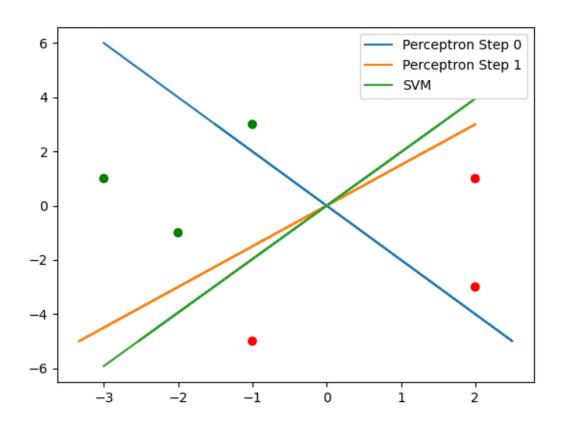
See Referencesappendix for code.



#### (a) Perceptron Learning:

Updating vector 
$$w = (0,0)$$
 using  $(x,y) = ((2,1), -1)$   
 $w = (-2, -1) \rightarrow w = (0,0) + y = -1 * x = (2,1)$ 

Updating vector 
$$w = (-2, -1)$$
 using  $(x, y) = ((-1, 3), 1)$   
 $w = (-3, 2) \rightarrow w = (-2, -1) + y = 1 * x = (-1, 3)$ 

Margin 
$$(\min_{(x,y)\in S} \frac{|\langle w,x\rangle|}{||w||})$$
: 1.1094003924504583

#### (b) SVM Learning:

$$w^*: (-0.6074814098863559, 0.30790724037405226)$$
 Margin  $(\min_{(x,y)\in S} \frac{|\langle w,x\rangle|}{||w||})$ : 1.331824259573374

- (a)  $\hat{w} = \mathbf{1} = (1, ..., 1) \in \{1\}^n$  is a suitable weight vector, since  $\langle \hat{w}, x \rangle$  is only positive, iff x contains more 1's than -1's.
- (b)  $\lambda = n$ , since ||x|| is maximum when x consists of either only 1's or only -1's.  $\gamma = \frac{1}{n}$  since the margin is minimal for a x which consists of an by one number off amount of 1's and -1'. Thus,  $\frac{|\langle w, x \rangle|}{||w||} = \frac{1}{n}$  Using Theorem 1.13 we can derive that the perceptron algorithm finds a linear separator after at most  $\left(\frac{\lambda}{\gamma}\right)^2 = \left(\frac{n}{\frac{1}{n}}\right)^2 = n^4$  updates.
- (c) The smallest possible number of updates is 1. Let  $(x_1 := (1, ..., 1), y_1 := 1)$  be the first element in S. Initially the weight vector is w = ((0, ..., 0)). Thus,  $sgn(\langle w, x_1 \rangle) \neq y_1$  holds and we update  $w \leftarrow w + y_1x_1 = (1, ..., 1)$ . As discussed previously, this is already a suitable weight vector, therefore we do not have to update w ever again.
- (d) No, we cannot. Counterexample: Let n=3,  $x=(1,1,x_3)\in\mathbb{R}^3$ . We know, that x should be classified as 1. However, for every weight vector  $w=(w_1,w_2,w_3)\in\mathbb{R}^3$  we can set  $x_3$  to the value of  $x_3:=-\frac{w_1+w_2}{w_3}$   $(x_3:=-(w_1+w_2)$  iff  $w_3=0)$ , that would lead to a false classification of x:

$$sgn(\langle w, x \rangle) = sgn(w_1 + w_2 + x_3 \cdot w_3) = sgn(0) = 0 \neq 1$$

So for every w we can compute a vector x so that w is not consistent with  $\{(x, maj(x))\}$ . Thus, no such linear separator exists.

### Exercise 3

(a) 
$$\tau: \mathbb{R}^2 \to \mathbb{R}^4, (x, y) \mapsto (x, y, (\sin(xy))^2, (\cos(xy))^2)$$

(b) 
$$\tau': \mathbb{R}^2 \to \mathbb{R}^3, (x, y) \mapsto (x, y, (\sin(xy))^2)$$

We make use of  $1 = (\sin(\phi))^2 + (\cos(\phi))^2$ . Hence:

$$h(x,y) = sgn(w_1x + w_2y + w_3(\sin(xy))^2 + w_4(\cos(xy))^2 - b)$$

$$= sgn(w_1x + w_2y + w_3(\sin(xy))^2 + w_4(1 - (\sin(xy)))^2 - b)$$

$$= sgn(w_1x + w_2y + w_3(\sin(xy))^2 + w_4 - w_4(\sin(xy))^2 - b)$$

$$= sgn(w_1x + w_2y + (w_3 + w_4) \cdot (\sin(xy))^2 - (b - w_4))$$

$$= sgn(w_1x + w_2y + w_3' \cdot (\sin(xy))^2 - b')$$

$$= sgn(w_1x + w_2y + w_3' \cdot (\sin(xy))^2 - b')$$

$$= h'(x, y)$$

where  $w_3' := w_3 + w_4$  and  $b' := b - w_4$ .

See Referencesappendix for code.

(a) Clusters: [[], [], []]

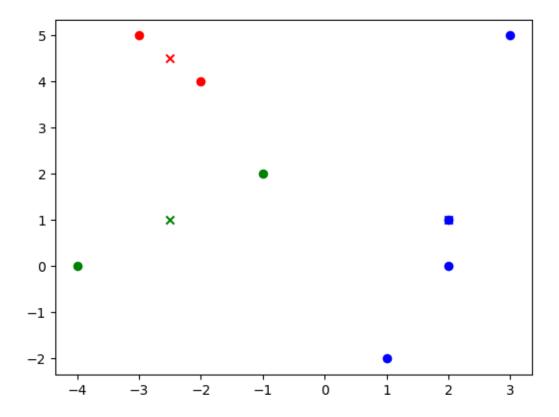
Centres: [(-3, 5), (-2, 4), (-1, 2)]

Clusters: [[(-3, 5)], [(-2, 4)], [(-1, 2), (-4, 0), (1, -2), (2, 0), (2, 1), (3, 5)]]Centres: [(-3.0, 5.0), (-2.0, 4.0), (0.5, 1.0)]

Clusters: [[(-3, 5)], [(-2, 4), (-4, 0)], [(-1, 2), (1, -2), (2, 0), (2, 1), (3, 5)]]Centres: [(-3.0, 5.0), (-3.0, 2.0), (1.4, 1.2)]

Clusters: [[(-3, 5), (-2, 4)], [(-1, 2), (-4, 0)], [(1, -2), (2, 0), (2, 1), (3, 5)]]Centres: [(-2.5, 4.5), (-2.5, 1.0), (2.0, 1.0)]

Final Clusters: [[(-3, 5), (-2, 4)], [(-1, 2), (-4, 0)], [(1, -2), (2, 0), (2, 1), (3, 5)]]Final Centers: [(-2.5, 4.5), (-2.5, 1.0), (2.0, 1.0)]



(b)

(c) Circumcenter c = (-0.25, 2.75)

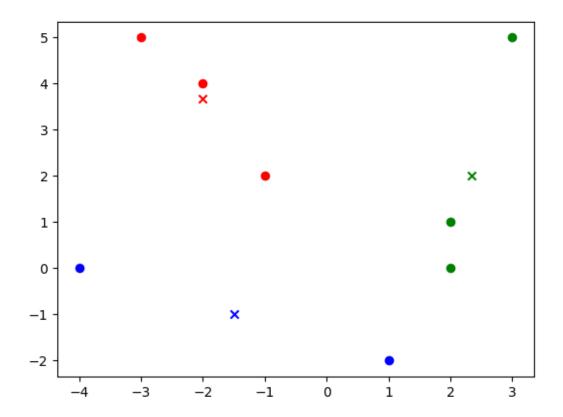
Line 1: y = 2.75 (separating red and green)

Line 2: x = -0.25 (separating green and blue)

Line 3:  $y = 2.75 + \frac{x + 0.25}{3.5} \cdot 0.5$  (separating red and blue)

(d) 
$$z^1 = x_1 = (-3, 5), z^2 = x_8 = (3, 5), z^2 = x_4 = (-4, 0)$$

produces following clustering:



(e) Yes, for example 
$$z^1=\begin{bmatrix} -4\\ 3 \end{bmatrix}, z^2=\begin{bmatrix} -1.5\\ 3 \end{bmatrix}, z^3=\begin{bmatrix} 2\\ -2 \end{bmatrix},$$

#### Exercise 5

(a) 
$$\mathbb{E}[Y_n] = \mathbb{E}[\prod_{i=1}^n X_i] = \prod_{i=1}^n \mathbb{E}[X_i] = \prod_{i=1}^n 3.5 = 3.5^n$$

$$\operatorname{Var}(Y_n) = \mathbb{E}[(Y_n - \mathbb{E}[Y_n])^2] = \mathbb{E}[(Y_n - 3.5^n)^2] = \mathbb{E}[Y_n^2 - 2 \cdot 3.5^n \cdot Y_n + 3.5^{2n}]$$

$$= \mathbb{E}[Y_n^2] - 2 \cdot 3.5^n \cdot \mathbb{E}[Y_n] + 3.5^{2n}$$

$$= \mathbb{E}[Y_n] \cdot \mathbb{E}[Y_n] - 2 \cdot 3.5^n \cdot 3.5^n + 3.5^{2n}$$

$$= 3.5^n \cdot 3.5^n - 2 \cdot 3.5^n \cdot 3.5^n + 3.5^{2n}$$

$$= 0$$

(b) (i) 
$$Pr(Z_{300} \le 10) = 1 - Pr(Z_{300} \ge 11) \ge 1 - \frac{\frac{50}{11}}{300} = 1 - \frac{65}{66} = \frac{1}{66} = 0.015$$
 (ii)

$$P(|Z_{300} - E(X)| \le 10) = P(|Z_{300} - E(X)| < 11) \ge 1 - \frac{V(X)}{11^2} = 1 - \frac{\frac{125}{3}}{11^2} = \frac{238}{363} = 0.656$$

(iii) Chernoff:

$$P\left[\sum X_i \le (1 - \delta) \cdot pn\right] \le \exp\left(-\frac{\delta^2}{2}pn\right)$$
  
 
$$\Rightarrow (1 - \delta) \cdot 50 = 10 \Leftrightarrow 1 - \delta = \frac{1}{5} \Leftrightarrow -\delta = -\frac{4}{5} \Leftrightarrow \delta = \frac{4}{5}$$

$$\Rightarrow P(X \le 10) \le \exp(-\frac{\frac{4}{5}^2}{2} \cdot 50) = 1.125 \cdot 10^{-7}$$

(iv) 
$$\Pr\left[\sum (X_i - \mathrm{E}[X_i]) \ge c\right] \le \exp\left(\frac{-2c^2}{\sum (b_i - a_i)^2}\right)$$

with a=0 and b=1. Centering around the mean of 50 leads to a=-50 and b=-49 and c=10-50=-40:

$$P(X \le 10) = 1 - P(X10) > 1 - \exp\left(\frac{-2(-40)^2}{300 \cdot (-49 + 50)^2}\right) = 0.999$$

The best bound is given by the Chernoff inequality as the actual probability is binomially distributed with

$$P(X \le 10) = 3.03 \cdot 10^{-13}$$

with n = 300 and  $p = \frac{1}{6}$ .

(a)

$$\begin{split} &H(X|Y) + H(X) \Leftrightarrow (\sum_{y \in rg(Y)} Pr(Y = y) \left( \sum_{x \in rg(X)} Pr(X = x | Y = y) \cdot \log(\frac{1}{Pr(X = x | Y = y)} \right)) \\ &+ (\sum_{y \in rg(Y)} Pr(Y = y) \cdot \log(\frac{1}{Pr(Y = y)})) \\ &\Leftrightarrow (\sum_{y \in rg(Y)} \sum_{x \in rg(X)} \left( Pr(X = x, Y = y) \cdot \log(\frac{Pr(Y = y)}{Pr(X = x, Y = y)} \right)) \\ &+ (\sum_{y \in rg(Y)} \sum_{x \in rg(X)} (Pr(X = x, Y = y) \cdot \log(\frac{1}{Pr(Y = y)}))) \\ &\Leftrightarrow (\sum_{y \in rg(Y)} \sum_{x \in rg(X)} (Pr(X = x, Y = y) \cdot \log(Pr(Y = y) - \log(Pr(X = x, Y = y))))) \\ &- (\sum_{y \in rg(Y)} \sum_{x \in rg(X)} (Pr(X = x, Y = y) \cdot \log(Pr(Y = y)))) \\ &+ (\sum_{y \in rg(Y)} \sum_{x \in rg(X)} (Pr(X = x, Y = y) \cdot \log(Pr(X = x, Y = y))))) \\ &- (\sum_{y \in rg(Y)} Pr(Y = y, X = x) \cdot \log(Pr(Y = y)))) \\ &\Leftrightarrow (\sum_{y \in rg(Y)} \sum_{x \in rg(X)} (Pr(X = x, Y = y) \cdot \log(Pr(Y = y)))) \\ &+ H(X, Y) \\ &\Leftrightarrow H(X, Y) \end{split}$$

(b)

$$H(X|Y) \Leftrightarrow \sum_{y \in rg(Y)} Pr(Y = y) \left( \sum_{x \in rg(X)} Pr(X = x | Y = y) \cdot \log(\frac{1}{Pr(X = x | Y = y)}) \right)$$

$$\Leftrightarrow \sum_{y \in rg(Y)} Pr(Y = y) \left( \sum_{x \in rg(X)} Pr(X = x) \cdot \log(\frac{1}{Pr(X = x)}) \right)$$

$$\Leftrightarrow \sum_{y \in rg(Y)} Pr(Y = y) (H(X))$$

$$\Leftrightarrow H(X) \cdot \sum_{y \in rg(Y)} Pr(Y = y)$$

$$\Leftrightarrow H(X)$$

# Appendix

#### Code for Exercise 1

```
1 from matplotlib import pyplot
2 from sklearn.svm import LinearSVC
3 from math import sqrt
5 S = [
      ((2, 1), -1),
6
      ((-1, 3), 1),
      ((-3, 1), 1),
      ((-2, -1), 1),
      ((-1, -5), -1),
      ((2, -3), -1),
11
12
  ]
13
14
  def plot(S, w_percs, w_svm):
15
      # scatter points
      x_values = [s[0][0] for s in S]
17
      y_values = [s[0][1] for s in S]
18
      colors = ['green' if s[1] == 1 else 'red' for s in S]
19
      pyplot.scatter(x_values, y_values, c=colors)
21
22
23
      # plot linear seperators
      x_{min} = min(x_{values})
      x_max = max(x_values)
25
      y_{min} = min(y_{values})
26
      y_{max} = max(y_{values})
      w_list = list(w_percs + [w_svm])
29
30
      for i in range(len(w_list)):
31
           w = w_list[i]
32
           ortho_w = (-w[1], w[0])
33
           p_1 = (x_min, ortho_w[1] * (x_min / ortho_w[0]))
           p_2 = (x_max, ortho_w[1] * (x_max / ortho_w[0]))
           p_3 = (ortho_w[0] * (y_min / ortho_w[1]), y_min)
37
          p_4 = (ortho_w[0] * (y_max / ortho_w[1]), y_max)
38
           p_x_values = (p_1[0], p_2[0], p_3[0], p_4[0])
40
           p_y-values = (p_1[1], p_2[1], p_3[1], p_4[1])
41
42
           pyplot.plot(p_x_values, p_y_values, label=('SVM' if w==w_svm else f'
     Perceptron Step {i}'))#
44
      pyplot.legend()
45
      # save to file
47
      pyplot.savefig(f'exercise_01.png')
48
49
50
  def sgn(value) -> int:
51
      if value > 0:
          return 1
53
      elif value == 0:
         return 0
```

```
56
           return -1
57
58
  def dot_product(a, b) -> int:
60
       return a[0] * b[0] + a[1] * b[1]
61
62
63
  def check_consistency(S, w) -> bool:
64
      for s in S:
65
           if sgn(dot_product(s[0], w)) != s[1]:
67
               return False
       return True
68
69
  def perceptron(S) -> list:
71
72
      w_list = list()
      w = (0, 0)
73
       while not check_consistency(S, w):
           for s in S:
75
               if sgn(dot_product(s[0], w)) != s[1]:
76
                   w_old = w
77
                   # w < - w + yx
                   w_x = w[0] + s[1] * s[0][0]
79
                   w_y = w[1] + s[1] * s[0][1]
80
                   w = (w_x, w_y)
81
                   w_list.append(w)
                   # printing formatted for latex. Just copy and paste
83
                   print(f'Updating vector $w=\{w_old\}$ using $(x,y)=\{s\}$ \\\')
84
                   print (
85
                       f'^{w=\{w\}} \simeq \{s[0]\}
      return w_list
87
89
  def margin(S, w) -> float:
90
       distances = [abs(dot_product(w, s[0]))/sqrt(dot_product(w, w)) for s in
91
      S1
       distances = sorted(distances)
92
      return distances[0]
93
94
  def svm(S) -> tuple:
96
      classifier = LinearSVC(fit_intercept=False) # force heterogenous (
97
      fit_intercept=False)
      classifier.fit([[s[0][0], s[0][1]] for s in S], [s[1] for s in S])
       return (classifier.coef_[0][0], classifier.coef_[0][1])
99
100
   if __name__ == '__main__':
      print(f'Perceptron Learning: \\\\ \n\\bigskip \n')
      w_percs = perceptron(S)
104
      print(f'Margin: ${margin(S, w_percs[-1])}$')
106
      print(f'SVM Learning: \\\\ \n\\bigskip \n')
107
      w_svm = svm(S)
108
      print(f'$w^*: {w_svm}$ \\\\')
      print(f'Margin: ${margin(S, w_svm)}$')
110
111
      plot(S, w_percs, w_svm)
112
```

#### Code for Exercise 4

```
1 from math import sqrt
2 from matplotlib import pyplot
_{4} X = [
      (-3, 5),
5
      (-2, 4),
      (-1, 2),
      (-4, 0),
      (1, -2),
9
      (2, 0),
10
      (2, 1),
      (3, 5),
12
13
14
Z = [X[0], X[1], X[2]] # a+b
  #Z = [X[0], X[7], X[3]] # d
16
17
  def plot(C, Z, k=3):
      colors = ['red', 'green', 'blue']
19
      for j in range(k):
20
           x_values = [cj[0] for cj in C[j]]
21
           y_values = [cj[1] for cj in C[j]]
           pyplot.scatter(x_values, y_values, c=colors[j])
           pyplot.scatter([Z[j][0]], [Z[j][1]], marker='x', c=colors[j])
24
25
      # save to file
      pyplot.savefig(f'exercise_04.png')
27
28
29
  def equals_list_of_lists(C_1, C_2) -> bool:
      11_1 = list([set(l_1) for l_1 in C_1])
31
      11_2 = list([set(1_2) for 1_2 in C_2])
32
      for l_1 in list(ll_1):
33
           for 1_2 in list(11_2):
               if 1_1 == 1_2:
35
                   ll_1.remove(l_1)
36
                   11_2.remove(1_2)
                    break
39
      return len(11_1) == 0 and len(11_2) == 0
40
41
  def dot_product(a, b) -> float:
43
      return a[0] * b[0] + a[1] * b[1]
44
45
46
  def k_means(X, Z, k=3) -> tuple:
47
      C = [[] for j in range(k)]
48
      C_{-} = list(C) # copy of C_{-}
49
50
      first_iteration = True
      while not equals_list_of_lists(C, C_) or first_iteration:
           first_iteration = False
           C = list(C_{-})
           C_{-} = [[] for j in range(k)]
54
           print(f'Clusters: {C} \\\\')
56
           print(f'Centres: {Z} \\\\n')
57
58
```

```
for x in X:
59
               distances = list()
60
                for j in range(k):
61
                    \# x_i - z_j
                    tmp = (x[0] - Z[j][0], x[1] - Z[j][1])
63
                    distances.append((j, sqrt(dot_product(tmp, tmp))))
64
               # get min j
               min_distance = float('inf')
               min_j = float('inf')
67
                for d in distances:
                    j = d[0]
                    distance = d[1]
70
                    if distance < min_distance:</pre>
71
                        min_distance = distance
72
                        \min_{j} = j
                    elif distance == min_distance and j < min_j:</pre>
74
                        \min_{j} = j
75
               \# add x_i to C_j
76
               C_{-} = [C_{-}[j] \text{ if } j != \min_{j} else C_{-}[j] + [x] for j in range(k)]
           # update z_j
78
           Z = [(sum([x[0] for x in C_[j]])/len(C_[j]), sum([x[1] for x in C_[j]))]
79
     ]])/len(C_[j])) if len(C_[j]) != 0 else Z[j] for j in range(k)]
      return (C_, Z)
81
82
  if __name__ == '__main__':
83
       (C, Z) = k_{means}(X, Z, k=3)
      print(f'Final Clusters: {C} \\\\')
85
      print(f'Final Centers: {Z} \\\\n')
86
      plot(C, Z, k=3)
```