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## Q2 . Solution.

Note: The function linear\_regression(X\_tr, y\_tr) returns weight vector the last element of the weight vector is the bias.

The cost fMSE on the training set Dtr is 39.24296299.

The cost fMSE on the training set Dte is 206.79647485.

## Q3 a. Solution.

We have x and a are any two column vectors, we have,

$$x^T = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} \tag{1}$$

$$a^T = \begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix} \tag{2}$$

$$x^{T} a = \begin{bmatrix} x_{1} & x_{2} & \cdots & x_{n} \end{bmatrix} \begin{bmatrix} a_{1} \\ a_{2} \\ \vdots \\ a_{n} \end{bmatrix} = x_{1} a_{1} + x_{2} a_{2} + x_{3} a_{3} \cdots x_{n} a_{n}$$
(3)

Similarly,

$$a^{T}x = a_{1}x_{1} + a_{2}x_{2} + a_{3}x_{3} \cdots a_{n}x_{n} \tag{4}$$

$$\nabla_{x}(x^{T}a) = \begin{bmatrix} \frac{\partial x^{T}a}{x_{1}} \\ \vdots \\ \frac{\partial x^{T}a}{x_{n}} \end{bmatrix} = \begin{bmatrix} a_{1} \\ a_{2} \\ \vdots \\ a_{n} \end{bmatrix} = a$$

$$(5)$$

Similarly,

$$\nabla_x(a^T x) = a \tag{6}$$

## Q3 b. Solution.

We have,

$$x^{T}Ax = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & & & \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

$$(7)$$

$$x^{T}Ax = \begin{bmatrix} \Sigma_{i=1}^{n} a_{i1} x_{i} & \cdot & \cdot & \Sigma_{i=1}^{n} a_{in} x_{i} \end{bmatrix} \begin{bmatrix} x_{1} \\ x_{2} \\ \cdot \\ \cdot \\ x_{n} \end{bmatrix}$$

$$(9)$$

$$x^{T}Ax = \begin{bmatrix} x_1 \sum_{i=1}^{n} a_{i1} x_i & \cdot & \cdot & x_n \sum_{i=1}^{n} a_{in} x_i \end{bmatrix}$$
 (10)

$$x^T A x = \sum_{i=1}^n x_i \sum_{i=1}^n a_{ij} x_i \tag{11}$$

$$x^T A x = \sum_{i=1}^n \sum_{i=1}^n a_{ij} x_i x_j \tag{12}$$

$$\frac{\partial x^T A x}{x} = \begin{bmatrix}
\frac{\partial}{x_1} (\Sigma_{i=1}^n a_{ij} x_i x_j) \\
\frac{\partial}{\partial x_2} (\Sigma_{i=1}^n a_{ij} x_i x_j) \\
\vdots \\
\frac{\partial}{\partial x_n} (\Sigma_{i=1}^n a_{ij} x_i x_j)
\end{bmatrix}$$
(13)

$$\frac{\partial x^{T} A x}{x} = \begin{bmatrix}
\Sigma_{j=1}^{n} a_{1j} x_{j} + \Sigma_{i=1}^{n} a_{i1} x_{i} \\
\Sigma_{j=1}^{n} a_{2j} x_{j} + \Sigma_{i=1}^{n} a_{i2} x_{i} \\
\vdots \\
\Sigma_{j=1}^{n} a_{nj} x_{j} + \Sigma_{i=1}^{n} a_{in} x_{i}
\end{bmatrix} = \begin{bmatrix}
\Sigma_{j=1}^{n} a_{1j} x_{j} \\
\Sigma_{j=1}^{n} a_{2j} x_{j} \\
\vdots \\
\Sigma_{j=1}^{n} a_{nj} x_{j}
\end{bmatrix} \begin{bmatrix}
\Sigma_{i=1}^{n} a_{i1} x_{i} \\
\Sigma_{i=1}^{n} a_{i2} x_{i} \\
\vdots \\
\Sigma_{j=1}^{n} a_{nj} x_{j}
\end{bmatrix} (14)$$

$$\frac{\partial x^T A x}{x} = A x + A^T x \tag{15}$$

Thus,

$$\nabla_x(x^T A x) = A x + A^T x \tag{16}$$

Hence Proved.

Q3 c. Solution.

We have from Q3.b eq. 16

$$\nabla_x(x^T A x) = A x + A^T x \tag{17}$$

For a symmetric matrix A we know

$$A_T = A (18)$$

$$\nabla_x(x^T A x) = (A + A)x = 2Ax \tag{19}$$

Hence Proved.

Q3 d. Solution.

$$\nabla_x[(Ax+b)^T(Ax+b)] \tag{20}$$

$$(Ax + b)^{T} = (Ax)^{T} + b^{T} = x^{T}A^{T} + b^{T}$$
(21)

$$(Ax + b)^{T}(Ax + b) = (x^{T}A^{T} + b^{T})(Ax + b)$$
(22)

$$= (x^{T}A^{T}Ax + x^{T}A^{T}b + b^{T}Ax + b^{T}b)$$
(23)

$$\nabla_x[(Ax+b)^T(Ax+b)] = \nabla_x(x^TA^TAx) + \nabla_x(x^TA^Tb) + \nabla_x(b^TAx) + \nabla_x(b^Tb)$$
(24)

We get from Q 3.b,

$$\nabla_x(x^T(A^TA)x) = (A^TA + AA^T)x\tag{25}$$

As A is symmetric,

$$= (A^T A + A^T A)x \tag{26}$$

Thus,

$$\nabla_x[(Ax+b)^T(Ax+b)] = 2A^TAx \tag{27}$$

From Q3. a

$$\nabla_x(x^T(A^Tb)) = A^Tb \tag{28}$$

As A is symmetric,

$$b_T(Ax) = (Ax)^T b (29)$$

$$\nabla_x(b^T A x) = \nabla(x^T A^T b) \tag{30}$$

$$\nabla_x(b^T A x) = \nabla(x^T A^T b) \tag{31}$$

We have,

$$\nabla_x(b^T b) = 0 \tag{32}$$

Substituting above equations in eq. 24

$$\nabla_x[(Ax+b)^T(Ax+b)] = 2A^TAx + 2A^Tb = 2A^T(Ax+b)$$
(33)