"Machine Learning and Computational Statistics"

4th Homework

Exercise 1:

Consider the **regression problem** $y=g(x)+\eta$

It is known that $\mathbb{E}[y|x]$ is the minimum MSE estimate of y given x. Consider the estimator f(x;D).

- (a) Under what conditions (theoretically) the quantity $E_D[(f(x;D)-E[y|x])^2]$ becomes zero?
- (b) Why this cannot be achieved in practice?

Exercise 2:

Consider a regression task modelled by the relation $y = g(x) + \eta$. Let f_{θ} be an estimator of g, parameterized by the vector θ . Let $Tr = \{(x_n, y_n), n = 1, ..., N_1\}$ be the training set (the set that will be used for the estimation of θ) and $Te = \{(x_n, y_n), n = 1, ..., N_2\}$ be the test (which will be used for testing the performance of $f_{\widehat{\theta}}$ (where $\widehat{\theta}$ is the estimate of θ based on Tr)).

- (a) What indicates a **large** error value on the training set *Tr*?
- (b) What may indicate a large error value on the test set *Te*?
- (c) What indicates a **small** error value on the training set *Tr*?
- (d) What may indicate a **small** error value on the test set *Te*?

Exercise 3:

Consider a regression task $y = g(x) + \eta$, where y and x are modeled by the random variables y and x. The joint pdf of y and x is:

$$p(x,y) = \frac{3}{2}$$
, for $x \in (0,1), y \in (x^2, 1)$.

Determine the optimum MSE estimate E[y|x], for a given x, by performing the following steps:

- (a) Verify that p(x, y) is a pdf (prove that it integrates to 1).
- (b) Compute the marginal pdf of x, $p_x(x)$.
- (c) Compute the conditional pdf of y, given x.

(d) Compute and plot E[y|x].

Hint: It is
$$\int_a^b x^n dx = \left[\frac{1}{n+1}x^{n+1}\right]_a^b = \frac{1}{n+1}b^{n+1} - \frac{1}{n+1}a^{n+1}$$

Exercise 4 (python code + text):

Consider the regression problem (1-dep., 1-indep. variables)

$$y=g(x)+\eta$$

where y and x are jointly distributed according to the normal distribution $p(y,x) = N(\mu, \Sigma)$

with
$$\boldsymbol{\mu} = \begin{bmatrix} \mu_y \\ \mu_x \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \end{bmatrix}$$

$$\Sigma = \begin{bmatrix} \sigma_y^2 & \sigma_{yx} \\ \sigma_{yx} & \sigma_x^2 \end{bmatrix} = \begin{bmatrix} 3 & 2 \\ 2 & 4 \end{bmatrix}$$

- (a) Determine E[y|x] and plot the corresponding curve (recall the relevant theory concerning the normal distribution case).
- (b) Generate 100 data sets D_i , i=1,...100, each one consisting of N=50 randomly selected pairs (y_n,x_n) , n=1,...,N, from p(y,x).
- (c) Adopt the linear estimator f(x;D) and determine its instances $f(x;D_1),..., f(x;D_{100})$, utilizing the LS criterion.
- (d) Plot in a single figure (i) the lines corresponding to the above 100 estimates (blue color) and (ii) the line corresponding to the optimal MSE estimate (green color).
- (e) Repeat steps (b)-(d) where now each data set consists of N=5000 points.
- (f) Discuss the results (in your discussion, take into account the decomposition of the MSE to a variance and a bias term).

Exercise 5 (python code + text): Consider the setup of exercise 3. Generate a set D of N = 100 data pairs $\mathbf{z}_n = (y_n, x_n)$.

(a) For each x_n compute the optimal MSE estimate \hat{y}_n , n = 1, ..., 100 (use the results of exercise 3).

(b) Compute
$$\boldsymbol{\mu} = \begin{bmatrix} \mu_{x} \\ \mu_{y} \end{bmatrix} = \begin{bmatrix} \frac{1}{N} \sum_{n=1}^{N} x_{n} \\ \frac{1}{N} \sum_{n=1}^{N} y_{n} \end{bmatrix}$$
 and $\boldsymbol{\Sigma} = \frac{1}{N} \sum_{n=1}^{N} (\boldsymbol{\mu} - \boldsymbol{z}_{n}) (\boldsymbol{\mu} - \boldsymbol{z}_{n})^{T}$.

- (c) Pretend that you do not know the true distribution that generates the data and you (**erroneously**) **assume** that the joint pdf of x and y, p(x, y) is a normal one with mean and covariance matrix those computed in (b). Derive the optimum MSE estimate function for this assumption and compute the MSE estimate for each one of the $100 \, x_n$'s, n = 1, ..., 100.
- (d) Discuss the results obtained from (a) and (c).

NOTE: Please give **brief explanations** in all **exercises**.