

FECD-B, 2026: Homework 01

Renato Assunção

Easy (Concept Check)

1. Explain the fundamental difference between $g(\mathbf{x})$ and $g(\mathbf{X})$ in the context of predicting a random variable Y .
2. What specific function $g(\mathbf{x})$ provides the solution to the optimization problem of minimizing the Mean Squared Error, $MSE(g) = \mathbb{E}[(Y - g(\mathbf{X}))^2]$?
3. Suppose the conditional expectation $\mathbb{E}[Y|X = \mathbf{x}]$ is estimated directly from a dataset using the empirical arithmetic average of Y values in the examples for which $X = \mathbf{x}$. Why does having a large number of features create a practical difficulty (often called the "curse of dimensionality")?
4. In the context of the linear model $(Y|\mathbf{X} = \mathbf{x}) = \beta_0 + \beta_1x_1 + \dots + \beta_kx_k + \epsilon$, what is the practical interpretation of the coefficient β_j ?

Medium (Application & Calculation)

5. Let Y be a random variable with finite expectation $\mu = \mathbb{E}[Y]$. Let $\varepsilon = Y - \mathbb{E}[Y]$ and consequently $Y = \mathbb{E}[Y] + \varepsilon$. Answer the following:
 - (a) Is ε a random variable?
 - (b) Is $\mathbb{E}[Y]$ a random variable or a constant?
 - (c) Show that $\mathbb{E}(\varepsilon) = 0$.
6. **Distinguishing $g(\mathbf{x})$ from $g(\mathbf{X})$.** Let $g(x_1, x_2) = 2 + 3x_1 - x_2$. Assume the random vector $\mathbf{X} = (X_1, X_2)$ can take only three possible values: $(1, 0)$, $(2, 1)$, and $(0, -1)$ with probabilities 0.2, 0.5, 0.3, respectively.
 - (a) Compute the three scalar values $g(1, 0)$, $g(2, 1)$, and $g(0, -1)$.
 - (b) List the possible values of the *random variable* $g(\mathbf{X})$ and the list of associated probabilities.
 - (c) Compute $\mathbb{E}[g(\mathbf{X})]$.
7. **Best constant predictor.** Consider the restricted class of predictors $g(\mathbf{X}) = c$, where c is a constant. That is, we have no additional information represented by features \mathbf{X} , and we must predict the value of the random variable Y with a single constant value c . The prediction error is the random variable $\epsilon = Y - c$. Using a given c , we want to know how much we can expect in terms of the prediction error ϵ . Take the expected (squared) prediction error $\mathbb{E}[\epsilon^2] = \mathbb{E}[(Y - c)^2]$. Show that the value of c that minimizes this expected (squared) prediction error is $c = \mathbb{E}(Y)$.
8. Using the iterated expectation formula, write down the mathematical steps to show that minimizing the overall $MSE(g)$ is equivalent to minimizing the inner expectation $h(\mathbf{x}) = E_{Y|X}[(Y - g(\mathbf{x}))^2|X = \mathbf{x}]$ for each fixed value of \mathbf{x} .
9. Prove that the function $h(\mathbf{x}) = E[(Y - g(\mathbf{x}))^2|X = \mathbf{x}]$ is minimized exactly when $g(\mathbf{x}) = \mu(\mathbf{x})$, where $\mu(\mathbf{x}) = E[Y|X = \mathbf{x}]$. (Hint: start your proof by adding and subtracting $\mu(\mathbf{x})$ inside the squared term).
10. Given the true surface $\mu(\mathbf{x}) = 1.0 + 0.75x + 0.22 \sin((x - 0.3)^2) + 0.04 \exp(-(x - 0.3)^2)$, calculate the first-order Taylor approximation (the tangent line) around the mean $\bar{x} = 0.0$. Plot the function and its approximating tangent line.

11. Using the same function $\mu(\mathbf{x}) = 1.0 + 0.75x + 0.22 \sin((x - 0.3)^2) + 0.04 \exp(-(x - 0.3)^2)$, do the following:
- (a) Compute $\mu''(\mathbf{x})$ and $\mu''(0)$.
 - (b) Write the second-order Taylor approximation around $\bar{x} = 0$.
 - (c) Plot and visually compare the first-order and second-order approximations with the original function $\mu(\mathbf{x})$. Which one gives a better local approximation near $x = 0$, and why?
12. For the multivariable function $g(\mathbf{x}) = \frac{e^{-3x_1^2}}{1+2x_1x_2+x_2^2}$, compute the gradient vector $\nabla g(\mathbf{x})$ evaluated at the point $p = (1, 1)$, and use it to write the first-order Taylor expansion (tangent plane) around this point.

Hard (Derivation & Advanced Application)

13. To be completed in the future