

Mock Exam - Midterm 1

RHS: $-3\left(\frac{x_1+x_n}{2}\right) + 4$

$\frac{\min + \max}{2}$

1. (6 points) Define the extreme mean (EM) of a dataset to be the average of its largest and smallest values. Let

$f(x) = -3x + 4.$

Show that for any dataset $x_1 \leq x_2 \leq \dots \leq x_n,$

$$EM(f(x_1), f(x_2), \dots, f(x_n)) = f\left(\frac{x_1 + x_n}{2}\right).$$

$f(x)$
 $\max: f(x_1)$
 $\min: f(x_n)$
 LHS:
 $\frac{(-3x_1 + 4) + (-3x_n + 4)}{2}$

2. (10 points) Consider a new loss function,

$L(h, y) = e^{(h-y)^2}.$

Given a dataset $y_1, y_2, \dots, y_n,$ let $R(h)$ represent the empirical risk for the dataset using this loss function.

- a) (4 points) For the dataset $\{1, 3, 4\},$ calculate $R(2).$ Simplify your answer as much as possible without a calculator.
- b) (6 points) For the same dataset $\{1, 3, 4\},$ perform one iteration of gradient descent on $R(h),$ starting at an initial prediction of $h_0 = 2$ with a step size of $\alpha = \frac{1}{2}.$ Show your work and simplify your answer.
- 3. (8 points) Suppose you have a dataset

$\{(x_1, y_1), (x_2, y_2), \dots, (x_8, y_8)\}$

with $n = 8$ ordered pairs such that the variance of $\{x_1, x_2, \dots, x_8\}$ is 50. Let m be the slope of the regression line fit to this data.

$\text{Var}(X) = \frac{1}{n} \sum_i (x_i - \mu)^2$

Suppose now we fit a regression line to the dataset

$\{(x_1, y_2), (x_2, y_1), \dots, (x_8, y_8)\}$

where the first two y -values have been swapped. Let m' be the slope of this new regression line.

If $x_1 = 3, y_1 = 7, x_2 = 8,$ and $y_2 = 2,$ what is the difference between the new slope and the old slope? That is, what is $m' - m?$ The answer you get should be a number with no variables.

$\text{Cov}(X, Y) = \frac{E(X \cdot Y)}{n}$
 $\mu_x, \mu_y = 0$
 "cross variance"

Hint: There are many equivalent formulas for the slope of the regression line. We recommend using the version of the formula without $\bar{y}.$

$\hat{y} = X\hat{w}$
 $m = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2}$ ①
 "total variance"
 $= \frac{\sum_i (x_i - \bar{x}) \cdot y_i}{\sum_i (x_i - \bar{x})^2}$ ② ✓
 $= \frac{\sum_i (y_i - \bar{y}) \cdot x_i}{\sum_i (x_i - \bar{x})^2}$ ③

4. (9 points) Consider the dataset shown below.

$m - m' = \frac{1}{8.50} \cdot [3 \times 7 + 8 \times 2 - (6 + 7 \times 8)]$
 $21 + 16 - 6 - 56 = -35 + 16 = -25$

| $x^{(1)}$ | $x^{(2)}$ | $x^{(3)}$ | y |
|-----------|-----------|-----------|-----|
| 0 | 6 | 8 | -5 |
| 3 | 4 | 5 | 7 |
| 5 | -1 | -3 | 4 |
| 0 | 2 | 1 | 2 |

a) (5 points) We want to use multiple regression to fit a prediction rule of the form

$H(x^{(1)}, x^{(2)}, x^{(3)}) = w_0 + w_1 x^{(1)} x^{(3)} + w_2 (x^{(2)} - x^{(3)})^2.$

Write down the design matrix X and observation vector \vec{y} for this scenario. No justification needed.

b) (4 points) For the X and \vec{y} that you have written down, let \vec{w} be the optimal parameter vector, which comes from solving the normal equations $X^T X \vec{w} = X^T \vec{y}.$ Let $\vec{e} = \vec{y} - X \vec{w}$ be the error vector, and let e_i be the i th component of this error vector. Show that

$m' - m = \frac{1}{16}$
 $e \perp \text{column}(X) \implies 4e_1 + e_2 + 4e_3 + e_4 = 0.$
 $X^T e = X^T y - X^T \hat{w}$
 $= X^T y - X^T (X^T X)^{-1} X^T y = X^T y - X^T y = \vec{0}$

$X_{\text{new}} = \begin{bmatrix} 1 & 0 & 4 \\ 1 & 15 & 1 \\ 1 & -18 & 4 \\ 1 & 0 & 1 \end{bmatrix}$
 $\begin{bmatrix} w_0 \\ w_1 \\ w_2 \end{bmatrix}$

$$L(h, y) = e^{(h-y)^2} \quad y \in \{1, 3, 4\}$$

↑ estimation
↑ sample

$$R(h) = \frac{1}{n} \sum_{i=1}^n e^{(h-y_i)^2}$$

$$\frac{\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}}{I_3} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

$$y_i \quad 1 \quad 3 \quad 4 \quad (h=2)$$

$$z(h-y_i) \quad 2 \quad -2 \quad -4 \quad R(2) = \frac{1}{3} (2e + e^4)$$

$$(h-y_i)^2 \quad 1 \quad 1 \quad 4$$

$$e^{(h-y_i)^2} \quad e \quad e \quad e^4$$

$$\hat{h}_{i+1} = \hat{h}_i - \alpha \cdot R'(h_i) \quad \text{grad descent update rule}$$

$$R(h) = \frac{1}{n} \sum_i e^{(h-y_i)^2} \Rightarrow R'(h) = \frac{1}{n} \sum_i e^{(h-y_i)^2} \cdot 2(h-y_i)$$

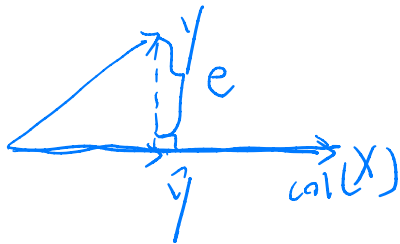
$$\frac{d}{dx} e^x = e^x$$

$$\underline{R(2)} = \frac{1}{3} (e \cdot 2 + e \cdot -2 + e^4 \cdot -4) = -\frac{4}{3} e^4$$

$$h_{\text{new}} = 2 - \frac{1}{2} \cdot \left(-\frac{4}{3}\right) e^4$$

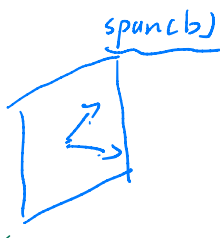
$$= 2 + \frac{2}{3} e^4$$

In dis 4:



$$e = a - \hat{a} \text{ or } \hat{a} - a$$

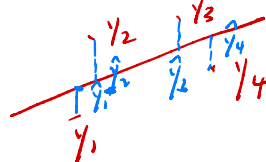
$$e \perp b, \perp \text{space}(b)$$



" $y = Xw$ "
 $w \in \mathbb{R}^{3 \times 1}$

samples

each row is x_i , is one data sample



Over-determined linear system

To "locate" a straight line, I need only 2 point

\hat{y} in column space (X), such that, it achieves

minimized "error"

$$e = \hat{y} - y$$

Loss: $\|\hat{y} - y\|_2$ ✓
 $\sum e_i^2 = \sum (\hat{y}_i - y_i)^2$ ✗

$$y \neq Xw$$

$$X^T y = \underbrace{X^T X}_{CXC} w$$

$\mathbb{R}^{n \times c}$ ← compones / colms.

$$\hat{y} = X \cdot \hat{w}$$

$$= \underbrace{X(X^T X)^{-1} X^T}_{\text{projection matrix}} y$$

y onto column (X)

$$\underbrace{(X^T X)^{-1} X^T y}_{\text{minimized error}} = \hat{w}$$

