

# Assignment 3

## Machine Learning: Algorithms and Theory

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### Exercise 1 (Multidimensional derivatives, 1 + 2 points)

- (a) Let  $f(X) = a^T X$ , where  $X \in \mathbb{R}^3$  is a column vector, and  $a^T = [2, -1, 5]$ . Compute the following derivative  $\frac{\partial f}{\partial X}$ .
- (b) Let  $f(X) = X^T A X$ , where  $X \in \mathbb{R}^2$  is a column vector of two elements and

$$A = \begin{pmatrix} 1 & 2 \\ 5 & 3 \end{pmatrix}$$

Compute the following derivative:  $\frac{\partial f}{\partial X}$ .

You may check if your results match with the derivation rules of the following table : [https://en.wikipedia.org/wiki/Matrix\\_calculus#Scalar-by-vector\\_identities](https://en.wikipedia.org/wiki/Matrix_calculus#Scalar-by-vector_identities). **Note:** You are not allowed to just use the table to come up with the solutions.

### Exercise 2 (Optimality and uniqueness for linear regression, 2+4+1 points)

In this exercise let  $X \in \mathbb{R}^{n \times d}$  be a matrix.

- (a) Show that  $X^T X$  is positive semidefinite and that  $\text{rank}(X^T X) = \text{rank}(X)$ .
- (b) Suppose  $\text{rank}(X^T X) \leq d$  and let  $\omega^*$  be an optimal solution for the linear regression problem

$$\min_{\omega} \|Y - X\omega\|^2 \tag{1}$$

show that  $X(\omega^* - \omega_0) = 0$  where  $\omega_0 = (X^T X)^+ X^T Y$ .

- (c) Use part (b) to prove that if  $\text{rank}(X^T X) = d$  then (1) has a unique solution.

### Exercise 3 (Manual linear and ridge regression, 2+3+2 points)

Let

$$\begin{array}{llll} X_1 = (1, 1, 0) & X_2 = (1, -1, 2) & X_3 = (2, 3, -1) & X_4 = (-1, 2, -3) \\ Y_1 = 3 & Y_2 = 1 & Y_3 = 7 & Y_4 = 0 \end{array}$$

- (a) Find 3 optimal solutions for the linear regression problem

$$\min_{\omega} \|Y - X\omega\|^2$$

- (b) Predict  $\hat{Y}$  for  $X_5 = (0, 2, -2)$  and  $X_6 = (1, 0, 0)$  using each of the 3 solutions that you found in (a). Can you explain why the prediction matches in one case but not in the other?
- (c) Find 3 optimal solutions for the ridge regression problem

$$\min_{\omega} \|Y - X\omega\|^2 + \lambda \|\omega\|^2 \text{ where } \lambda = 1$$

**Exercise 4 (Linear and ridge regression in python, 1+2+1+3+1+2 points)**

In this exercise you will implement linear and ridge regression.

(a) Let

$$\begin{aligned}x &\sim \text{Unif}([0, 2]) \\ y(x) &\sim 2 \sin 2x + \varepsilon\end{aligned}$$

Where  $\varepsilon \sim \mathcal{N}(0, 2)$ . Do a scatter plot of the sampled points.

(b) Write a function

```
def ridge_regression(X, Y, lam=1)
```

that, given an  $n \times D$  matrix  $X$  and  $X \times 1$  vectors  $Y$ , returns the weights  $\omega$  of computed by the ridge regression.

(c) For  $\lambda$  use the values 0.1, 1, 10, compute the ridge regression for the values sampled as in a) and compare the mean squared error (MSE). Plot all three predictions.

(d) For every  $x$  as in a) compute the representation of  $x$  in the basis given by

$$\{1, x, x^2\}$$

and then perform ridge regression on this basis. Use  $\lambda = 0.001, 0.01, 0.1, 1, 10$  and compare the MSE. Plot the best prediction. Set  $\lambda = 0$ , see what happens with the linear regression and explain what you observe.

(e) In `X_test` and `Y_test` you will find 20 new samples. Run linear and ridge regression (trained on the original samples) on them for  $\lambda = 0.001, 0.01, 0.1$ . Which one works best and why?

(f) Let

$$\begin{aligned}x &\sim \text{Unif}([0, 2]^2) \\ y(x) &\sim 2x_1^2 + 2x_2 + 1 + \varepsilon\end{aligned}$$

where  $\varepsilon \sim \mathcal{N}(0, 2)$ . For every  $x$  compute the representation of  $x$  in the basis given by

$$\{1, x_1, x_1^2, x_2, x_2^2, x_1x_2\}$$

For  $\lambda = 0.001, 0.01, 0.1, 1, 10$  perform ridge regression on this basis, using  $x$  and  $y$  as inputs, and plot the MSE as a function of  $\lambda$ .