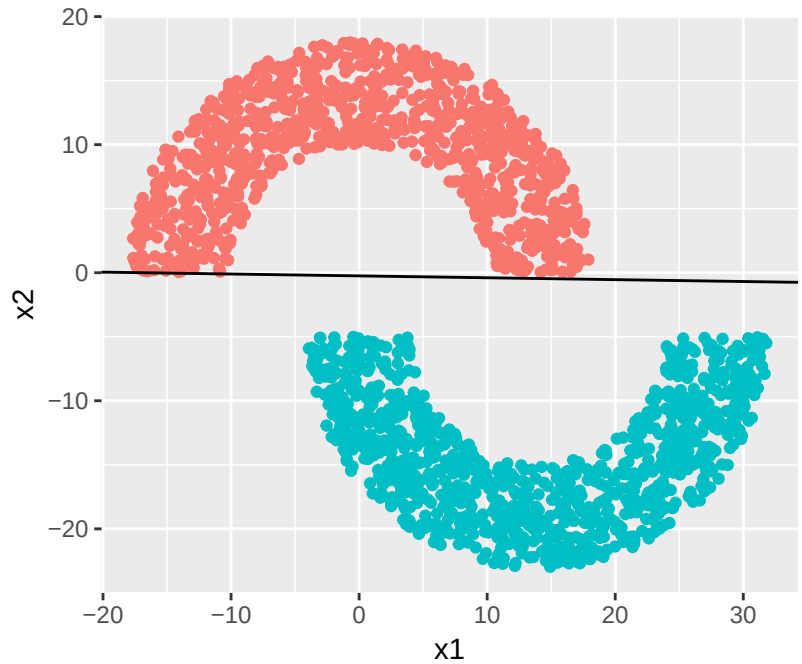
First, we generate 2000 examples uniformly for the two semi-circles, this means that we will have approximately 1000 examples for each class.

```
set.seed(101)

init_data <- function(N, rad, thk, sep) {
  D <- data.frame(x = numeric(), y = numeric())
  y <- numeric()
  repeat {
    x1 <- runif(1, min = -25, max = 40)
    x2 <- runif(1, min = -30, max = 20)
    if ((x2 >= 0) && (rad^2 <= x1^2 + x2^2) && (x1^2 + x2^2 <= (rad + thk)^2)) {
      D <- rbind(D, c(x1, x2))
      y <- c(y, -1)
    }
    else if ((x2 < -sep) && (rad^2 <= (x1 - rad - thk / 2)^2 + (x2 + sep)^2) &&
             ((x1 - rad - thk / 2)^2 + (x2 + sep)^2 <= (rad + thk)^2)) {
      D <- rbind(D, c(x1, x2))
      y <- c(y, +1)
    }
    if (nrow(D) >= N)
      break
  }
  colnames(D) <- c("x1", "x2")

  return(cbind(D, y))
}

rad <- 10
thk <- 8
sep <- 5
D <- init_data(2000, rad, thk, sep)
p <- ggplot(D, aes(x = x1, y = x2, col = as.factor(y + 3))) + geom_point() +
  theme(legend.position = "none") +
  coord_fixed()
p
```



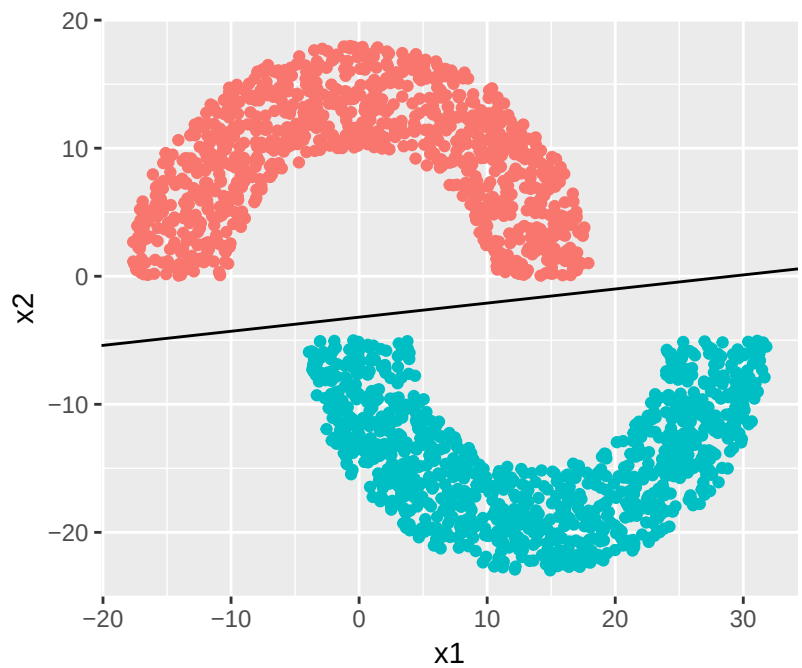
(a) Then, we run the PLA starting from $w = 0$ until it converges and we plot the data with the final hypothesis.

```
h <- function(D, w) {
  scalar_prod <- cbind(1, D$x1, D$x2) %*% w

  return(as.vector(sign(scalar_prod)))
}

iter <- 0
w_PLA <- c(0, 0, 0)
repeat {
  y_pred <- h(D, w_PLA)
  D_mis <- subset(D, y != y_pred)
  if (nrow(D_mis) == 0)
    break
  xt <- D_mis[1, ]
  w_PLA <- w_PLA + c(1, xt$x1, xt$x2) * xt$y
  iter <- iter + 1
}
p + geom_abline(slope = -w_PLA[2] / w_PLA[3], intercept = -w_PLA[1] / w_PLA[3])
```



(b) Now, we use linear regression for classification to obtain w_{lin}.

```
X <- as.matrix(cbind(1, D[, c("x1", "x2")]))
y <- D$y
X_cross <- solve(t(X) %*% X) %*% t(X)
w_lin <- as.vector(X_cross %*% y)
p + geom_abline(slope = -w_lin[2] / w_lin[3], intercept = -w_lin[1] / w_lin[3])
```

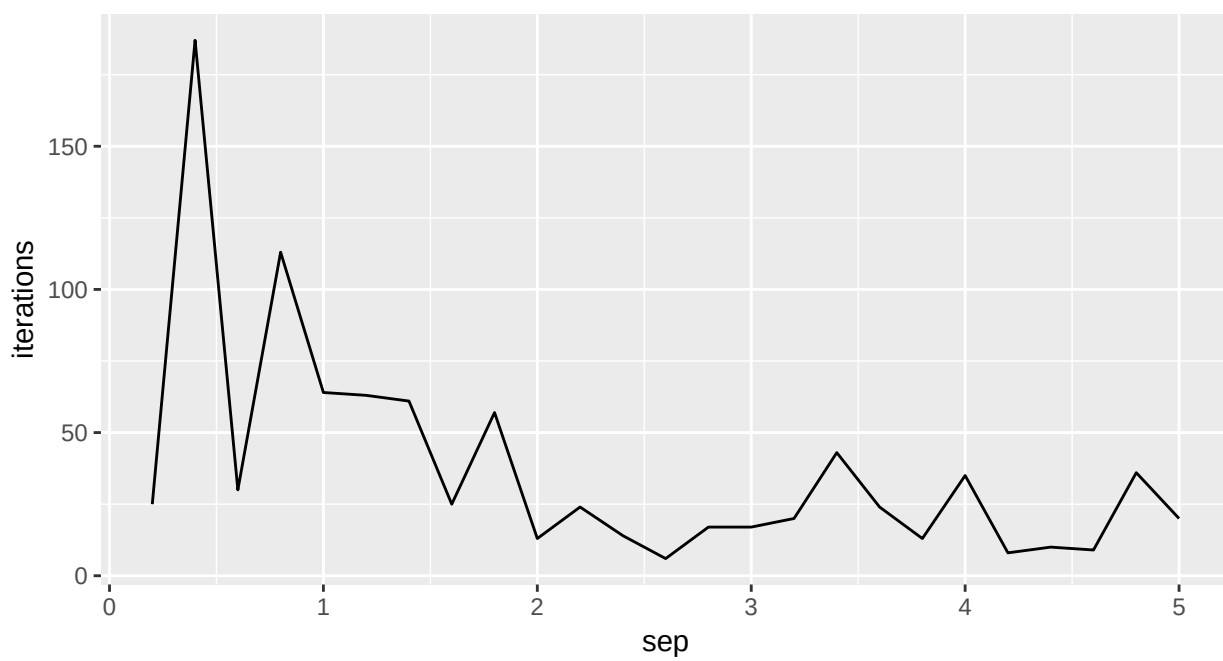


As we may see, linear regression can also be used for classification (the values $\text{sign}(w_{lin}^T x)$ will likely make good classification predictions). The linear regression weights w_{lin} are also an approximate solution for the perceptron model.

Problem 3.2

In this problem, we consider again the double-semi-circle of Problem 3.1 and we vary *sep* in the range $\{0.2, 0.4, \cdots, 5\}$, with these values we generate 2000 examples and we run PLA starting with $w = 0$. Below, we plot *sep* versus the number of iterations PLA takes to converge.

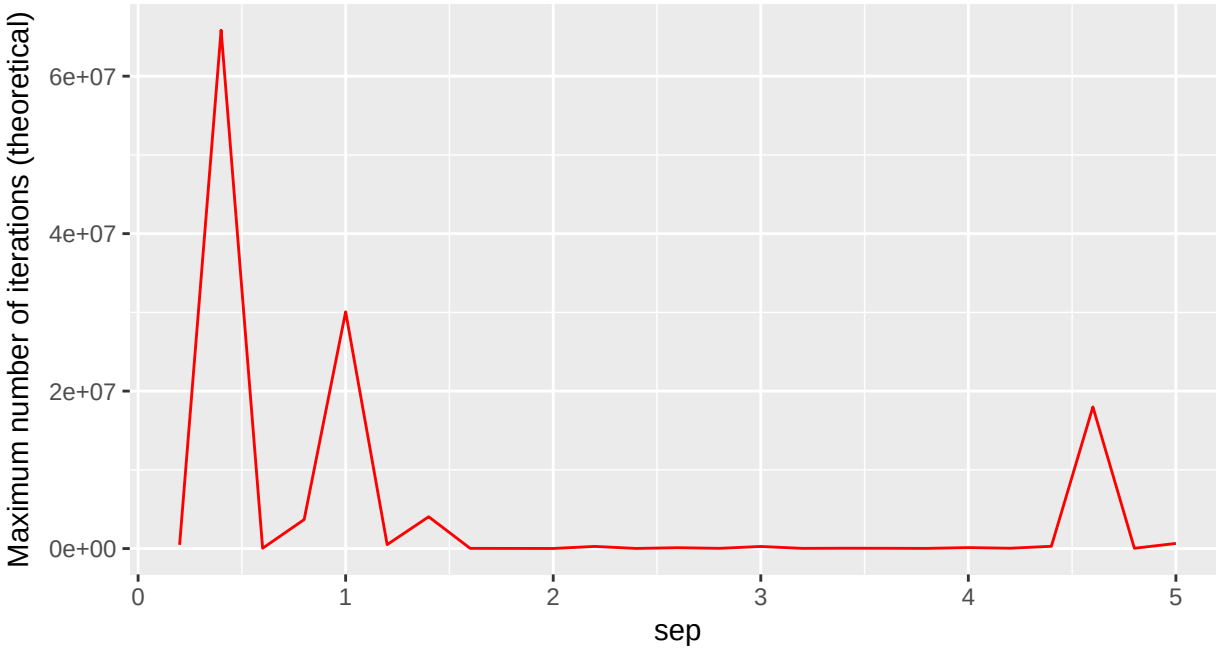
```
set.seed(10)

sep_seq <- seq(0.2, 5, 0.2)
iterations <- numeric()
iterations_max <- numeric()
for (sep in sep_seq) {
  D <- init_data(2000, rad, thk, sep)
  iter <- 0
  w_PLA <- c(0, 0, 0)
  repeat {
    y_pred <- h(D, w_PLA)
    D_mis <- subset(D, y != y_pred)
    if (nrow(D_mis) == 0)
      break
    xt <- D_mis[1, ]
    w_PLA <- w_PLA + c(1, xt$x1, xt$x2) * xt$y
    iter <- iter + 1
  }
  iterations <- c(iterations, iter)
  R <- max(apply(cbind(1, D[, 1:2]), 1, FUN = function(x) sqrt(1 + x[2]^2 + x[3]^2)))
  Rho <- min(D$y * apply(cbind(1, D[, 1:2]), 1, FUN = function(x) sum(w_PLA * x)))
  iterations_max <- c(iterations_max, R^2 * sum(w_PLA^2) / Rho^2)
}
ggplot(data.frame(sep = sep_seq, iterations = iterations), aes(x = sep, y = iterations)) +
  geom_line()
```



We may see that the number of iterations tends to decrease when *sep* increases. This trend is confirmed by the theoretical results (see Problem 1.3), to see this we plot below *sep* versus the theoretical maximum

number of iterations.

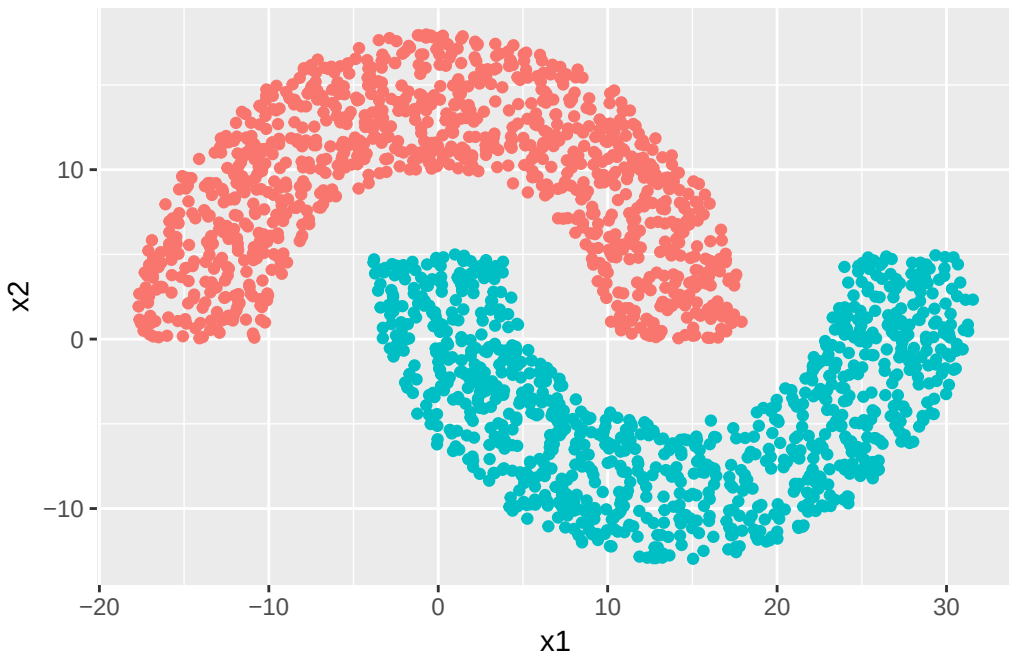
```
ggplot(data.frame(sep = sep_seq, iterations = iterations_max), aes(x = sep, y = iterations)) +
  geom_line(col = "red") +
  ylab("Maximum number of iterations (theoretical)")
```



Problem 3.3

Here again, we consider the double-semi-circle of Problem 3.1 and we set $sep = -5$ (which makes the data non linearly separable) and we generate 2000 examples.

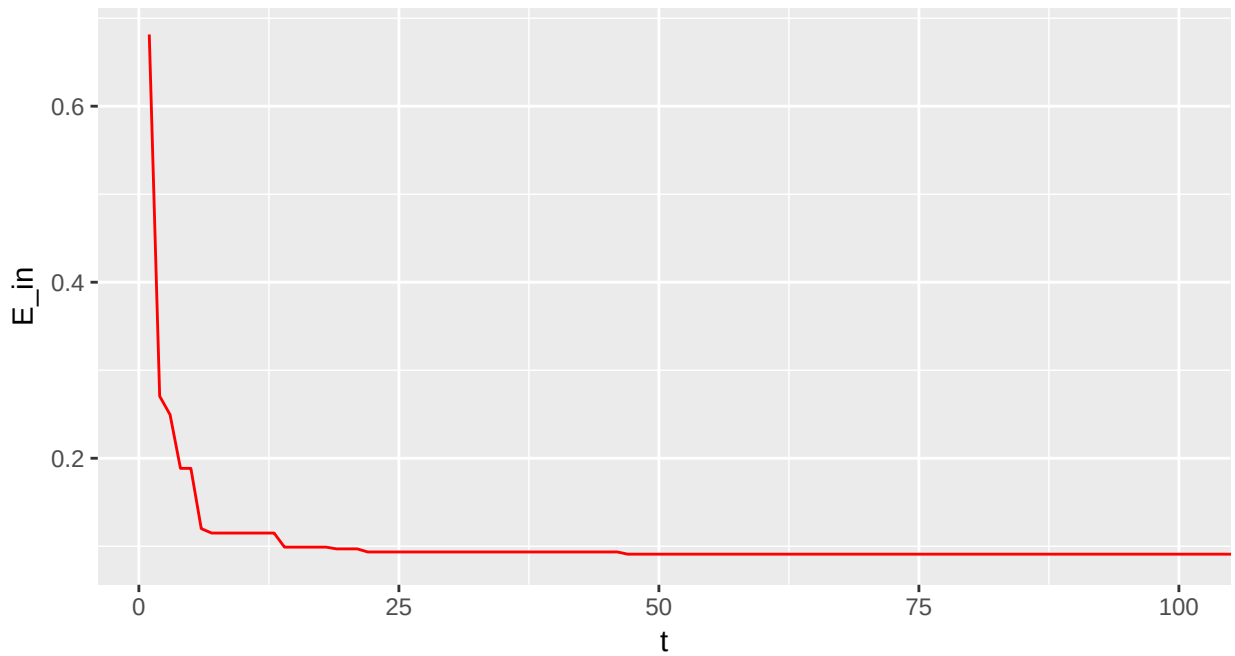
```
set.seed(101)

sep <- -5
D <- init_data(2000, rad, thk, sep)
p <- ggplot(D, aes(x = x1, y = x2, col = as.factor(y + 3))) + geom_point() +
  theme(legend.position = "none") +
  coord_fixed()
p
```



(a) If we run PLA on these examples, it will never stop updating.

(b) Now, we run the pocket algorithm for 100000 iterations and we plot E_{in} versus the iteration number t for $t = 1, \cdots, 100$.

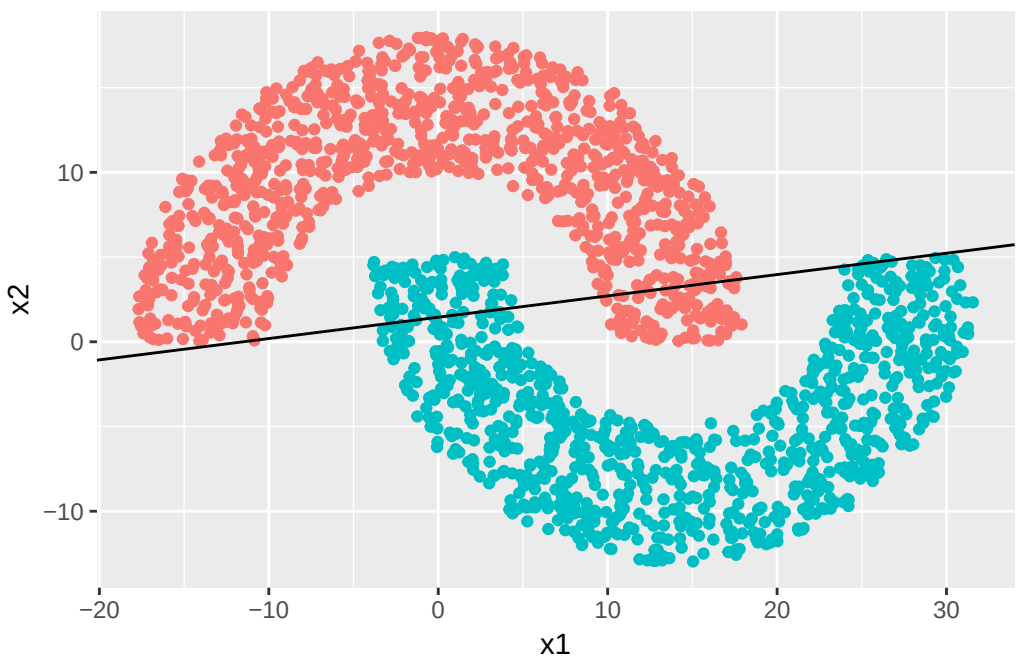
```
set.seed(101)

start_time_pocket <- Sys.time()
E_in <- numeric()
E_in_pocket <- numeric()
w <- c(0, 0, 0)
w_pocket <- w
E_in <- c(E_in, mean(D$y != h(D, w)))
E_in_pocket <- E_in
for (iter in 1:100000) {
  D_mis <- subset(D, y != h(D, w))
  if (nrow(D_mis) == 0)
    break
  xt <- D_mis[sample(nrow(D_mis), 1), ]
  w <- w + c(1, xt$x1, xt$x2) * xt$y
  E_in <- c(E_in, mean(D$y != h(D, w)))
  if (E_in[length(E_in)] < E_in_pocket[length(E_in_pocket)]) {
    w_pocket <- w
  }
  E_in_pocket <- c(E_in_pocket, mean(D$y != h(D, w_pocket)))
}
end_time_pocket <- Sys.time()
ggplot(data.frame(t = 1:100000, E_in = E_in_pocket[-1]), aes(x = t, y = E_in)) +
  geom_line(col = "red") +
  coord_cartesian(xlim = c(1, 100))
```



We clearly see that the E_{in} is monotonously decreasing (as opposed to what would happen if we had used the PLA).

(c) Below, we plot the data and the final hypothesis obtained in (b).

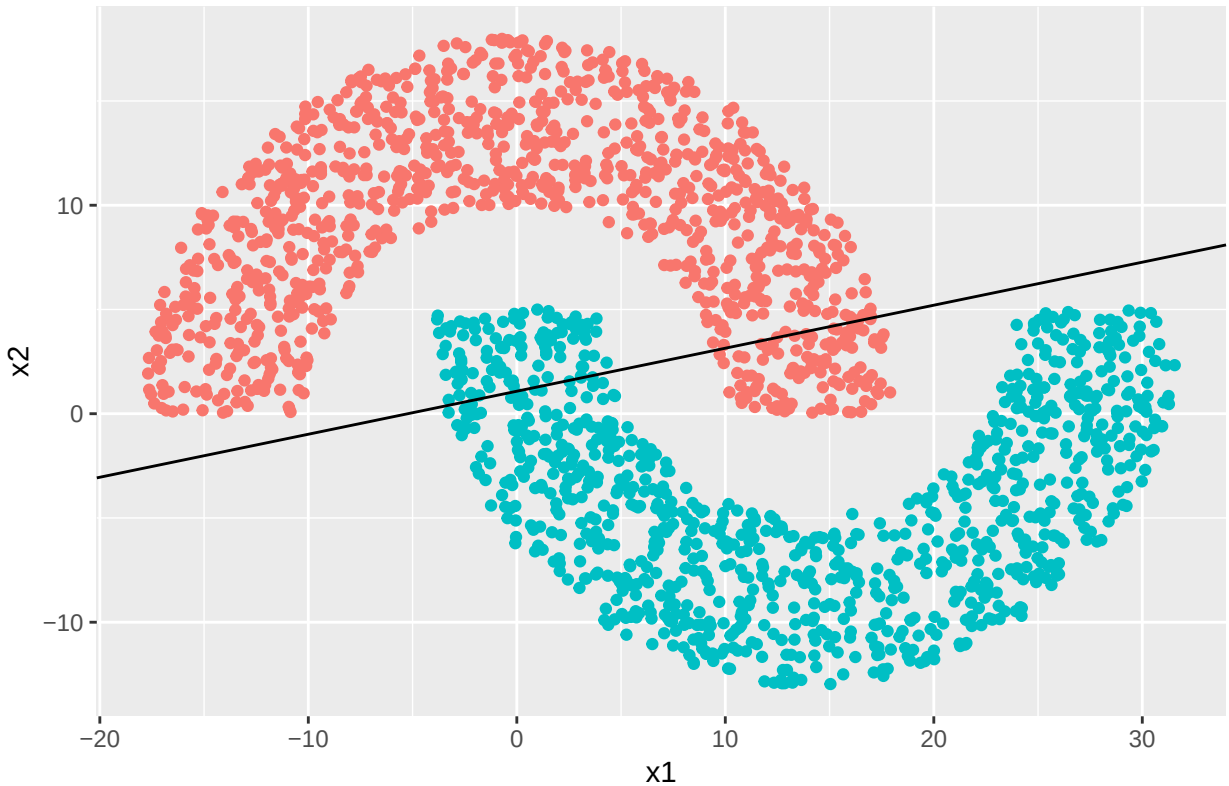
```
p + geom_abline(slope = -w_pocket[2] / w_pocket[3], intercept = -w_pocket[1] / w_pocket[3])
```



(d) Here, we use the linear regression algorithm to obtain w and we compare this result with the pocket algorithm in terms of computation time and quality of the solution.

```
start_time_lin <- Sys.time()
X <- as.matrix(cbind(1, D[, c("x1", "x2")]))
y <- D$y
X_cross <- solve(t(X) %*% X) %*% t(X)
```

```r
w_lin <- as.vector(X_cross %*% y)
E_in_lin <- mean(D$y != h(D, w_lin))
end_time_lin <- Sys.time()
p + geom_abline(slope = -w_lin[2] / w_lin[3], intercept = -w_lin[1] / w_lin[3])
```



For the pocket algorithm (with 100000 iterations), we have a computation time of 1.7378043, and for the linear regression algorithm, we have a computation time of 0.0074768. The linear regression algorithm is clearly better than the pocket algorithm in terms of computation time. When we take into account the quality of the solution, the pocket algorithm has a (final) E_{in} of 0.086, and the linear regression algorithm has a E_{in} of 0.0995. So, regarding the quality of the solution, the pocket algorithm is a little better than the linear regression algorithm.

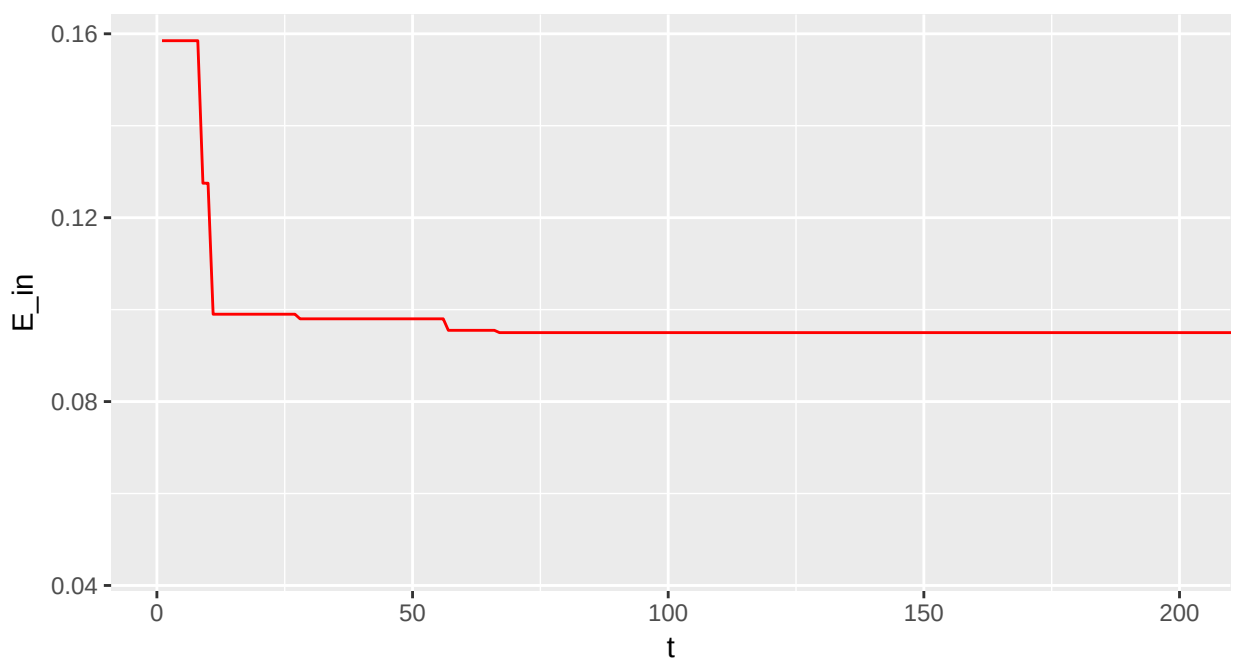
(e) Here, we repeat the points (b) to (d) with a 3rd order polynomial feature transform

$$\Phi(x) = (1, x_1, x_2, x_1^2, x_1x_2, x_2^2, x_1^3, x_1^2x_2, x_1x_2^2, x_2^3).$$

First, we run the pocket algorithm for 100000 iterations and we plot E_{in} versus the iteration number t.

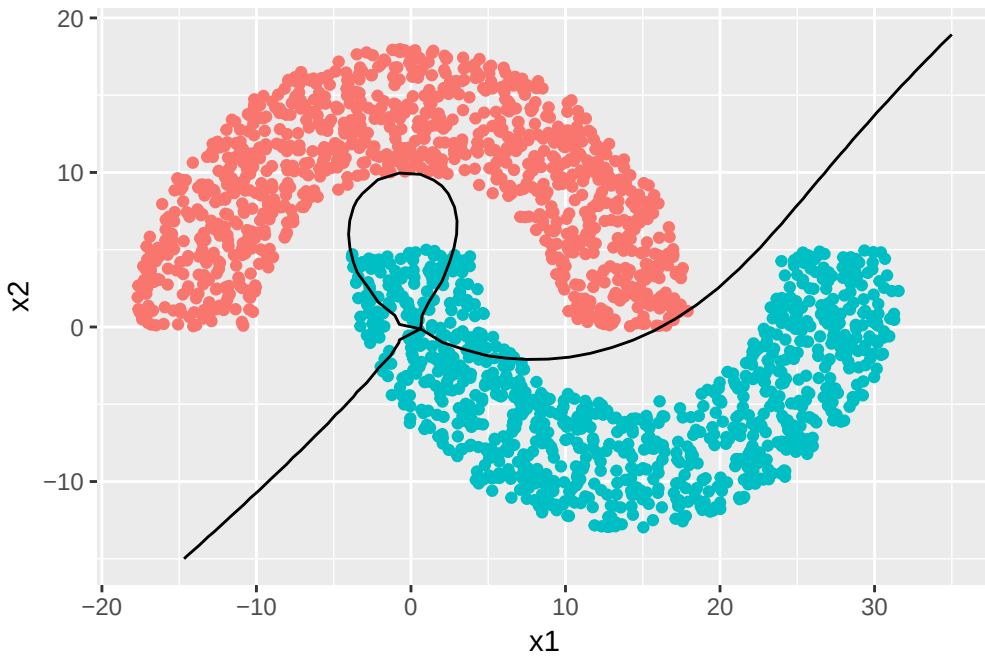
```r
set.seed(11)

D_trans <- data.frame(x1 = D$x1, x2 = D$x2,
                      x1_sq = D$x1^2, x1x2 = D$x1 * D$x2, x2_sq = D$x2^2,
                      x1_cub = D$x1^3, x1_sqx2 = D$x1^2 * D$ x2,
                      x1x2_sq = D$x1 * D$x2^2, x2_cub = D$x2^3, y = D$y)

h_trans <- function(D, w) {
  scalar_prod <- as.matrix(cbind(1, D[, 1:9])) %*% w

  return(as.vector(sign(scalar_prod)))
}
```

```r
start_time_pocket <- Sys.time()
E_in <- numeric()
E_in_pocket <- numeric()
w <- rep(0, 10)
w_pocket <- w
E_in <- c(E_in, mean(D_trans$y != h_trans(D_trans, w)))
E_in_pocket <- E_in
for (iter in 1:100000) {
  D_mis <- subset(D_trans, y != h_trans(D_trans, w))
  if (nrow(D_mis) == 0)
    break
  xt <- D_mis[sample(nrow(D_mis), 1), ]
  w <- w + c(1, as.numeric(xt[1:9])) * xt$y
  E_in <- c(E_in, mean(D_trans$y != h_trans(D_trans, w)))
  if (E_in[length(E_in)] < E_in_pocket[length(E_in_pocket)]) {
    w_pocket <- w
  }
  E_in_pocket <- c(E_in_pocket, mean(D_trans$y != h_trans(D_trans, w_pocket)))
}
end_time_pocket <- Sys.time()
ggplot(data.frame(t = 1:100000, E_in = E_in_pocket[-1]), aes(x = t, y = E_in)) +
  geom_line(col = "red") +
  coord_cartesian(xlim = c(1, 200))
```



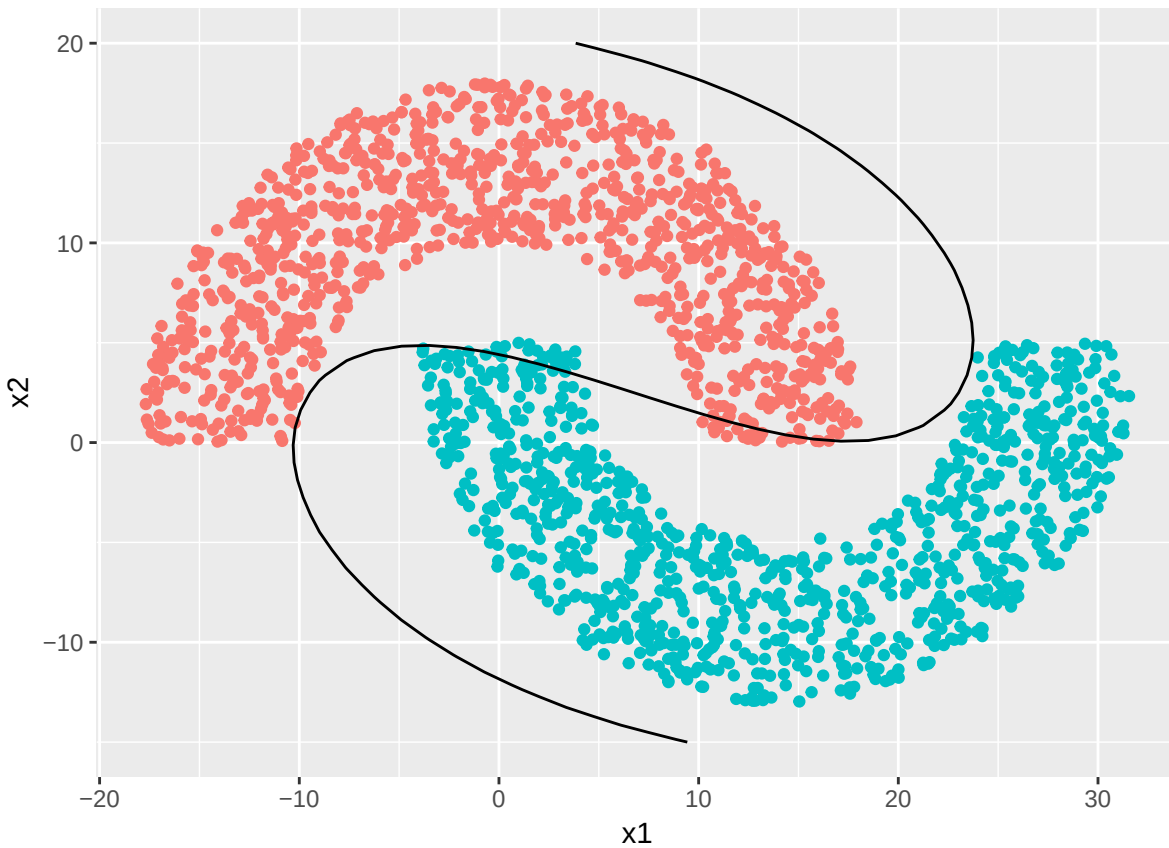
Then, we plot the data and the final hypothesis obtained above.

```r
cc <- emdbook::curve3d(1 * w_pocket[1] + x * w_pocket[2] + y * w_pocket[3] + x^2 * w_pocket[4] +
                         x * y * w_pocket[5] + y^2 * w_pocket[6] + x^3 * w_pocket[7] +
                         x^2 * y * w_pocket[8] + x * y^2 * w_pocket[9] + y^3 * w_pocket[10],
                       xlim = c(-20, 35), ylim = c(-15, 20), sys3d = "none")
dimnames(cc$z) <- list(cc$x, cc$y)
mm <- reshape2::melt(cc$z)
p + geom_contour(data = mm, aes(x = Var1, y = Var2, z = value), breaks = 0, colour = "black")
```



Finally, we use the linear regression algorithm to obtain the weights w.

```
start_time_lin <- Sys.time()
X <- as.matrix(cbind(1, D_trans[, 1:9]))
y <- D_trans$y
X_cross <- solve(t(X) %*% X) %*% t(X)
w_lin <- as.vector(X_cross %*% y)
E_in_lin <- mean(D_trans$y != h_trans(D_trans, w_lin))
end_time_lin <- Sys.time()
cc <- emdbook::curve3d(1 * w_lin[1] + x * w_lin[2] + y * w_lin[3] + x^2 * w_lin[4] +
                         x * y * w_lin[5] + y^2 * w_lin[6] + x^3 * w_lin[7] +
                         x^2 * y * w_lin[8] + x * y^2 * w_lin[9] + y^3 * w_lin[10],
                       xlim = c(-20, 35), ylim = c(-15, 20), sys3d = "none")
dimnames(cc$z) <- list(cc$x, cc$y)
mm <- reshape2::melt(cc$z)
p + geom_contour(data = mm, aes(x = Var1, y = Var2, z = value), breaks = 0, colour = "black")
```



For the pocket algorithm (with 100000 iterations), we have a computation time of 2.7625689, and for the linear regression algorithm, we have a computation time of 0.0071368. The linear regression algorithm is once again clearly better than the pocket algorithm in terms of computation time. When we take into account the quality of the solution, the pocket algorithm has a (final) E_{in} of 0.0445, and the linear regression algorithm has a E_{in} of 0.021. In this case, regarding the quality of the solution, the linear regression algorithm is also better than the pocket algorithm.

Problem 3.4

(a) We can write $e_n(w)$ as a piecewise function

$$e_n(w) = \begin{cases} 0 & \text{si} \quad y_n w^T x_n > 1 \\ (1 - y_n w^T x_n)^2 & \text{si} \quad y_n w^T x_n < 1 \end{cases} ;$$

and this function is actually continuous as we have

$$\lim_{w: y_n w^T x_n \to 1^{\pm}} e_n(w) = 0.$$

This function is also differentiable, to see this we note that

$$\nabla e_n(w) = \begin{cases} 0 & \text{si} \quad y_n w^T x_n > 1 \\ -2y_n(1 - y_n w^T x_n)x_n & \text{si} \quad y_n w^T x_n < 1 \end{cases} ,$$

and

$$\lim_{w: y_n w^T x_n \to 1^{\pm}} \nabla e_n(w) = 0.$$

(b) Let us consider first the case where $\text{sign}(w^T x_n) \neq y_n$, which means that $y_n w^T x_n \leq 0 < 1$. In this case, we have $[[\text{sign}(w^T x_n) \neq y_n]] = 1$ and $e_n(w) = (1 - y_n w^T x_n)^2 \geq 1$, consequently

$$[[\text{sign}(w^T x_n) \neq y_n]] \leq e_n(w).$$

Now we consider the second case where $\text{sign}(w^T x_n) = y_n$, which means that $y_n w^T x_n \geq 0$. In this case, we have $[[\text{sign}(w^T x_n) \neq y_n]] = 0$, $e_n(w) = (1 - y_n w^T x_n)^2 \geq 0$ if $0 \leq y_n w^T x_n < 1$ and $e_n(w) = 0$ if $y_n w^T x_n \geq 1$; consequently

$$[[\text{sign}(w^T x_n) \neq y_n]] \leq e_n(w).$$

In conclusion, we have that

$$E_{in}(w) = \frac{1}{N} \sum_{n=1}^{N} [[\text{sign}(w^T x_n) \neq y_n]] \leq \frac{1}{N} \sum_{n=1}^{N} e_n(w).$$

(c) If we apply SGD to our upper bound above, we get the following algorithm.

1. Select an initial w.
2. Repeat until CONDITION :
   Select (x_n, y_n) randomly and let $s_n = w^T x_n$. If $y_n s_n = y_n w^T x_n \leq 1$, we have

   $$\nabla e_n(w) = -2y_n(1 - y_n s_n)x_n,$$

   and we update w as

   $$w \leftarrow w - \eta \nabla e_n(w) = w + 2\eta y_n(1 - y_n s_n)x_n = w + 2\eta(y_n - s_n)x_n = w + \eta'(y_n - s_n)x_n.$$

   And if $y_n s_n = y_n w^T x_n > 1$, we have $\nabla e_n(w) = 0$, and we update w as

   $$w \leftarrow w - \eta \nabla e_n(w) = w - \eta \cdot 0 = w.$$

Which is exactly the Adaline algorithm.

Problem 3.5

(a) We can write $e_n(w)$ as a piecewise function

$$e_n(w) = \begin{cases} 0 & \text{si} \quad y_n w^T x_n > 1 \\ 1 - y_n w^T x_n & \text{si} \quad y_n w^T x_n < 1 \end{cases};$$

and this function is actually continuous everywhere as we have

$$\lim_{w: y_n w^T x_n \to 1^{\pm}} e_n(w) = 0.$$

However, this function is not differentiable everywhere, to see this we note that

$$\nabla e_n(w) = \begin{cases} 0 & \text{si} \quad y_n w^T x_n > 1 \\ -y_n x_n & \text{si} \quad y_n w^T x_n < 1 \end{cases};$$

moreover

$$\lim_{w: y_n w^T x_n \to 1^+} \nabla e_n(w) = 0 \text{ and } \lim_{w: y_n w^T x_n \to 1^-} \nabla e_n(w) = -y_n x_n \neq 0.$$

Thus, the function $e_n(w)$ is differentiable everywhere except when $y_n w^T x_n = 1$ ($\Leftrightarrow y_n = w^T x_n$).

(b) Let us consider first the case where $\text{sign}(w^T x_n) \neq y_n$, which means that $y_n w^T x_n \leq 0 < 1$. In this case, we have $[[\text{sign}(w^T x_n) \neq y_n]] = 1$ and $e_n(w) = 1 - y_n w^T x_n \geq 1$, consequently

$$[[\text{sign}(w^T x_n) \neq y_n]] \leq e_n(w).$$

Now we consider the second case where $\text{sign}(w^T x_n) = y_n$, which means that $y_n w^T x_n \geq 0$. In this case, we have $[[\text{sign}(w^T x_n) \neq y_n]] = 0$, $e_n(w) = 1 - y_n w^T x_n \geq 0$ if $0 \leq y_n w^T x_n < 1$ and $e_n(w) = 0$ if $y_n w^T x_n \geq 1$; consequently

$$[[\text{sign}(w^T x_n) \neq y_n]] \leq e_n(w).$$

In conclusion, we have that

$$E_{in}(w) = \frac{1}{N} \sum_{n=1}^{N} [[\text{sign}(w^T x_n) \neq y_n]] \leq \frac{1}{N} \sum_{n=1}^{N} e_n(w).$$

(c) If we apply SGD to our upper bound above, we get the following algorithm.

1. Select an initial w.
2. Repeat until CONDITION :
   Select (x_n, y_n) randomly. If $y_n w^T x_n < 1$, we have

   $$\nabla e_n(w) = -y_n x_n,$$

   and we update w as

   $$w \leftarrow w - \eta \nabla e_n(w) = w + \eta y_n x_n.$$

   And if $y_n s_n = y_n w^T x_n > 1$, we have $\nabla e_n(w) = 0$, and we update w as

   $$w \leftarrow w - \eta \nabla e_n(w) = w - \eta \cdot 0 = w.$$

Which is a new perceptron learning algorithm.

Problem 3.6

(a) For linearly separable data, we obviously have that there exists w^* so that $y_n (w^*)^T x_n > 0$ for all $n = 1, \cdots, N$. By the density property of the real numbers, we know that we may find $\epsilon > 0$ so that $y_n (w^*)^T x_n \geq \epsilon$ for all $n = 1, \cdots, N$, and consequently if we let $w = w^*/\epsilon$, we get

$$y_n w^T x_n \geq 1$$

for all $n = 1, \cdots, N$.

(b) The task of finding w for separable data may be formulated as the following linear program

$$\begin{cases} \min_w & c^T w \\ \text{subject to} & Aw \leq b \end{cases}$$

where $c^T = (0, \cdots, 0)$, $b^T = (-1, \cdots, -1)$, and

$$A = -\begin{pmatrix} - & y_1 x_1^T & - \\ \vdots & \vdots & \vdots \\ - & y_N x_N^T & - \end{pmatrix} (N \times (d+1)).$$

(c) When the data is not separable, the minimization problem may be formulated as a linear program as follows

$$\begin{cases} \min_{(w,\xi)} & c^T (w, \xi)^T \\ \text{subject to} & A(w, \xi)^T \leq b \end{cases}$$

where $c^T = (0, \cdots, 0, 1, \cdots, 1)$, $b^T = (-1, \cdots, -1, 0, \cdots, 0)$, and

$$A = -\left(\begin{array}{ccc|ccc} - & y_1 x_1^T & - & 1 & & \\ \vdots & \vdots & \vdots & & \ddots & \\ - & y_N x_N^T & - & & & 1 \\ \hline 0 & \cdots & 0 & 1 & & \\ \vdots & \vdots & \vdots & & \ddots & \\ 0 & \cdots & 0 & & & 1 \end{array}\right) (2N \times (d+1+N)).$$

(d) In Problem 3.5, we sought to minimize the expression

$$\frac{1}{N} \sum_{n=1}^{N} e_n(w)$$

with

$$e_n(w) = \begin{cases} 0 & \text{si} \quad y_n w^T x_n > 1 \\ 1 - y_n w^T x_n & \text{si} \quad y_n w^T x_n < 1 \end{cases}.$$

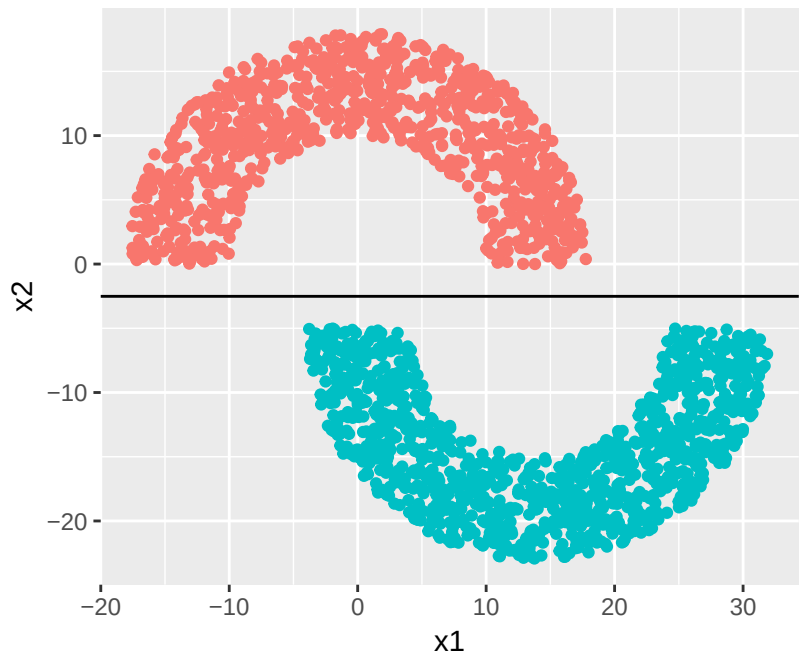
If we take a look at $e_n(w)$, we may note that when x_n is correctly classified by w and at least at a margin of one of the linear separator ($y_n w^T x_n \geq 1$), we get $e_n(w) = 0$ which means that in this case this term does not contribute to the overall error. However, when x_n is in the margin of one, the deeper x_n is into the margin of one, the higher the term $e_n(w) = 1 - y_n w^T x_n$ contributes to the overall error. For example, if x_n is correctly classified by w but into the margin of one ($0 < y_n w^T x_n < 1$), then the error term for this point is $0 < e_n(w) < 1$; and if x_n is not correctly classified by w ($y_n w^T x_n < 0$), then the error term for this point is $e_n(w) > 1$. In conclusion, the overall error characterizes the amount of violation of the margin, which is exactly what we seek to minimize in point (c) above.

Problem 3.7

First, we use the linear programming algorithm from Problem 3.6 on the learning task in Problem 3.1 for the separable case.

```
set.seed(10)

rad <- 10
thk <- 8
sep <- 5
D <- init_data(2000, rad, thk, sep)

p <- ggplot(D, aes(x = x1, y = x2, col = as.factor(y + 3))) + geom_point() +
  theme(legend.position = "none") +
  coord_fixed()

d <- 2
N <- nrow(D)
c_T <- rep(0, d + 1)
b_T <- rep(-1, N)
A <- -diag(D$y) %*% as.matrix(cbind(1, D[, 1:2]))
dir <- rep("<=", N)
linear_prog <- lp("min", c(c_T, -c_T), cbind(A, -A), const.dir = dir, const.rhs = b_T)
w <- linear_prog$solution[1:(d+1)] - linear_prog$solution[(d+2):(2 * (d + 1))]

X <- as.matrix(cbind(1, D[, c("x1", "x2")]))
```

```
y <- D$y
X_cross <- solve(t(X) %*% X) %*% t(X)
w_lin <- as.vector(X_cross %*% y)

D_trans <- data.frame(x1 = D$x1, x2 = D$x2,
                      x1_sq = D$x1^2, x1x2 = D$x1 * D$x2, x2_sq = D$x2^2,
                      x1_cub = D$x1^3, x1_sqx2 = D$x1^2 * D$ x2,
                      x1x2_sq = D$x1 * D$x2^2, x2_cub = D$x2^3, y = D$y)
X <- as.matrix(cbind(1, D_trans[, 1:9]))
y <- D_trans$y
X_cross <- solve(t(X) %*% X) %*% t(X)
w_pol <- as.vector(X_cross %*% y)

p + geom_abline(slope = -w[2] / w[3], intercept = -w[1] / w[3])
```

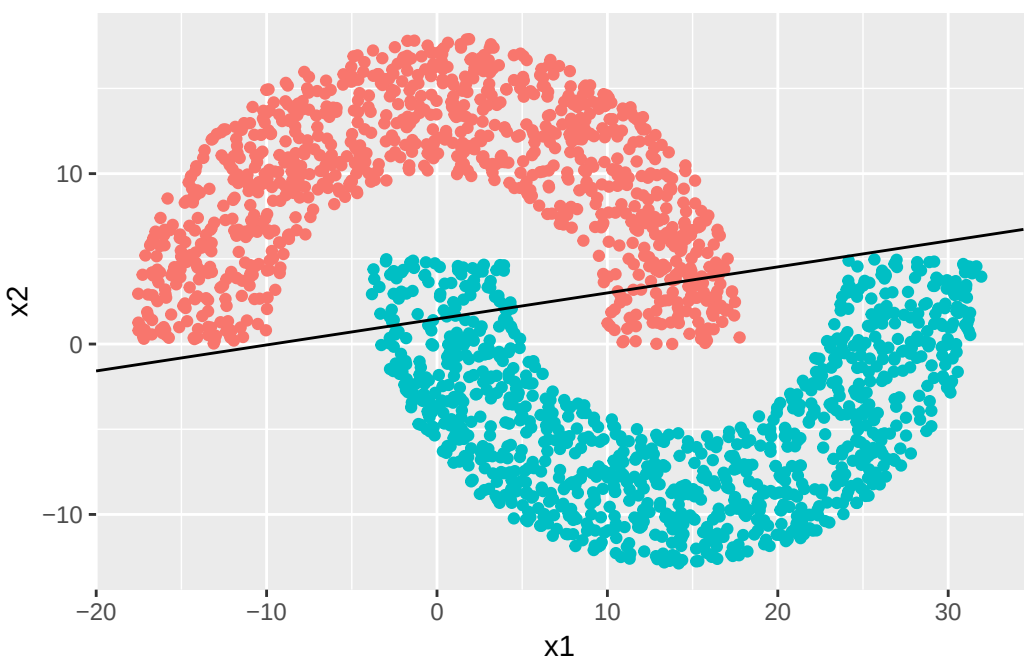


As we may see, our linear programming algorithm solution perfectly separates the dataset so we have an E_{in} of 0; the linear regression approach gives us an E_{in} of 0, and the 3rd order polynomial feature transform gives us an E_{in} of 0 as well.

Now, we use the linear programming algorithm from Problem 3.6 on the learning task in Problem 3.1 for the non separable case.

```
set.seed(10)

rad <- 10
thk <- 8
sep <- -5
D <- init_data(2000, rad, thk, sep)

p <- ggplot(D, aes(x = x1, y = x2, col = as.factor(y + 3))) + geom_point() +
  theme(legend.position = "none") +
  coord_fixed()

d <- 2
```

```r
N <- nrow(D)
c_T <- c(rep(0, d + 1), rep(1, N))
b_T <- c(rep(-1, N), rep(0, N))
A1 <- rbind(diag(D$y) %*% as.matrix(cbind(1, D[, 1:2])), matrix(0, nrow = N, ncol = d + 1))
A2 <- rbind(diag(1, nrow = N, ncol = N), diag(1, nrow = N, ncol = N))
A <- -cbind(A1, A2)
dir <- rep("<=", 2 * N)
linear_prog <- lp("min", c(c_T, -c_T), cbind(A, -A), const.dir = dir, const.rhs = b_T)
w <- linear_prog$solution[1:(d + 1 + N)] - linear_prog$solution[(d + 1 + N + 1):(2 * (d + 1 + N))]

X <- as.matrix(cbind(1, D[, c("x1", "x2")]))
y <- D$y
X_cross <- solve(t(X) %*% X) %*% t(X)
w_lin <- as.vector(X_cross %*% y)

D_trans <- data.frame(x1 = D$x1, x2 = D$x2,
                      x1_sq = D$x1^2, x1x2 = D$x1 * D$x2, x2_sq = D$x2^2,
                      x1_cub = D$x1^3, x1_sqx2 = D$x1^2 * D$ x2,
                      x1x2_sq = D$x1 * D$x2^2, x2_cub = D$x2^3, y = D$y)
X <- as.matrix(cbind(1, D_trans[, 1:9]))
y <- D_trans$y
X_cross <- solve(t(X) %*% X) %*% t(X)
w_pol <- as.vector(X_cross %*% y)

p + geom_abline(slope = -w[2] / w[3], intercept = -w[1] / w[3])
```



Here, our linear programming algorithm solution gives us an E_{in} of 0.072; the linear regression approach gives us an E_{in} of 0.0855, and the 3rd order polynomial feature transform gives us an E_{in} of 0.0205 which is the best of the three approaches.

Problem 3.8

First, we will show that $h^*(x) = \mathbb{E}_{y|x}[y|x]$ minimizes the E_{out} expression. For any hypothesis h, we have that

$$\begin{aligned}
E_{out}(h) &= \mathbb{E}_{(x,y)}[(h(x)-y)^2] \\
&= \mathbb{E}_{(x,y)}[((h(x)-h^*(x))+(h^*(x)-y))^2] \\
&= \mathbb{E}_{(x,y)}[(h(x)-h^*(x))^2] + 2\underbrace{\mathbb{E}_{(x,y)}[(h(x)-h^*(x))(h^*(x)-y)]}_{(*)} + \mathbb{E}_{(x,y)}[(h^*(x)-y)^2].
\end{aligned}$$

Let us examine the $(*)$ term more closely, we have

$$\begin{aligned}
(*) &= \mathbb{E}_x[\mathbb{E}_{y|x}[(h(x)-h^*(x))(h^*(x)-y)|x]] \\
&= \mathbb{E}_x[(h(x)-h^*(x))\mathbb{E}_{y|x}[(h^*(x)-y)|x]] \\
&= \mathbb{E}_x[(h(x)-h^*(x))(\mathbb{E}_{y|x}[h^*(x)|x]-\mathbb{E}_{y|x}[y|x])] \\
&= \mathbb{E}_x[(h(x)-h^*(x))(h^*(x)-h^*(x))] = 0.
\end{aligned}$$

So, we may write that

$$E_{out}(h) = \mathbb{E}_{(x,y)}[(h(x)-y)^2] = \mathbb{E}_{(x,y)}[(h(x)-h^*(x))^2] + \mathbb{E}_{(x,y)}[(h^*(x)-y)^2] \geq \mathbb{E}_{(x,y)}[(h^*(x)-y)^2]$$

for any hypothesis h, which means that $h^*(x)$ is actually the one hypothesis that minimizes E_{out}.

Now, it is obvious that we are able to write that

$$y = h^*(x) + (y - h^*(x)) = h^*(x) + \epsilon(x)$$

if we let $\epsilon(x) = y - h^*(x)$. Moreover, we immediately get that

$$\mathbb{E}_{y|x}[\epsilon(x)|x] = \mathbb{E}_{y|x}[y|x] - \mathbb{E}_{y|x}[h^*(x)|x] = h^*(x) - h^*(x) = 0.$$

Problem 3.9

Let us expand the expression $(*)$ to consider, we get

$$\begin{aligned}
(*) &= \frac{1}{N}[(w-(X^TX)^{-1}X^Ty)^T(X^TX)(w-(X^TX)^{-1}X^Ty) + y^T(1-X(X^TX)^{-1}X^T)y] \\
&= \frac{1}{N}[(w^T - y^TX(X^TX)^{-1})(X^TX)(w-(X^TX)^{-1}X^Ty) + y^Ty - y^TX(X^TX)^{-1}X^Ty] \\
&= \frac{1}{N}[w^T(X^TX)w - 2w^TX^Ty + y^Ty] = E_{in}(w).
\end{aligned}$$

So, we may write that

$$E_{in}(w) = \frac{1}{N}[(w-(X^TX)^{-1}X^Ty)^T(X^TX)(w-(X^TX)^{-1}X^Ty) + y^T(1-H)y] \geq \frac{1}{N}[y^T(1-H)y],$$

as X^TX is positive definite (which implies that $x^T(X^TX)x > 0$ for any $x \neq 0$). So, the minimum value for E_{in} is $\frac{1}{N}[y^T(1-H)y]$ which is attained when

$$w = (X^TX)^{-1}X^Ty = w_{lin}.$$

Problem 3.10

(a) First, we note that H is idempotent as

$$H^2 = X(X^TX)^{-1}X^TX(X^TX)^{-1}X^T = X(X^TX)^{-1}X^T = H.$$

Then, if we let v be an eigenvector of H of eigenvalue λ, we get that

$$H^2v = Hv = \lambda v$$

and also that

$$H^2v = H(Hv) = \lambda Hv = \lambda^2 v.$$

Which means that

$$(\lambda^2 - \lambda)v = 0,$$

or more simply put that $\lambda^2 - \lambda = 0$ (as $v \neq 0$), which means that either $\lambda = 0$ or $\lambda = 1$.

(b) Let $A(N \times N)$ be a symmetric matrix, in this case A is diagonalizable which means that it exists an invertible matrix V (whose columns are the eigenvectors of A) such that

$$V^{-1}AV = \text{diag}(\lambda_1, \cdots, \lambda_N) = D$$

where λ_i are the eigenvalues of A. Now, we may write that

$$\text{trace}(V^{-1}AV) = \text{trace}(D) = \sum_i \lambda_i$$

and also that

$$\text{trace}(V^{-1}AV) = \text{trace}(AVV^{-1}) = \text{trace}(A)$$

by the cyclic property of the trace. In conclusion, we get that $\text{trace}(A) = \sum_i \lambda_i$.

(c) It is easy to see that H is a symmetric matrix ($H^T = H$), so by (b) above, we get that $\text{trace}(H)$ is equal to the sum of its eigenvalues. However, once again by the cyclic proprty of the trace, we get that

$$\text{trace}(H) = \text{trace}(X(X^TX)^{-1}X^T) = \text{trace}(X^TX(X^TX)^{-1}) = \text{trace}(I_{d+1}) = d + 1.$$

This means that $d + 1$ eigenvalues are equal to 1. As H is symmetric, it is also diagonalizable, so there exists an invertible matrix V (whose columns are the eigenvectors of H) and a diagonal matrix D (whose elements are the eigenvalues of H) such that

$$\text{rank}(H) = \text{rank}(VDV^{-1}) = \text{rank}(DV^{-1}) = \text{rank}(D)$$

as V and V^{-1} are of maximum rank. As the rank of D is the number of eigenvalues not equal to 0, we finally get that

$$\text{rank}(H) = \text{trace}(H) = d + 1.$$

Problem 3.11

(a) Let x_0 be a test point, we may write the error at x_0 as

$$\begin{aligned}
\text{Err}(x_0) &= y_0 - g(x_0) = y_0 - x_0^T w_{lin} \\
&= y_0 - x_0^T(X^TX)^{-1}X^Ty = y_0 - x_0^T(X^TX)^{-1}X^T(Xw^* + \epsilon) \\
&= x_0^Tw^* + \epsilon_0 - x_0^T(X^TX)^{-1}X^TXw^* - x_0^T(X^TX)^{-1}X^T\epsilon \\
&= \epsilon_0 - x_0^T(X^TX)^{-1}X^T\epsilon.
\end{aligned}$$

(b) By taking the expectation with respect to x_0 and ϵ_0, we get the following expression for E_{out}. We have

$$\begin{aligned}
E_{out}(g) &= \mathbb{E}_{(x_0,\epsilon_0)}[(y_0 - g(x_0))^2] \\
&= \mathbb{E}_{(x_0,\epsilon_0)}[(\epsilon_0 - x_0^T(X^TX)^{-1}X^T\epsilon)^T(\epsilon_0 - x_0^T(X^TX)^{-1}X^T\epsilon)] \\
&= \mathbb{E}_{(x_0,\epsilon_0)}[\epsilon_0^T\epsilon_0 - 2\epsilon^TX(X^TX)^{-1}x_0\epsilon_0 + \epsilon^TX(X^TX)^{-1}x_0x_0^T(X^TX)^{-1}X^T\epsilon] \\
&= \underbrace{\mathbb{E}_{(x_0,\epsilon_0)}[\epsilon_0^2]}_{(1)} - 2\underbrace{\mathbb{E}_{(x_0,\epsilon_0)}[\epsilon^TX(X^TX)^{-1}x_0\epsilon_0]}_{(2)} + \underbrace{\mathbb{E}_{(x_0,\epsilon_0)}[\epsilon^TX(X^TX)^{-1}x_0x_0^T(X^TX)^{-1}X^T\epsilon]}_{(3)}.
\end{aligned}$$

Let us examine the expression (1) more closely, we get that

$$(1) = \mathbb{E}_{(x_0,\epsilon_0)}[\epsilon_0^2] = \mathbb{E}_{x_0}[\mathbb{E}_{\epsilon_0|x_0}[\epsilon_0^2|x_0]] = \mathbb{E}_{x_0}[\mathbb{E}_{\epsilon_0}[\epsilon_0^2]] = \mathbb{E}_{\epsilon_0}[\epsilon_0^2] = \mathrm{Var}(\epsilon_0) = \sigma^2.$$

If we do the same for the expression (2), we now get that

$$\begin{aligned}
(2) &= \mathbb{E}_{x_0}[\mathbb{E}_{\epsilon_0|x_0}[\epsilon^TX(X^TX)^{-1}x_0\epsilon_0|x_0]] \\
&= \mathbb{E}_{x_0}[\epsilon^TX(X^TX)^{-1}x_0\mathbb{E}_{\epsilon_0|x_0}[\epsilon_0|x_0]] \\
&= \mathbb{E}_{x_0}[\epsilon^TX(X^TX)^{-1}x_0\mathbb{E}_{\epsilon_0}[\epsilon_0]] \\
&= 0.
\end{aligned}$$

Finally, we do the same for the expression (3), first, we note that

$$\mathrm{trace}(\epsilon^TX(X^TX)^{-1}x_0x_0^T(X^TX)^{-1}X^T\epsilon) = \mathrm{trace}(x_0x_0^T(X^TX)^{-1}X^T\epsilon\epsilon^TX(X^TX)^{-1})$$

by the cyclic property of the trace. Then we get that

$$\begin{aligned}
(3) &= \mathbb{E}_{(x_0,\epsilon_0)}[\mathrm{trace}(\epsilon^TX(X^TX)^{-1}x_0x_0^T(X^TX)^{-1}X^T\epsilon)] \\
&= \mathrm{trace}(\mathbb{E}_{(x_0,\epsilon_0)}[x_0x_0^T(X^TX)^{-1}X^T\epsilon\epsilon^TX(X^TX)^{-1}]) \\
&= \mathrm{trace}(\mathbb{E}_{x_0}[x_0x_0^T](X^TX)^{-1}X^T\epsilon\epsilon^TX(X^TX)^{-1}) \\
&= \mathrm{trace}(\Sigma(X^TX)^{-1}X^T\epsilon\epsilon^TX(X^TX)^{-1}).
\end{aligned}$$

In conclusion, we have

$$E_{out}(g) = \sigma^2 + \mathrm{trace}(\Sigma(X^TX)^{-1}X^T\epsilon\epsilon^TX(X^TX)^{-1}).$$

(c) We have that

$$\mathbb{E}_\epsilon[\epsilon\epsilon^T] = \mathbb{E}_\epsilon\left[\begin{pmatrix} \epsilon_1^2 & \epsilon_1\epsilon_2 & \cdots & \epsilon_1\epsilon_N \\ \vdots & \vdots & \cdots & \vdots \\ \epsilon_N\epsilon_1 & \epsilon_N\epsilon_2 & \cdots & \epsilon_N^2 \end{pmatrix}\right] = \begin{pmatrix} \sigma^2 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \sigma^2 \end{pmatrix} = \mathrm{diag}(\sigma^2, \cdots, \sigma^2).$$

(d) If we take the expectation of E_{out} with respect to ϵ, we get

$$\begin{aligned}
\mathbb{E}_\epsilon[E_{out}(g)] &= \sigma^2 + \mathbb{E}_\epsilon[\mathrm{trace}(\Sigma(X^TX)^{-1}X^T\epsilon\epsilon^TX(X^TX)^{-1})] \\
&= \sigma^2 + \mathrm{trace}(\Sigma(X^TX)^{-1}X^T\mathbb{E}_\epsilon[\epsilon\epsilon^T]X(X^TX)^{-1}) \\
&= \sigma^2 + \mathrm{trace}(\Sigma(X^TX)^{-1}X^T\mathrm{diag}(\sigma^2, \cdots, \sigma^2)X(X^TX)^{-1}) \\
&= \sigma^2 + \sigma^2\mathrm{trace}(\Sigma(X^TX)^{-1}) \\
&= \sigma^2 + \frac{\sigma^2}{N}\mathrm{trace}(\Sigma(\frac{1}{N}X^TX)^{-1}).
\end{aligned}$$

Moreover, if $\frac{1}{N}X^TX = \Sigma$, we get that

$$\mathbb{E}_\epsilon[E_{out}(g)] = \sigma^2 + \frac{\sigma^2}{N}\text{trace}(\Sigma\Sigma^{-1}) = \sigma^2\left(1 + \frac{d+1}{N}\right).$$

(e) As the matrix $\frac{1}{N}X^TX$ is the maximum likelihood estimator of Σ, we know that $\frac{1}{N}X^TX \to \Sigma$ in probability. Moreover, by the continuity of the inverse and of the trace functions, we also have that

$$x_N = \text{trace}(\Sigma(\frac{1}{N}X^TX)^{-1}) \to \text{trace}(I_{d+1}) = d+1$$

in probability. This means that with high probability, we have $|x_N - (d+1)| \leq \eta$ for any $\eta > 0$ provided N is big enough; in this case, we also have that

$$\left|\mathbb{E}_\epsilon[E_{out}(g)] - (\sigma^2 + \frac{\sigma^2}{N}(d+1))\right| = \left|(\sigma^2 + \frac{\sigma^2}{N}x_N) - (\sigma^2 + \frac{\sigma^2}{N}(d+1))\right| \leq \frac{\sigma^2}{N}\eta.$$

Thus, we are now able to write that

$$\mathbb{E}_\epsilon[E_{out}(g)] = \sigma^2\left(1 + \frac{d+1}{N} + o(\frac{1}{N})\right)$$

with high probability.

Problem 3.12

We have already proven that H is a symmetric and indempotent matrix, which makes it a projection matrix by definition. We may write that

$$\hat{y} = Hy = X[(X^TX)^{-1}X^Ty] \in \text{span}(X)$$

where $\text{span}(X)$ is the subspace generated by the columns of X. So, $\hat{y}$ is the projection of y onto the subspace generated by the columns of X.

Problem 3.13

(a) For the linear regression problem, we need $d+1$ weights, and in the classification problem we need $d+2$ weights (and also $2N$ violations in the non separable case).

(b) To solve this problem, we first consider the case where $d = 1$. The weights w obtained from the linear fit give us the hypothesis

$$h(x) = w_0 + w_1x,$$

and the weights w_{class} obtained from the classification problem give us the hypothesis

$$h'(x) = w_0^{class} + w_1^{class}x + w_2^{class}y.$$

The equation of the regression line is

$$y = w_0 + w_1x$$

in the first case, and in the second case

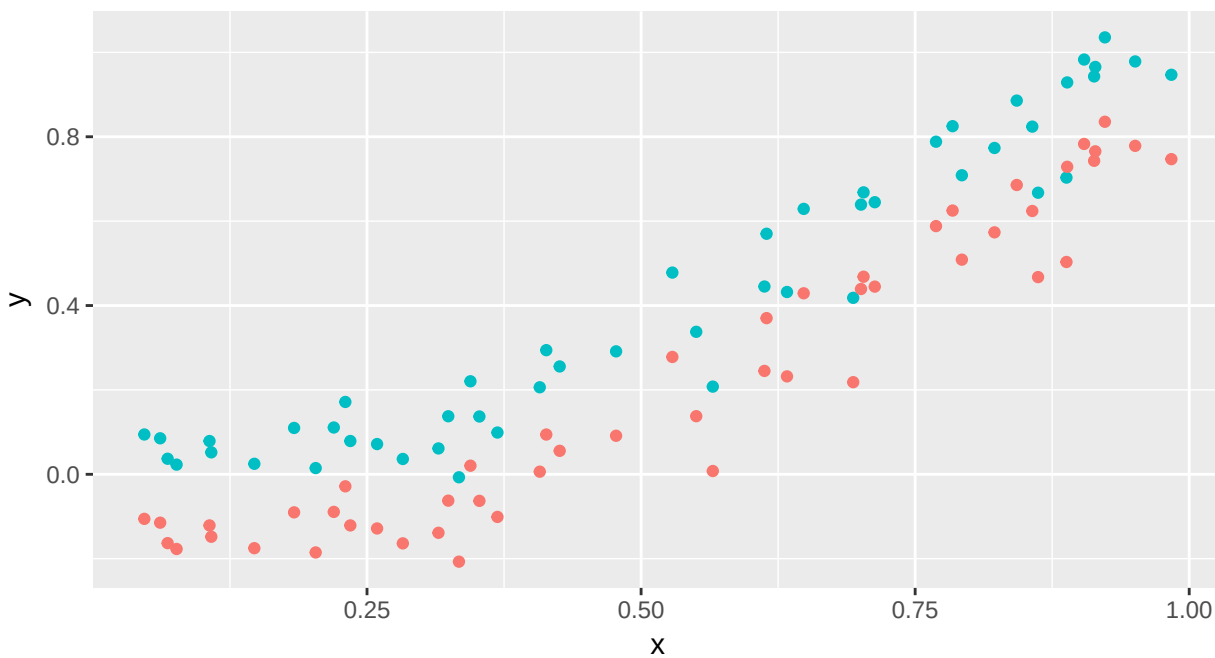
$$y = -w_0^{class}/w_2^{class} - w_1^{class}/w_2^{class}x.$$

We will now apply these results to the general case, we may write that

$$w = \left(-\frac{w_0^{class}}{w_{d+1}^{class}}, \cdots, -\frac{w_d^{class}}{w_{d+1}^{class}} \right).$$

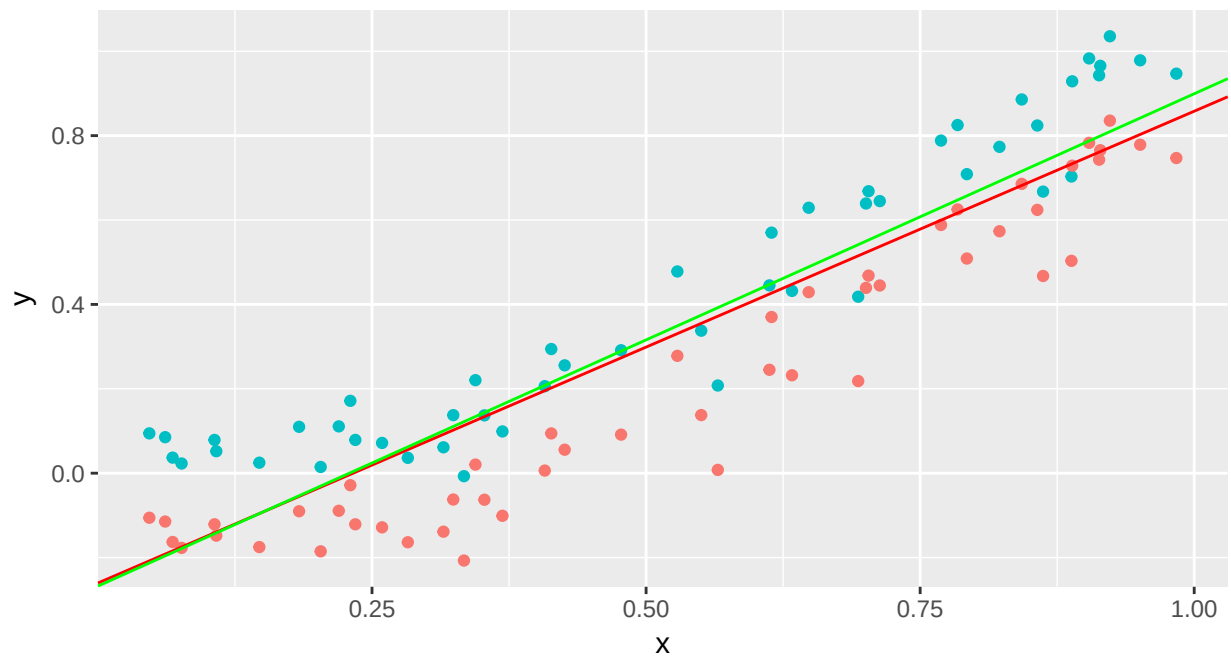
(c) We generate a data set $y_n = x_n^2 + \sigma\epsilon_n$ with $N = 50$, where x_n is uniform on $[0, 1]$ and ϵ_n is a zero mean Gaussian noise (with $\sigma = 0.1$). Below, we plot the positive and negative points $\mathcal{D}_+$ and $\mathcal{D}_-$ for $a = (0, 0.1)^T$.

```
set.seed(10)

N <- 50
sigma <- 0.1
epsilon <- rnorm(N, 0, 1)
xn <- runif(N, 0, 1)
yn <- xn^2 + sigma * epsilon
a <- c(0, 0.1)

D <- data.frame(x = xn, y = yn)
D_plus <- D + data.frame(ax = rep(a[1], N), ay = rep(a[2], N))
D_plus <- cbind(D_plus, class = +1)
D_minus <- D - data.frame(ax = rep(a[1], N), ay = rep(a[2], N))
D_minus <- cbind(D_minus, class = -1)

p <- ggplot(NULL, aes(x = x, y = y, col = as.factor(class + 3))) +
  geom_point(data = D_plus) +
  geom_point(data = D_minus) +
  theme(legend.position = "none")
p
```



(d) Here, we compare the resulting fits from running the classification approach and the analytic pseudo-inverse algorithm for linear regression. To do this, we first plot the two lines generated by the classification approach (in green) and by the linear regression algorithm (in red).

```r
D_union <- rbind(D_plus, D_minus)

d <- 2
N <- nrow(D_union)
c_T <- c(rep(0, d + 1), rep(1, N))
b_T <- c(rep(-1, N), rep(0, N))
A1 <- rbind(diag(D_union$class) %*%
              as.matrix(cbind(1, D_union[, 1:2])), matrix(0, nrow = N, ncol = d + 1))
A2 <- rbind(diag(1, nrow = N, ncol = N), diag(1, nrow = N, ncol = N))
A <- -cbind(A1, A2)
dir <- rep("<=", 2 * N)
linear_prog <- lp("min", c(c_T, -c_T), cbind(A, -A), const.dir = dir, const.rhs = b_T)
w <- linear_prog$solution[1:(d + 1 + N)] - linear_prog$solution[(d + 1 + N + 1):(2 * (d + 1 + N))]

X <- as.matrix(cbind(1, D[, c("x")]))
y <- D$y
X_cross <- solve(t(X) %*% X) %*% t(X)
w_lin <- as.vector(X_cross %*% y)

ggplot(D_union, aes(x = x, y = y, col = as.factor(class + 3))) +
  geom_point() +
  geom_abline(slope = w_lin[2], intercept = w_lin[1], col = "red") +
  geom_abline(slope = -w[2] / w[3], intercept = -w[1] / w[3], col = "green") +
  theme(legend.position = "none")
```



Here, our linear programming algorithm solution gives us an E_{in} of 0.0118877; the linear regression approach gives us an E_{in} of 0.0113588. These two results are very close to each other.

Problem 3.14

(a) We have that

$$
\begin{aligned}
\overline{g}(x) &= \mathbb{E}_{\mathcal{D}}[g^{(\mathcal{D})}(x)] \\
&= \mathbb{E}_{\mathcal{D}}[x^T w_{lin}] \\
&= \mathbb{E}_X[\mathbb{E}_{y|X}[x^T(X^TX)^{-1}X^Ty|X]] \\
&= \mathbb{E}_X[x^T(X^TX)^{-1}X^T \underbrace{\mathbb{E}_{y|X}[y|X]}_{Xw_f+\mathbb{E}_\epsilon[\epsilon]=Xw_f}] \\
&= \mathbb{E}_X[x^T(X^TX)^{-1}X^TXw_f] \\
&= x^Tw_f = f(x).
\end{aligned}
$$

Moreover, we may write that

$$\text{bias}(x) = [\overline{g}(x) - f(x)]^2 = 0,$$

and consequently bias $= \mathbb{E}_x[\text{bias}(x)] = 0$.

(b) If we examine the variance, we have that

$$
\begin{aligned}
\text{var}(x) &= \mathbb{E}_{\mathcal{D}}[(g^{(\mathcal{D})}(x) - \overline{g}(x))^2] = \mathbb{E}_{\mathcal{D}}[(g^{(\mathcal{D})}(x) - f(x))^2] \\
&= \mathbb{E}_{\mathcal{D}}[g^{(\mathcal{D})}(x)^2] - 2f(x)\mathbb{E}_{\mathcal{D}}[g^{(\mathcal{D})}(x)] + f(x)^2 \\
&= \underbrace{\mathbb{E}_{\mathcal{D}}[g^{(\mathcal{D})}(x)^2]}_{(*)} - f(x)^2.
\end{aligned}
$$

Now, we examine the expression $(*)$ more closely, we may write that

$$
\begin{aligned}
\mathbb{E}_{\mathcal{D}}[g^{(\mathcal{D})}(x)^2] &= \mathbb{E}_{\mathcal{D}}[x^T(X^TX)^{-1}X^Tyy^TX(X^TX)^{-1}x] \\
&= \mathbb{E}_X[x^T(X^TX)^{-1}X^T \underbrace{\mathbb{E}_{y|X}[yy^T|X]}_{Xw_fw_f^TX^T+Xw_f\mathbb{E}_\epsilon[\epsilon^T]+\mathbb{E}_\epsilon[\epsilon]w_f^TX^T+\mathbb{E}_\epsilon[\epsilon\epsilon^T]=Xw_fw_f^TX^T+\text{diag}(\sigma^2,\cdots,\sigma^2)} X(X^TX)^{-1}x] \\
&= x^Tw_fw_f^Tx + \sigma^2x^T\mathbb{E}_X[(X^TX)^{-1}]x \\
&= f(x)^2 + \sigma^2x^T\mathbb{E}_X[(X^TX)^{-1}]x,
\end{aligned}
$$

and so we get

$$\text{var}(x) = \sigma^2x^T\mathbb{E}_X[(X^TX)^{-1}]x.$$

And finally, we have that

$$
\begin{aligned}
\text{var} &= \sigma^2\mathbb{E}_x[x^T\mathbb{E}_X[(X^TX)^{-1}]x] \\
&= \sigma^2\text{trace}(\mathbb{E}_x[x^T\mathbb{E}_X[(X^TX)^{-1}]x]) \\
&= \sigma^2\mathbb{E}_x[\text{trace}(x^T\mathbb{E}_X[(X^TX)^{-1}]x)] \\
&= \sigma^2\mathbb{E}_x[\text{trace}(xx^T\mathbb{E}_X[(X^TX)^{-1}])] \\
&= \sigma^2\text{trace}(\mathbb{E}_x[xx^T]\mathbb{E}_X[(X^TX)^{-1}])] \\
&= \frac{\sigma^2}{N}\text{trace}(\Sigma\mathbb{E}_X[(\frac{1}{N}X^TX)^{-1}]).
\end{aligned}
$$

As we saw in Problem 3.11 that $(\frac{1}{N}X^TX)^{-1}$ converges in probability to Σ^{-1}, we may assume that

$$(\frac{1}{N}X^TX)^{-1} \approx \Sigma^{-1}$$

and so that

$$\text{var} \approx \frac{\sigma^2}{N}\text{trace}(\Sigma\Sigma^{-1}) = \frac{\sigma^2(d+1)}{N}.$$

Problem 3.15

(a) We know that $\text{rank}(X^TX) < d+1$ as X^TX is not invertible, this means that we can find an $y \neq 0$ such that $X^TXy = 0$ (as the columns of X^TX are not linearly independant). We may now write that

$$0 = y^TX^TXy = ||Xy||^2,$$

conseqently $Xy = 0$ and $\rho = \text{rank}(X) < d+1$.

(b) If we let

$$w_{lin} = V\Gamma^{-1}U^Ty,$$

we have that

$$\begin{aligned} X^TXw_{lin} &= X^TXV\Gamma^{-1}U^Ty \\ &= V\Gamma U^TU\Gamma V^TV\Gamma^{-1}U^Ty \\ &= V\Gamma U^Ty \\ &= X^Ty. \end{aligned}$$

And so w_{lin} is a solution of the normal equations.

(c) First, we let w be any solution of the normal equations, we write that

$$w = w_{lin} + (w - w_{lin}) = w_{lin} + \delta.$$

As w and w_{lin} are both solutions of the normal equations, we have that

$$\begin{aligned} & X^TX(w - w_{lin}) = X^Ty - X^Ty && = 0 \\ \Rightarrow \quad & V\Gamma U^TU\Gamma V^T(w - w_{lin}) && = 0 \\ \Rightarrow \quad & V\Gamma^2V^T(w - w_{lin}) && = 0 \\ \Rightarrow \quad & \Gamma^{-2}V^TV\Gamma^2V^T(w - w_{lin}) && = 0 \\ \Rightarrow \quad & V^T(w - w_{lin}) && = 0. \end{aligned}$$

We may now see that w_{lin} and $\delta = (w - w_{lin})$ are orthogonal because

$$w_{lin}^T\delta = w_{lin}^T(w - w_{lin}) = y^TU\Gamma^{-1}\underbrace{V^T(w - w_{lin})}_{=0} = 0.$$

Finally, we have that

$$\begin{aligned} ||w||^2 &= ||w_{lin} - \delta||^2 \\ &= w_{lin}^Tw_{lin} + \underbrace{\delta^Tw_{lin}}_{=0} + \underbrace{w_{lin}^T\delta}_{=0} + \delta^T\delta \\ &= ||w_{lin}||^2 + ||\delta||^2 > ||w_{lin}||^2, \end{aligned}$$

so w_{lin} is the minimum norm solution of the normal equations.

Problem 3.16

(a) The expected cost if we accept the person is

$$\text{cost(accept)} = 0 \cdot \mathbb{P}[y = +1|x] + c_a \cdot \mathbb{P}[y = -1|x] = c_a(1 - g(x))$$

and the expected cost if we reject the person is

$$\text{cost(reject)} = c_r \cdot \mathbb{P}[y = +1|x] + 0 \cdot \mathbb{P}[y = -1|x] = c_r g(x).$$

(b) Our condition on $g(x)$ for accepting the person is

$$\begin{array}{rcl} & \text{cost(accept)} & = \text{cost(reject)} \\ \Leftrightarrow & c_a(1 - g(x)) & = c_r g(x) \\ \Leftrightarrow & g(x) & = \dfrac{c_a}{c_a + c_r}; \end{array}$$

and so we let the threshold be

$$\kappa = \frac{c_a}{c_a + c_r}.$$

(c) For the Supermarket, we have $\kappa = 1/11$, this makes sense as in this case, we want to avoid false rejects; so with $\kappa <<$, we are rejecting only when $g(x) < \kappa$ which is very close to 0. And for the CIA, we have $\kappa = 1000/1001$, here we want to avoid false accepts; so with $\kappa >>$ we want to accept only when $g(x) \geq \kappa$ which is really close to 1.

Problem 3.17

(a) We use the first order Taylor expansion to write

$$E(u + \Delta u, v + \Delta v) = E(u, v) + \nabla E(u, v)^T \begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} + \mathcal{O}(||(\Delta u, \Delta v)||^2).$$

So, around $(u, v) = (0, 0)$, we get

$$\begin{aligned} \hat{E}_1(\Delta u, \Delta v) &= E(0,0) + \nabla E(0,0)^T \begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} \\ &= 3 + (e^u + e^{uv}v + 2u - 3v - 3, 2e^{2v} + e^{uv}u - 3u + 8v - 5)|_{(0,0)} \begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} \\ &= a_u \Delta u + a_v \Delta v + a, \end{aligned}$$

where $a_u = -2$, $a_v = -3$, and $a = 3$.

(b) To minimize $\hat{E}_1$, we have that

$$\begin{aligned} \hat{E}_1(\Delta u, \Delta v) &= E(0,0) + \nabla E(0,0)^T \begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} \\ &= E(0,0) + ||\nabla E(0,0)|| \cdot ||(\Delta u, \Delta v)|| \cos(\nabla E(0,0), (\Delta u, \Delta v)) \\ &\geq E(0,0) - ||\nabla E(0,0)|| \cdot ||(\Delta u, \Delta v)||. \end{aligned}$$

Thus the optimal vector $(\Delta u^*, \Delta v^*)^T$ such that $||(\Delta u, \Delta v)|| = 0.5$ is given by

$$\begin{pmatrix} \Delta u^* \\ \Delta v^* \end{pmatrix} = -\frac{\nabla E(0,0)}{||\nabla E(0,0)||}||(\Delta u, \Delta v)|| = \frac{1}{2\sqrt{13}}\begin{pmatrix} 2 \\ 3 \end{pmatrix}.$$

(c) With the second order Taylor expansion, we may write that

$$E(u+\Delta u, v+\Delta v) = E(u,v) + \nabla E(u,v)^T \begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} + \frac{1}{2}(\Delta u, \Delta v)\nabla^2 E(u,v)\begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} + \mathcal{O}(||(\Delta u, \Delta v)||^3).$$

And around $(u,v) = (0,0)$, we get

$$\begin{aligned}
\hat{E}_3(\Delta u, \Delta v) &= E(0,0) + \nabla E(0,0)^T \begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} + \frac{1}{2}(\Delta u, \Delta v)\nabla^2 E(0,0)\begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} \\
&= 3 + (-2,-3)\begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} + \frac{1}{2}(\Delta u, \Delta v)\begin{pmatrix} e^u + e^{uv}v^2 + 2 & e^{uv}(uv+1) - 3 \\ e^{uv}(uv+1) - 3 & 4e^{2v} + e^{uv}u^2 + 8 \end{pmatrix}\begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} \\
&= 3 - 2\Delta u - 3\Delta v + \frac{1}{2}(\Delta u, \Delta v)\begin{pmatrix} 3 & -2 \\ -2 & 12 \end{pmatrix}\begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} \\
&= b_{uu}(\Delta u)^2 + b_{vv}(\Delta v)^2 + b_{uv}\Delta u \Delta v + b_u \Delta u + b_v \Delta v + b
\end{aligned}$$

where $b_{uu} = 3/2$, $b_{vv} = 6$, $b_{uv} = -2$, $b_u = -2$, $b_v = -3$, and $b = 3$.

(d) To minimize $\hat{E}_2$, we write that

$$\nabla \hat{E}_2(\Delta u, \Delta v) = \nabla E(0,0) + \nabla^2 E(0,0)\begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} = 0$$

if

$$\begin{pmatrix} \Delta u \\ \Delta v \end{pmatrix} = -(\nabla^2 E(0,0))^{-1}\nabla E(0,0).$$

However, for the vector above to be a mimimum, the matrix $\nabla^2 E(0,0)$ must be positive semidefinite and invertible; in our case we have

$$\det(\nabla^2 E(0,0)) = 32 \neq 0,$$

which means that it is actually invertible, and

$$(u,v)\begin{pmatrix} 3 & -2 \\ -2 & 12 \end{pmatrix}\begin{pmatrix} u \\ v \end{pmatrix} = 2u^2 + 8v^2 + (u-2v)^2 \geq 0$$

for any (u,v), which means that it is actually positive semidefinite. Thus the optimal vector $(\Delta u^*, \Delta v^*)^T$ is given by

$$\begin{pmatrix} \Delta u^* \\ \Delta v^* \end{pmatrix} = -(\nabla^2 E(0,0))^{-1}\nabla E(0,0) = \frac{1}{32}\begin{pmatrix} 30 \\ 13 \end{pmatrix}.$$

Problem 3.18

(a) Since $\mathcal{H}_\Phi$ is the perceptron in $\mathcal{Z}$, we know that its VC dimension is equal to $\tilde{d} + 1 = 6$, so $d_{VC}(\mathcal{H}_\Phi) \leq 6$ (the $\leq$ is because some points $z \in \mathcal{Z}$ may not be valid transforms of any $x \in \mathcal{X}$, so some dichotomies may not be realizable).

(b)

(c) By the same reasoning as in point (a), we get that $d_{VC}(\mathcal{H}_{\Phi_k}) \leq \tilde{d} + 1$. Moreover, as $\tilde{d}$ is the number of terms in a polynomial of degree k in d variables, it is well known that

$$\tilde{d} = \binom{k+d}{d} - 1.$$

To conclude, we have the following upper bound

$$d_{VC}(\mathcal{H}_{\Phi_k}) \leq \binom{k+d}{d}.$$

(d) It is easy to see that

$$\begin{aligned}
\tilde{h}(\tilde{\Phi}_2(x)) &= \tilde{w}_0 + \tilde{w}_1 x_1 + \tilde{w}_2 x_2 + \tilde{w}_3(x_1 + x_2) + \tilde{w}_4(x_1 - x_2) + \tilde{w}_5 x_1^2 + \tilde{w}_6 x_1 x_2 + \tilde{w}_7 x_2 x_1 + \tilde{w}_8 x_2^2 \\
&= \tilde{w}_0 + (\tilde{w}_1 + \tilde{w}_3 + \tilde{w}_4)x_1 + (\tilde{w}_2 + \tilde{w}_3 - \tilde{w}_4)x_2 + \tilde{w}_5 x_1^2 + (\tilde{w}_6 + \tilde{w}_7)x_1 x_2 + \tilde{w}_8 x_2^2 \in \mathcal{H}_{\Phi_2}
\end{aligned}$$

The reverse is also true, so we actually have $d_{VC}(\mathcal{H}_{\Phi_2}) = d_{VC}(\mathcal{H}_{\tilde{\Phi}_2})$.

Problem 3.19

(a) The first problem with this feature tansform is that $\mathcal{Z}$ has a very large dimension (N) which we know to be computationnaly expensive. The second problem is that it maps each point not in the dataset to the origin, it is not unusual for a transformation not being injective but here it is way worse.

(b) This transformation may be a good idea, actually it is a well known transformation called *radial basis function*.

(c) This transformation is also another type of radial basis function.