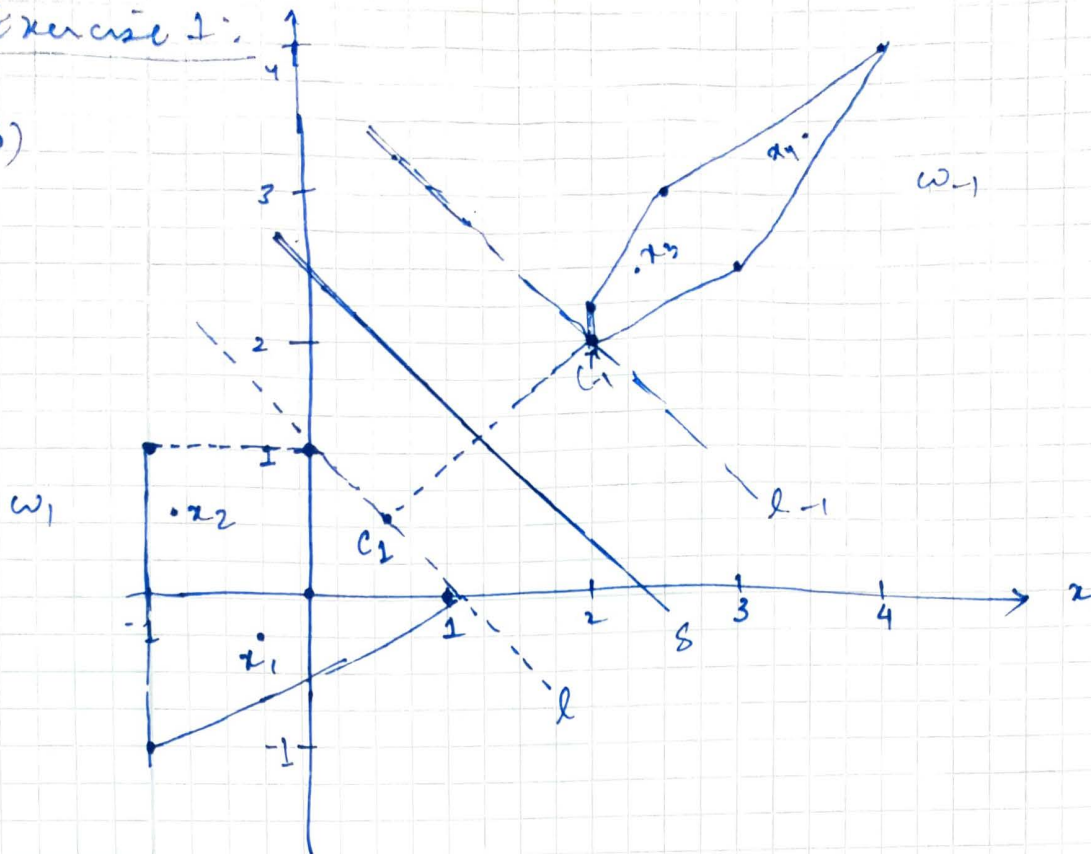
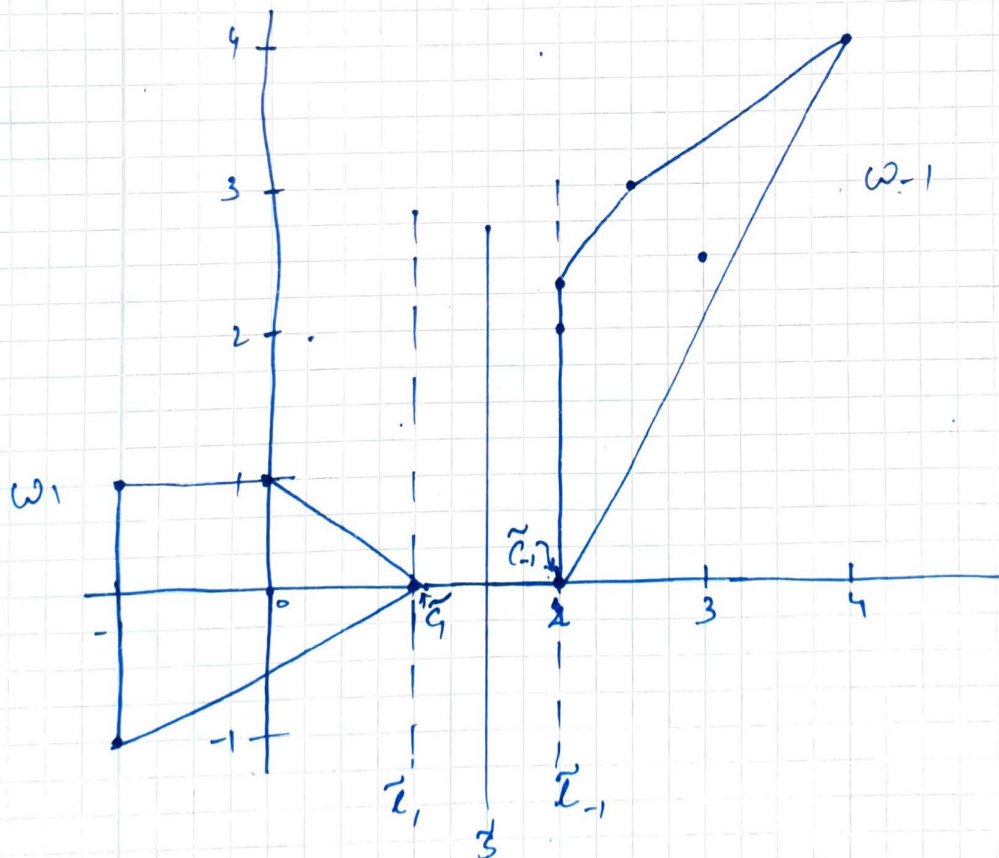


Exercise 1:

(1-5)



6)



7) In both approach we try to find hyperplanes which divides the linearly separable classes data points. The only difference is that in SVM, we find a separation plane with maximal distance to the data. But in perceptron, we just find hyperplane without any restriction.

Exercise 2:

$$x_1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \in \omega_1, \quad \omega_1 = \left\{ x_i \mid T_i = 1 \right\}$$

$$x_2 = \begin{pmatrix} 1 \\ 3 \end{pmatrix} \in \omega_2, \quad \omega_2 = \left\{ x_i \mid T_i = -1 \right\}$$

Given: $L(\omega, \omega_0, \alpha_1, \alpha_2) = L(\alpha_1, \alpha_2) = \sum_{i=1}^2 \alpha_i - \frac{1}{2} \sum_{i=1}^2 \sum_{j=1}^2 \alpha_i \alpha_j T_i T_j x_i^T x_j$

constraint: $\sum_{i=1}^2 \alpha_i T_i = 0$

1) Opening up the summation:

$$L(\alpha_1, \alpha_2) = \sum_{i=1}^2 \alpha_i - \frac{1}{2} \left(\alpha_1 \alpha_1 T_1 T_1 x_1^T x_1 + \alpha_1 \alpha_2 T_1 T_2 x_1^T x_2 + \alpha_2 \alpha_1 T_2 T_1 x_2^T x_1 + \alpha_2 \alpha_2 T_2 T_2 x_2^T x_2 \right)$$

$$= \alpha_1 + \alpha_2 - \frac{1}{2} \left(\alpha_1^2 T_1^2 x_1^T x_1 + \alpha_1 \alpha_2 T_1 T_2 x_1^T x_2 + \alpha_2 \alpha_1 T_2 T_1 x_2^T x_1 + \alpha_2^2 T_2^2 x_2^T x_2 \right)$$

(Simplifying) Using the constraint given $\left(\sum_{i=1}^2 \alpha_i T_i = 0 \right)$

$$\left(\alpha_1 T_1 + \alpha_2 T_2 = 0 \Rightarrow \alpha_1 - \alpha_2 = 0 \Rightarrow \alpha_1 = \alpha_2 \right)$$

But before that, simplifying substituting the value of T_i & x_i .

$$= \alpha_1 + \alpha_2 - \frac{1}{2} \left(\alpha_1^2 \cdot (1, 1) \cdot \begin{pmatrix} 1 \\ 1 \end{pmatrix} + \alpha_1 \alpha_2 (1)(-1) \begin{pmatrix} 1 & 1 \end{pmatrix} \begin{pmatrix} 2 \\ 3 \end{pmatrix} + \alpha_2 \alpha_1 (-1)(1) \begin{pmatrix} 2 & 3 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} + \alpha_2^2 \cdot (-1)^2 \cdot (2, 3) \begin{pmatrix} 2 \\ 3 \end{pmatrix} \right)$$

$$= \alpha_1 + \alpha_2 - \frac{1}{2} \left(2\alpha_1^2 - 5\alpha_1 \alpha_2 - 5\alpha_2 \alpha_1 + 10\alpha_2^2 \right)$$

$$= \alpha_1 + \alpha_2 - \alpha_1^2 + 5\alpha_1 \alpha_2 - \frac{13\alpha_2^2}{2} \quad \text{with constraint } \alpha_1 = \alpha_2$$

$$= +4\alpha_1^2 - \alpha_1^2 + 5\alpha_1^2 - \frac{13\alpha_1^2}{2} + 2\alpha_1$$

$$= \frac{(-2+10-13)\alpha_1^2}{2} + 2\alpha_1$$

$$= -\frac{5\alpha_1^2}{2} + 2\alpha_1$$

2).

$$\Lambda(\alpha_1, \alpha_2, \lambda) = L(\alpha_1, \alpha_2) + \lambda \left(\sum_{i=1}^2 \alpha_i T_i \right)$$

$$= \alpha_1 + \alpha_2 - \alpha_1^2 + 5\alpha_1\alpha_2 - \frac{13}{2}\alpha_2^2 + \lambda \left(\sum_{i=1}^2 \alpha_i T_i \right)$$

$$\frac{\partial \Lambda}{\partial \alpha_1} = 1 - 2\alpha_1 + 5\alpha_2 + \lambda = 0 \quad (i)$$

$$\frac{\partial \Lambda}{\partial \alpha_2} = 1 + 5\alpha_1 - 13\alpha_2 + \lambda = 0 \quad (ii)$$

$$\frac{\partial \Lambda}{\partial \lambda} = \sum_{i=1}^2 \alpha_i T_i = 0 \quad (iii) \quad (\text{already given as constraint})$$

$\Rightarrow \alpha_1 = \alpha_2$ from equation (iii)

Substituting in (i) & (ii) and adding (i) & (ii)

$$\begin{array}{rcl} 1 - 2\alpha_1 + 5\alpha_1 + \lambda & & 1 + 3\alpha_1 + \lambda \\ 1 + 5\alpha_1 - 13\alpha_1 + \lambda & & 1 - 8\alpha_1 + \lambda \\ \hline & & 2 - 5\alpha_1 = 0 \end{array}$$

$$\alpha_1^* = \frac{2}{5} = \alpha_2^* \quad (\text{due to constraint})$$

$$3) \quad \omega = \sum_{i=1}^N \alpha_i T_i x_i \quad (\text{cf. 100})$$

$$= \alpha_1 T_1 x_1 + \alpha_2 T_2 x_2 = \frac{2}{5} \cdot 1 \cdot \begin{pmatrix} 1 \\ 1 \end{pmatrix} + \frac{2}{5} \cdot (-1) \cdot \begin{pmatrix} 2 \\ 3 \end{pmatrix}$$

$$= \begin{pmatrix} 2/5 \\ 2/5 \end{pmatrix} - \begin{pmatrix} 4/5 \\ 6/5 \end{pmatrix} = \begin{pmatrix} -2/5 \\ -4/5 \end{pmatrix}$$

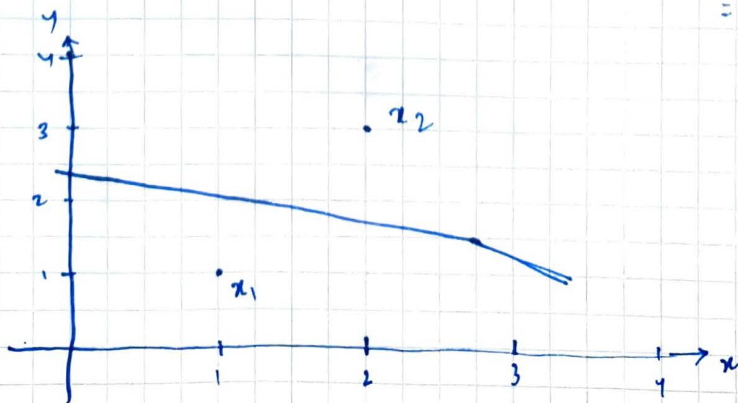
$$\omega_0 := \frac{1}{T_{i_0}} - \omega^T x_{i_0} = T_{i_0} - \omega^T x_{i_0} \quad (\text{cf. 102})$$

We have two support vectors, taking one

$$(-1) - \begin{pmatrix} -2/5 & -4/5 \end{pmatrix} \begin{pmatrix} 2 \\ 3 \end{pmatrix} = -1 + \left(\frac{4}{5} + \frac{12}{5} \right)$$

$$= -1 + \frac{16}{5} = \frac{11}{5}$$

4)



5) $x_3 = (2, 2)$

a) Graphically \rightarrow w_{-1}

b) $f(x) = \text{sig} \left(\sum_{i=1}^N \alpha_i^* T_i (x_i^T x) + w_0^* \right)$

$$= \text{sig} \left(\sum \left(\alpha_i^* \cdot (1) \cdot ((2, 2) \cdot \begin{pmatrix} 2 \\ 2 \end{pmatrix}) + \frac{11}{5} \right) + \left(\alpha_2^* (-1) \cdot ((2, 3) \cdot \begin{pmatrix} 2 \\ 2 \end{pmatrix}) + \frac{11}{5} \right) \right)$$

$$= \text{sig} \left(\frac{2}{5} \times 8 - \frac{2}{5} \times 10 + \frac{11}{5} \right)$$

$$\text{sig} \left(\frac{8}{5} - \frac{20}{5} + \frac{11}{5} \right)$$

$$\text{sig} \left(-\frac{1}{5} \right) = -1 \quad \text{So, label is } w_{-1}$$

6) a) Equation 1 would expand exponentially upon simplifying or expanding the summation. In other words, for 2 points we have 4 terms, for 3 inputs we will have 9 terms, and as the points increases we get N^2 terms. (Range of summation is from 1 to N)

$$L(w, w_0, \alpha, x_i) = \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j T_i \cdot T_j \cdot x_i^T x_j$$

b) If $x_i \cdot \alpha_i \neq 0$, then x_i lies on the margin and thus contributes to the separation line. That is why these vectors are also called support vectors (c.f. also in the script)