



Exercise Sheet 4

NNTI Tutorial

Deadline: 07.12.2022 08:00

Exercise 4.1 - Maximum Likelihood Estimate (MLE)

(1+1 points)

- a) Show how a linear regression procedure can be justified as an MLE procedure, assuming that mean squared error is used as a metric. Recall that

$$MSE = \frac{1}{m} \sum_{i=1}^m \|\hat{y}^{(i)} - y^{(i)}\|^2.$$

Justify and motivate the assumptions you make along the way. This particular deduction is not covered in the lecture. Consult the book to gain further understanding.

- b) Given an i.i.d. sample X_1, \dots, X_n from a Poisson distribution with parameter λ , find the MLE of the parameter λ . Recall that

$$\Pr(X = x|\lambda) = \frac{\lambda^x e^{-\lambda}}{x!}.$$

Exercise 4.2 - Supervised and Unsupervised Learning

(0.5+0.5+1 points)

The following explanations should be kept concise (max. 100 words).

- a) Describe some disadvantages of using mean squared error as a metric for a supervised regression task. How would the above answer change if the relevant task was a binary classification task?¹
- b) We have only covered PCA and briefly discussed other methods for unsupervised learning. Research other unsupervised methods and discuss how they differ from PCA and what problems they address.
- c) In supervised learning, the *softmax* function can have a temperature parameter T , such that

$$\text{softmax}(\mathbf{x})_i = \frac{\exp(x_i/T)}{\sum_{j=1}^n \exp(x_j/T)}.$$

Explain what effect a high and a low temperature would have on the function. Do this by plotting the function with distinct T values. Finally, discuss when manipulating the temperature could be useful.

¹Tasks which aim to assign a category $C \in \{0, 1\}$ to an example x_i .

The topic of temperature is not covered in the lecture and you are encouraged to do some research to reach an answer yourself.

Exercise 4.3 - Gradient Descent

(2 points)

a) Let $f : \mathbb{R}^2 \rightarrow \mathbb{R}$ be the following real function:

$$f(\mathbf{x}) = \frac{1}{1 + \exp(-(x_1^2 + x_2^2))}$$

Perform gradient descent on f in order to minimize it. Use the following value as x_0

$$x_0 = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \quad (1)$$

Use a learning rate $\epsilon = 0.2$. Do 3 iterations or until the gradient becomes zero, whichever happens first. On each iteration make sure to show the following:

- The value of \mathbf{x}
- The value of $\nabla f(\mathbf{x})$
- The value of $f(\mathbf{x})$

Once finished, compare the values $f(\mathbf{x})$ and $f(\mathbf{x}_0)$.

What would happen if a learning rate of ϵ_2 or ϵ_3 were used? Where

$$\epsilon < \epsilon_2 \lll \epsilon_3.$$

Finally, find an $\hat{\mathbf{x}}$ that minimizes f , by using gradient descent. You are free to choose your own learning rate; justify your decision. Is this $\hat{\mathbf{x}}$ guaranteed to be a global minimum given the nature of gradient descent and the function?

Exercise 4.4 - Feedforward Networks

(2+2 points)

- Implement your own feed-forward neural network from scratch. Check the attached `ipynb` file.
- Implement your own feed-forward neural network using `pytorch`. Check the attached `ipynb` file.

Submission instructions

The following instructions are mandatory. If you are not following them, tutors can decide to not correct your exercise.

- Please submit the assignment as a **team of two to three** students.
- Write the Microsoft Teams user name, student id and the name of each member of your team on your submission.

- Hand in zip file containing a **single** PDF with your solutions and the completed ipython notebook. Do not include any data or cache files (e.g. `--pycache--`).
- Important: please name the submitted zip folder and files inside using the format: **Name1_id1_Name2_id2**.
- Your assignment solution must be uploaded by only **one** of your team members to the 'Assignments' tab of the tutorial team (in **Microsoft Teams**). Please remember to press the **Hand In** button after uploading your work.
- If you have any trouble with the submission, contact your tutor **before** the deadline.