

# Advanced topics in Machine Learning

## Assignment 1

## Question 1

I assign random variable  $X_i$  with sample space  $X_i = \{0,1\}$  where value 0 means that passenger did not show up and 1 means that the passenger has shown up.

Since 5% of the 10000 passengers did not show up, it means that 9500 have shown up so we can estimate the expected value for 100 passengers:

$$E \left[ \sum_{i=1}^{100} X_i \right] = 95$$

By applying the Hoeffding's inequality, I obtain the bound:

$$P \left[ \sum_{i=1}^{100} X_i - E \left[ \sum_{i=1}^{100} X_i \right] > \varepsilon \right] \leq \exp \left( - \frac{2\varepsilon^2}{\sum_{i=1}^{100} (1-0)^2} \right)$$

Because we want to calculate the bound the probability that the number of people that show up is larger than the number of seats, we have that  $\varepsilon = 99 - 95 = 4$

$$P \left[ \sum_{i=1}^{100} X_i - 95 > 4 \right] \leq \exp \left( - \frac{2 * 4^2}{\sum_{i=1}^{100} (1-0)^2} \right)$$

$$P \left[ \sum_{i=1}^{100} X_i \geq 99 \right] \leq \exp \left( - \frac{32}{100} \right) = 0.726$$

As a comparison, if I use Markov's inequality to bound the same probability, I obtain:

$$P \left( \sum_{i=1}^{100} X_i \geq 99 \right) \leq \frac{E \left[ \sum_{i=1}^{100} X_i \right]}{99} = \frac{95}{99} = 0.9595$$

## Question 2

For this problem, the objective function is the Euclidean distance between (x,y) and the point (-2,2):

$$f(x,y) = \sqrt{(x - (-2))^2 + (y - 2)^2}$$

And after doing some basic calculation, I could bring that to the form:

$$f(x, y) = \sqrt{x^2 + y^2 + 4(x - y)}$$

So  $f(x, y)$  that will be the function we want to minimize, but there is the constraint that the point  $(x, y)$  to be inside the circle with radius 1 around the origin, so we also have the constraint function :

$$x^2 + y^2 = 1 \Rightarrow x^2 + y^2 - 1 = 0$$

So given this optimization problem, I define the Lagrangian function by combining the objective and the constraint function:

$$F(x, y, \lambda) = \sqrt{x^2 + y^2 + 4(x - y)} + \lambda(x^2 + y^2 - 1)$$

Now, I calculate 3 partial derivatives of  $F(x, y, \lambda)$  with respect to  $x$ ,  $y$  and  $\lambda$ .

Since it is a quite tricky function to calculate derivative and to avoid doing mistakes, I used an online tool to calculate the derivatives with respect to  $x$  and  $y$ . I obtained:

$$\frac{\partial F(x, y, \lambda)}{\partial x} = \frac{2x + 4}{2\sqrt{x^2 + 4x + y^2 + 4y}} + 2\lambda x$$

$$\frac{\partial F(x, y, \lambda)}{\partial y} = \frac{2y + 4}{2\sqrt{x^2 + 4x + y^2 + 4y}} + 2\lambda y$$

$$\frac{\partial F(x, y, \lambda)}{\partial \lambda} = x^2 + y^2 - 1$$

For solving the optimization problem, I obtain a system with 3 equations to be solved:

$$\begin{cases} \frac{2x + 4}{2\sqrt{x^2 + 4x + y^2 + 4y}} + 2\lambda x = 0 \\ \frac{2y + 4}{2\sqrt{x^2 + 4x + y^2 + 4y}} + 2\lambda y = 0 \\ x^2 + y^2 - 1 = 0 \end{cases}$$

The optimal solution is found by solving the above system of equation, but I unfortunately did not manage to solve that one.

I am not sure how correct is, but I think I can approach the problem in a simpler way so I can make the calculations easier. Since we want to minimize the objective function:

$$f(x, y) = \sqrt{x^2 + y^2 + 4(x - y)}$$

I am also going to minimize the result of what is below the square root, so I will reduce to the function:

$$f(x, y) = x^2 + y^2 + 4(x - y)$$

that is also going to minimize the Euclidean distance.

By using the same constraint function as previously, the Lagrangian function becomes:

$$F(x, y, \lambda) = x^2 + y^2 + 4(x - y) + \lambda(x^2 + y^2 - 1)$$

And now it is a lot easier to calculate the derivatives:

$$\frac{\partial F(x, y, \lambda)}{\partial x} = 2x + 4 + 2\lambda x$$

$$\frac{\partial F(x, y, \lambda)}{\partial y} = 2y - 4 + 2\lambda y$$

$$\frac{\partial F(x, y, \lambda)}{\partial \lambda} = x^2 + y^2 - 1$$

With that simplification, I also get a system of equations that is a lot easier to solve:

$$\begin{cases} 2x + 4 + 2\lambda x = 0 \Rightarrow x = \frac{2}{1 + \lambda} \\ 2y - 4 + 2\lambda y = 0 \Rightarrow y = -\frac{2}{1 + \lambda} \\ x^2 + y^2 - 1 = 0 \Rightarrow \frac{4}{(1 + \lambda)^2} + \frac{4}{(1 + \lambda)^2} - 1 = 0 \end{cases}$$

Now, I can calculate the value of  $\lambda$ :

$$1 = \frac{8}{(1 + \lambda)^2} \Rightarrow \lambda^2 + 2\lambda + 1 = 8 \Rightarrow \lambda^2 + 2\lambda - 7 = 0$$

In the next step, I calculate the possible values of  $\lambda$ :

$$\lambda = 1.82 \text{ or } \lambda = -3.82$$

By making the replacements, I obtain the possible values for  $\lambda$ ,  $x$  and  $y$  I obtain:

$$(\lambda = 1.82 ; x = 0.71 ; y = -0.71) \text{ or } (\lambda = -3.82 , x = -0.71 ; y = 0.71)$$

If I look at the graphic with the circle and the second pair of values for  $x$  and  $y$  ( $x = -0.71 ; y = 0.71$ ) I see these are exactly the coordinates of the closest point on the circle to our objective  $(-2, 2)$ . The other pair of coordinates that I obtained are symmetric on the other side of  $y$  axis.

## Question 3

### 1. Learning with $H_d$

For deriving this high probability bound, because  $H_d$  is finite, I use the bound for the finite hypothesis classes:

$$P \left\{ \exists h \in H_d : L(h) > L'(h, S) + \frac{\sqrt{\ln \left( \frac{M}{\delta} \right)}}{2n} \right\} \leq \delta$$

Where  $h$  is the hypothesis that takes strings from  $\Sigma^d$  and returns  $\{0,1\}$  according to the prediction that is made.  $L(h)$  is the expected loss of  $h$  and  $L'(h, S)$  is the empirical loss of  $h$  on the training set  $S$  that is provided.  $M$  is the size of  $H_d$  and  $n$  is the number of samples from the training set.  $\delta$  is our confidence budget.

With probability greater than  $1 - \delta$  we have:

$$L(h) \leq L'(h, S) + \frac{\sqrt{\ln \left( \frac{M}{\delta} \right)}}{2n}$$

So we can say that:

$$L(h) - L'(h, S) \leq \frac{\sqrt{\ln \left( \frac{M}{\delta} \right)}}{2n}$$

Because  $H_d$  is the set of all functions from  $\Sigma^d$  to  $\{0,1\}$  then I guess the size of  $H_d$  is equal with the number of strings with size  $d$  from the set which will make that  $M$  to have a large value and it will result in a tight bound.

### 2. Learning with $H$

Because in this case, the size of hypothesis space is infinite, we will have the bound:

$$P \left\{ \exists h \in H : L(h) > L'(h, S) + \frac{\sqrt{\ln \left( \frac{1}{p(h)\delta} \right)}}{2n} \right\} \leq \delta$$

For the high probability bound  $1 - \delta$  we have:

$$L(h) \leq L'(h, S) + \frac{\sqrt{\ln\left(\frac{1}{p(h)\delta}\right)}}{2n}$$

Where we have that  $\sum_{h \in H} p(h) \leq 1$

$$L(h) - L'(h, S) \leq \frac{\sqrt{\ln\left(\frac{1}{p(h)\delta}\right)}}{2n}$$

In this case, the bound is a lot wider because the budget is distributed along all the spaces with strings of different sizes.