

I. Pen-and-paper

1)

a)

Homework - 3

① $\text{Quadrants } \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ -1 \end{pmatrix}, \begin{pmatrix} -1 \\ 1 \end{pmatrix} \right\}$ (angles: $\{0, 4, 96, 9, 9, 9, 9\}$)

$\begin{pmatrix} 0 \\ 0 \end{pmatrix}$:

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 0 \\ 0 \end{pmatrix} \|^2}{2}\right) = 0,948$$

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 0 \\ 0 \end{pmatrix} \|^2}{2}\right) = 0,8146$$

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 0 \\ 0 \end{pmatrix} \|^2}{2}\right) = 0,912$$

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 0 \\ 0 \end{pmatrix} \|^2}{2}\right) = 0,8825$$

$\begin{pmatrix} 1 \\ -1 \end{pmatrix}$:

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 1 \\ -1 \end{pmatrix} \|^2}{2}\right) = 0,348$$

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 1 \\ -1 \end{pmatrix} \|^2}{2}\right) = 0,271$$

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 1 \\ -1 \end{pmatrix} \|^2}{2}\right) = 0,095$$

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 1 \\ -1 \end{pmatrix} \|^2}{2}\right) = 0,161$$

$\begin{pmatrix} -1 \\ 1 \end{pmatrix}$:

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} -1 \\ 1 \end{pmatrix} \|^2}{2}\right) = 0,107$$

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} -1 \\ 1 \end{pmatrix} \|^2}{2}\right) = 0,331$$

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} -1 \\ 1 \end{pmatrix} \|^2}{2}\right) = 0,272$$

$$\phi_j(x) = \exp\left(-\frac{\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} -1 \\ 1 \end{pmatrix} \|^2}{2}\right) = 0,654$$

Minimize: $w^T w + \lambda w^T z$

$\phi w = z$

$w = (\phi^T \phi + \lambda I)^{-1} \cdot \phi^T z$

Design Matrix

$$\phi = \begin{bmatrix} 1 & 0,778 & 0,248 & 0,101 \\ 1 & 0,8146 & 0,271 & 0,331 \\ 1 & 0,712 & 0,096 & 0,212 \\ 1 & 0,8725 & 0,161 & 0,654 \end{bmatrix}$$

$$\phi^T \phi = \begin{bmatrix} 4 & 3,133 & 1,276 & 1,758 \\ 3,133 & 2,5 & 0,66 & 1,42 \\ 1,276 & 0,66 & 0,33 & 1,05 \\ 1,758 & 1,42 & 0,33 & 1,05 \end{bmatrix}$$

$$\phi^T \phi + \lambda I = \begin{bmatrix} 4,1 & 3,133 & 1,276 & 1,758 \\ 3,133 & 2,6 & 0,66 & 1,42 \\ 1,276 & 0,66 & 0,33 & 1,05 \\ 1,758 & 1,42 & 0,33 & 1,05 \end{bmatrix}$$

$$(\phi^T \phi + \lambda I)^{-1} = \begin{bmatrix} 1,55 & -3,33 & -1,86 & -1,25 \\ -3,33 & 3,58 & -9,88 & -1,16 \\ -1,86 & -9,88 & 4,33 & 2,21 \\ -1,25 & -1,16 & 2,21 & 4,12 \end{bmatrix}$$

$$\phi^T z = [2 \quad 1,565 \quad 0,2381 \quad 0,6956]$$

$$w = \begin{bmatrix} 0,339 \\ 0,193 \\ 0,4 \\ -0,296 \end{bmatrix} \quad \text{Bias}$$

b)

$$b) \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (z_i - \hat{z}_i)^2}$$

$$z_1 = 0,8 ; z_2 = 0,6 ; z_3 = 0,3 ; z_4 = 0,3$$

$$\hat{z} = w^T \phi(x)$$

$$\phi(x) = [1 \ \phi_1(x) \ \phi_2(x) \ \phi_3(x)]^T //$$

$$\hat{z}_1 = [0,33314 \ 0,15945 \ 0,4 \ -0,256] \cdot \begin{bmatrix} 1 \\ 0,147 \\ 0,148 \\ -0,1 \end{bmatrix} = 0,758$$

$$\hat{z}_2 = [0,33314 \ 0,15945 \ 0,4 \ -0,256] \cdot \begin{bmatrix} 1 \\ 0,81 \\ 0,29 \\ 0,33 \end{bmatrix} = 0,51$$

$$\hat{z}_3 = [0,333 \ 0,153 \ 0,4 \ -0,256] \cdot \begin{bmatrix} 1 \\ 0,31 \\ 0,03 \\ 0,71 \end{bmatrix} = 0,303$$

$$\hat{z}_4 = [0,333 \ 0,153 \ 0,4 \ -0,256] \cdot \begin{bmatrix} 1 \\ 0,87 \\ 0,101 \\ 0,65 \end{bmatrix} = 0,326$$

$$\text{RMSE} = \frac{1}{2} \sqrt{(z_1 - \hat{z}_1)^2 + (z_2 - \hat{z}_2)^2 + (z_3 - \hat{z}_3)^2 + (z_4 - \hat{z}_4)^2} =$$

$$= 0,06503$$

2)

② Transfer functions: $\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$ Forward
 $\frac{N(s)}{D(s)} = \frac{C(s)}{D(s)}$

x_1 :
 $Z(1) = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 3 \\ 3 \\ 3 \end{pmatrix}$ $\phi(s) = \ln(3s+1)$
 $\phi(Z(1)) = \begin{pmatrix} 0.44 \\ 0.46 \\ 0.46 \end{pmatrix} - x_{s1}$
 $Z(2) = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \cdot \begin{pmatrix} 0.44 \\ 0.46 \\ 0.46 \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 2.37 \\ 2.67 \\ 2.67 \end{pmatrix}$
 $\phi(Z(2)) = \begin{pmatrix} 0.45 \\ -0.57 \end{pmatrix} - x_{s1}$
 $Z(3) = \begin{pmatrix} 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{pmatrix} \cdot \begin{pmatrix} 0.45 \\ -0.57 \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 0.874 \\ 0.77 \\ 0.874 \end{pmatrix}$
 $\phi(Z(3)) = \begin{pmatrix} -0.51550 \\ -0.805 \\ -0.515 \end{pmatrix} - x_{s1}$ output $Z = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} A \\ B \\ C \end{bmatrix}$

x_2 :
 $Z(1) = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 3 \\ 2 \\ 3 \end{pmatrix}$
 $\phi(Z(1)) = \begin{pmatrix} -0.5515 \\ -0.5515 \\ -0.5515 \end{pmatrix} - x_{s2}$
 $Z(2) = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \cdot \begin{pmatrix} -0.5515 \\ -0.5515 \\ -0.5515 \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} -0.443 \\ -0.715 \\ -0.715 \end{pmatrix}$
 $\phi(Z(2)) = \begin{pmatrix} -0.555 \\ -0.555 \end{pmatrix} - x_{s2}$
 $Z(3) = \begin{pmatrix} 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{pmatrix} \cdot \begin{pmatrix} -0.555 \\ -0.555 \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} -0.555 \\ -0.555 \\ -0.555 \end{pmatrix}$
 $\phi(Z(3)) = \begin{pmatrix} -0.5764 \\ -0.558 \\ -0.586 \end{pmatrix} - x_{s2}$ output $Z = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} A \\ B \\ C \end{bmatrix}$

$$\text{Activation - Derivative}(x) = \frac{\partial \tanh(0,5x - 2)}{\partial x} = 0,5 (1 - \tanh(0,5x - 2))$$

Gradient of the error function

$$\frac{\partial E(z, \hat{z})}{\partial W^{L+1}} = \delta^{L+1} \cdot (X^{L+1})^T$$

Last Layer - Output

$$\frac{\partial E}{\partial \hat{z}} = \frac{\partial E(z, \hat{z})}{\partial \hat{z}} \odot \text{activation-derivative}(z^{L+1})$$

$$\frac{\partial E(z, \hat{z})}{\partial \hat{z}} = \frac{\partial (\frac{1}{2} \|z - \hat{z}\|_2^2)}{\partial \hat{z}} = z - \hat{z}$$

$z = A$ or B

\hat{z} - output from network, $X^{L+1} = \{z^{L+1} \text{ de } x_1 \text{ ou } x_2\}$

$$\frac{\partial E(z, \hat{z})}{\partial \hat{z}} = X^{L+1} - z$$

Output Layer

$$\delta^{L+1} = (W^{L+1})^T \delta^{L+1} \odot \text{activation-derivative}(z^{L+1})$$

Calculating δ^{L+1}

Output:

$$\delta^{L+1} = (X^{L+1} - z) \odot \text{activation-derivative}(z^{L+1})$$

$$x_1: \delta^{L+1}_{x_1} = \begin{bmatrix} -0,915 \\ -0,805 \\ -0,515 \end{bmatrix} \odot \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -0,915 \\ -0,805 \\ -0,515 \end{bmatrix}$$

$$x_2: \delta^{L+1}_{x_2} = \begin{bmatrix} -0,385 \\ -0,335 \\ -0,525 \end{bmatrix} \odot \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -0,385 \\ -0,335 \\ -0,525 \end{bmatrix}$$

Other layers:

$$\delta^{(1)} = (W^{(2)})^T \delta^{(2)} \odot \text{activation_derivative}(z^{(1)})$$

$$\delta^{(1)} = (W^{(2)})^T \delta^{(2)} \odot \text{activation_derivative}(z^{(1)})$$

$$x_1: \delta_{x_1}^{(1)} = \begin{pmatrix} 1 & 1 \\ 3 & 1 \\ 1 & 1 \end{pmatrix}^T \begin{pmatrix} 0.0068 \\ -0.3177 \\ 0.0068 \end{pmatrix} \odot f'(z^{(1)}) = \begin{bmatrix} -0.3745 \\ -0.1016 \end{bmatrix}$$

$$\delta_{x_1}^{(1)} = \begin{pmatrix} 1 & 1 \\ 3 & 1 \\ 1 & 1 \end{pmatrix}^T \begin{pmatrix} -0.3745 \\ -0.1016 \end{pmatrix} \odot f'(z^{(1)}) = \begin{pmatrix} -0.1771 \\ -0.3313 \\ -0.1876 \end{pmatrix}$$

$$x_2: \delta_{x_2}^{(1)} = \begin{pmatrix} 1 & 1 \\ 3 & 1 \\ 1 & 1 \end{pmatrix}^T \begin{pmatrix} -0.0266 \\ 0.0000377 \\ 0.00018 \end{pmatrix} \odot f'(z^{(1)}) = \begin{bmatrix} 0.0000115 \\ 0.000183 \end{bmatrix}$$

$$\delta_{x_2}^{(1)} = \begin{pmatrix} 1 & 1 \\ 3 & 1 \\ 1 & 1 \end{pmatrix}^T \begin{pmatrix} 0.0000115 \\ 0.000183 \end{pmatrix} \odot f'(z^{(1)}) = \begin{bmatrix} 0.00001666 \\ 0.00004378 \\ 0.00004666 \end{bmatrix}$$

$$\sum_{k=1}^2 \frac{\partial E(z_k, t_k)}{\partial W^{(2)}} = \delta_{x_1}^{(2)} (X_{x_1}^{(1)})^T + \delta_{x_2}^{(2)} (X_{x_2}^{(1)})^T =$$

$$= \begin{bmatrix} 0.0068 \\ -0.3177 \\ 0.0068 \end{bmatrix} \begin{bmatrix} 0.4505 & -0.5764 \end{bmatrix} + \begin{bmatrix} 0.026596 \\ 0.00000377 \\ 0.00018 \end{bmatrix} \begin{bmatrix} -0.5115 \\ -0.5815 \end{bmatrix} \quad \text{④}$$

$$\text{④} \quad [-0.5356 \quad -0.5334]$$

$$= \begin{bmatrix} 0.0296 & 0.0225 \\ -0.1431 & 0.1837 \\ 0.0023 & -0.0041 \end{bmatrix} //$$

$$\sum_{k=1}^2 \frac{\partial E(z_k, t_k)}{\partial W^{(2)}} = \delta_{x_1}^{(2)} (X_{x_1}^{(1)})^T + \delta_{x_2}^{(2)} (X_{x_2}^{(1)})^T =$$

$$= \begin{pmatrix} -0.3745 \\ -0.1016 \end{pmatrix} \begin{pmatrix} 0.46 \\ 0.76 \\ 0.46 \end{pmatrix}^T + \begin{pmatrix} 0.0000115 \\ 0.000183 \end{pmatrix} \begin{pmatrix} -0.5115 \\ -0.5815 \end{pmatrix} =$$

$$= \begin{bmatrix} -0.173 & -0.225 & -0.173 \\ -0.0467 & -0.077 & -0.0467 \end{bmatrix}$$

$$\sum_{k=1}^2 \frac{\partial E(z_k, \hat{z}_k)}{w^{(1)}} = \delta_{x_1}^{(1)} (X_{x_1}^{(0)})^T + \delta_{x_2}^{(1)} (X_{x_2}^{(0)})^T =$$

$$= \begin{pmatrix} -0,1772 \\ -0,3353 \\ -0,1872 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}^T + \begin{pmatrix} 0,0000 & 1666 \\ 0,0000 & 1578 \\ 0,0000 & 1666 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ 0 \\ -1 \end{pmatrix}^T =$$

$$= \begin{bmatrix} -0,187 & -0,187 & -0,177 & -0,187 \\ -0,33 & -0,33 & -0,33 & -0,33 \\ -0,18 & -0,18 & -0,18 & -0,18 \end{bmatrix}$$

Updating weights:

$$w^{(1)} = w^{(1)} - \eta \sum_{k=1}^2 \frac{\partial E(z_k, \hat{z}_k)}{\partial w^{(1)}} = \begin{bmatrix} 1,0187 & 1,0177 & 1,0187 & 1,0187 \\ 2,033 & 2,033 & 2,033 & 2,033 \\ 1,011 & 1,018 & 1,018 & 1,018 \end{bmatrix}$$

$$w^{(2)} = w^{(2)} - \eta \sum_{k=1}^2 \frac{\partial E(z_k, \hat{z}_k)}{\partial w^{(2)}} = \begin{bmatrix} 1,0173 & 4,0285 & 1,0173 \\ 1,00467 & 1,0077 & 1,00467 \end{bmatrix}$$

$$w^{(3)} = w^{(3)} - \eta \sum_{k=1}^2 \frac{\partial E(z_k, \hat{z}_k)}{\partial w^{(3)}} = \begin{bmatrix} 0,9570 & 0,9577 \\ 3,0743 & 0,9817 \\ 0,9557 & 1,000 \end{bmatrix}$$

Update Biases: Calculation

$$\frac{\partial E(z_k, \hat{z}_k)}{\partial b^{c13}} = \frac{\partial E(z_k, \hat{z}_k)}{\partial z^{c13}} \bar{x} \frac{\partial z^{c13}}{\partial b^{c13}} \quad x_1 = z^{c13}$$

$$\sum_{k=1}^2 \frac{\partial E(z_k, \hat{z}_k)}{\partial b^{c13}} = \delta_{x_1}^{c13} + \delta_{x_2}^{c13} = \begin{bmatrix} -0,1032 \\ -0,3355 \\ -0,1222 \end{bmatrix}$$

$$\sum_{k=1}^2 \frac{\partial E(z_k, \hat{z}_k)}{\partial b^{c23}} = \delta_{x_1}^{c23} + \delta_{x_2}^{c23} = \begin{bmatrix} -0,3745 \\ -0,1017 \end{bmatrix}$$

$$\sum_{k=1}^2 \frac{\partial E(z_k, \hat{z}_k)}{\partial b^{c33}} = \delta_{x_1}^{c33} + \delta_{x_2}^{c33} = \begin{bmatrix} -0,0452 \\ -0,3192 \\ 0,0070 \end{bmatrix}$$

Update Biases:

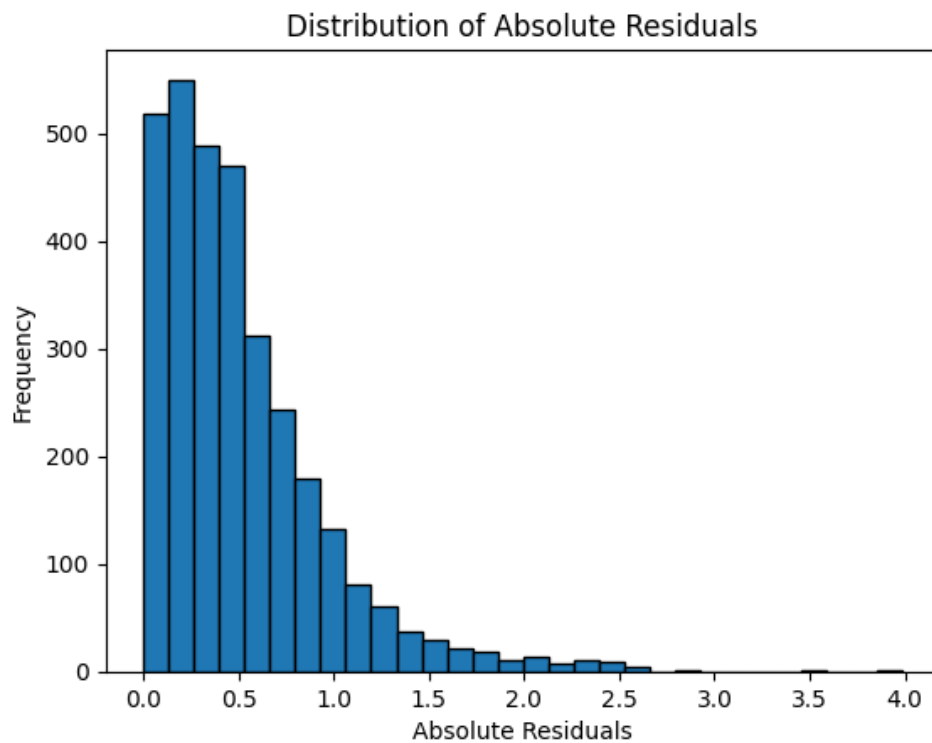
$$b^{c13}' = b^{c13} - \eta \sum_{k=1}^2 \frac{\partial E(z_k, \hat{z}_k)}{\partial b^{c13}} = \begin{bmatrix} 1,0187 \\ 1,0326 \\ 1,0177 \end{bmatrix}$$

$$b^{c23}' = b^{c23} - \eta \sum_{k=1}^2 \frac{\partial E(z_k, \hat{z}_k)}{\partial b^{c23}} = \begin{bmatrix} 1,0374 \\ 1,0106 \end{bmatrix}$$

$$b^{c33}' = b^{c33} - \eta \sum_{k=1}^2 \frac{\partial E(z_k, \hat{z}_k)}{\partial b^{c33}} = \begin{bmatrix} 1,0010 \\ 1,0318 \\ 0,9953 \end{bmatrix}$$

II. Programming and critical analysis

1)

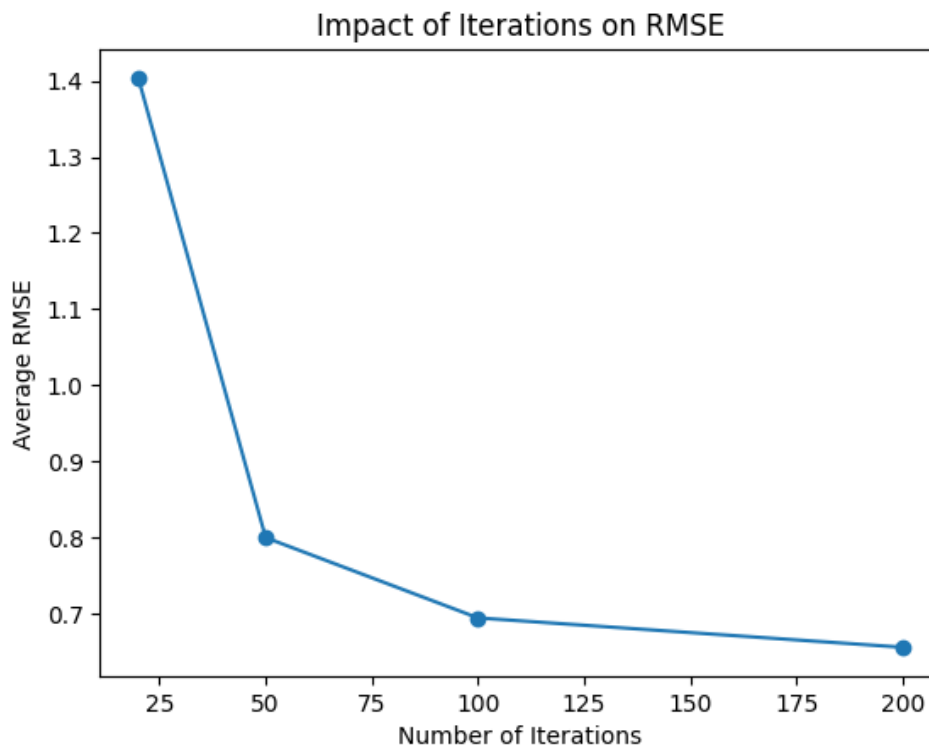


2) Original MAE: 0.5097171955009514 Rounded and Bounded MAE: 0.43875. The second MAE value suggests that rounding and bounding are effective techniques for improving the model's performance in this specific regression task.

3) RMSE with 20 iterations: 1.403978950992544
RMSE with 50 iterations: 0.7996073631460567

RMSE with 100 iterations: 0.6940361469112146

RMSE with 200 iterations: 0.6554543932216473



4) Early stopping at significantly smaller iteration numbers drastically worsens performance, since the model does not have the opportunities to refine its predictions. On the other hand, stopping at 200 iterations, while not perfect, give us a much better RMSE value. Having said this, more is not always better. We should be careful in finding a balance between overfitting and underfitting in order to achieve the best RMSE values possible.



Homework3.ipynb

END