$\begin{array}{c} {\rm COMP~3105-Assignment~1~Report}\\ {\rm -~Fall~2025-} \end{array}$

Due: Sunday September 28, 2025 23:59. Group 51 Andrew Wallace -

Question 1: (7.5%) Linear Regression

- (a) (1%) L_2 Regression Please see A1codes.py for implementation.
- (b) (3%) L_{∞} Regression Here we are going to solve the L_{∞} loss regression problem

$$\mathbf{w} = \operatorname{argmin}_{\mathbf{w} \in \mathbb{R}^d} = ||X\mathbf{w} - \mathbf{y}||$$

Recall that this optimization can be expressed as a linear programming problem with

the joint paramters $\begin{bmatrix} \mathbf{w} \\ d \times 1 \\ \delta \\ 1 \times 1 \end{bmatrix} \in \mathbb{R}^{d+1}$ as follows

$$\min_{\mathbf{w}, \delta} \delta$$
s.t.
$$\delta \ge 0 \iff -\delta \le 0$$

$$X\mathbf{w} - \mathbf{y} \le \delta \cdot \mathbf{1}_n \iff X\mathbf{w} - \delta \cdot \mathbf{1}_n \le \mathbf{y}$$

$$\mathbf{y} - X\mathbf{w} \le \delta \cdot \mathbf{1}_n \iff -X\mathbf{w} - \delta \cdot \mathbf{1}_n \le -\mathbf{y}$$

In the following answers, we will convert the optimization to a form that is solvable by the **cxvopt** linear programming (LP) solver, which solves the following form of LP

$$\min_{\mathbf{u}} \mathbf{c}^T \mathbf{u}$$
 s.t. $G\mathbf{u} \leq \mathbf{h}$

Let the unknown variables be $\mathbf{u} = \begin{bmatrix} \mathbf{w} \\ d \times 1 \\ \delta \\ 1 \times 1 \end{bmatrix} \in \mathbb{R}^{d+1}$

For the constraints, since we have three sets of constraints, the matrix G and \mathbf{h} can be decomposed into three parts

$$G \cdot \mathbf{u} = \begin{bmatrix} G^{(1)} \\ I \times (d+1) \\ G^{(2)} \\ n \times (d+1) \\ G^{(3)} \\ n \times (d+1) \end{bmatrix} \cdot \begin{bmatrix} \mathbf{w} \\ \delta \end{bmatrix} \preceq \begin{bmatrix} \mathbf{h}^{(1)} \\ I \times 1 \\ \mathbf{h}^{(2)} \\ d \times 1 \\ \mathbf{h}^{(3)} \\ d \times 1 \end{bmatrix}$$

(b.1) (0.25%) For the objective function, we want $\mathbf{c}^T \mathbf{u} = \delta$. What should $\mathbf{c} \in \mathbb{R}^{d+1}$ be? Recall that $\mathbf{u} = \begin{bmatrix} \mathbf{w} \\ \delta \end{bmatrix}$ For the objective function to be δ we have:

$$\mathbf{c}^{T}\mathbf{u} = [c_1, c_2, \dots c_d, c_{d+1}] \cdot \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \\ \delta \end{bmatrix} = c_1 w_1 + c_2 w_2 + \dots + w_d u_d + c_{d+1} \delta$$
Now let $c_1 = c_1 \cdots c_d = 0$

Now let $c_1 = c_2 = \ldots = c_d = 0$

And $c_{d+1} = 1$

This gives us:

 $0w_1 + 0w_2 + \dots 0w_d + \delta$ $- \delta$

Thus $\mathbf{c} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}$

Where $c_1 = c_2 = \ldots = c_d = 0$ and $c_{d+1} = 1$.

(b.2) (0.25%) We want $G^{(1)}\mathbf{u} \leq \mathbf{h}^{(1)} \iff \delta \geq 0$. What should $G^{(1)} \in \mathbb{R}^{1 \times (d+1)}$ and $h^{(1)} \in \mathbb{R}$ be?

Recall the first constraint: $-\delta \leq 0$

We want

$$\underset{1\times(d+1)}{G^{(1)}}\cdot\mathbf{u}\preceq \mathbf{h}_{1\times 1}^{(1)}$$

We will now map our constraint into this form.

$$\begin{bmatrix} G_{1\times d}^{(11)} & G_{1\times 1}^{(12)} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{w} \\ \delta \end{bmatrix} \preceq \mathbf{h}_{n\times 1}^{(1)} \iff -\delta \leq 0$$
$$G_{1\times d}^{(11)} \cdot \mathbf{w} + G_{1\times 1}^{(12)} \cdot \delta = -\delta \leq 0 = \mathbf{h}_{1\times 1}^{(1)}$$

So,

$$G_{1\times d}^{(11)} = \mathbf{0}_{1\times d}$$

 $G_{1\times 1}^{(12)} = -1$
 $G_{1\times (d+1)}^{(1)} = \begin{bmatrix} \mathbf{0}_{1\times d} & -1 \end{bmatrix}$
 $\mathbf{h}_{1\times 1}^{(1)} = \mathbf{0}_{1\times 1}$

(b.3) (0.25%) We want $G^{(2)}\mathbf{u} \leq \mathbf{h}^{(2)} \iff X\mathbf{w} - \mathbf{y} \leq \delta \cdot \mathbf{1_n}$. What should $G^{(2)} \in \mathbb{R}^{n \times (d+1)}$ and $h^{(2)} \in \mathbb{R}^n$ be?

Recall our second constraint is

 $X\mathbf{w} - \mathbf{y} \leq \delta \cdot \mathbf{1}_n \iff X\mathbf{w} - \delta \cdot \mathbf{1}_n \leq \mathbf{y}$

We want

$$G^{(2)}_{n\times(d+1)}\cdot\mathbf{u}\preceq\mathbf{h}^{(2)}_{n\times1}$$

We will now map our constraint into this form.

$$\begin{bmatrix} G^{(21)} & G^{(22)} \\ n \times d & n \times 1 \end{bmatrix} \cdot \begin{bmatrix} \mathbf{w} \\ \delta \end{bmatrix} \preceq \mathbf{h}^{(2)} \iff X\mathbf{w} - \delta \cdot \mathbf{1}_n \preceq \mathbf{y}$$
$$G^{(21)}_{n \times d} \cdot \mathbf{w} + G^{(22)}_{n \times 1} \cdot \delta = X\mathbf{w} - \delta \cdot \mathbf{1}_n \preceq \mathbf{y} = \mathbf{h}^{(1)}_{n \times 1}$$

So,

$$G_{n \times d}^{(21)} = X$$

 $G_{n \times 1}^{(22)} = -\mathbf{1}_{n \times 1}$
 $G_{n \times (d+1)}^{(2)} = \begin{bmatrix} X & -\mathbf{1}_{n \times 1} \end{bmatrix}$
 $h_{n \times 1}^{(2)} = \mathbf{y}$

(b.4) (0.25%) We want $G^{(3)}\mathbf{u} \leq \mathbf{h}^{(3)} \iff \mathbf{y} - X\mathbf{w} \leq \delta \cdot \mathbf{1_n}$. What should $G^{(3)} \in \mathbb{R}^{n \times (d+1)}$ and $h^{(3)} \in \mathbb{R}^n$ be?

Recall our third constraint is

$$\mathbf{y} - X\mathbf{w} \leq \delta \cdot \mathbf{1}_n \iff -X\mathbf{w} - \delta \cdot \mathbf{1}_n \leq -\mathbf{y}$$

We want

$$\underset{n\times(d+1)}{G^{(3)}}\cdot\mathbf{u}\preceq\underset{n\times1}{\mathbf{h}^{(3)}}$$

We will now map our constraint into this form.

$$\begin{bmatrix} G^{(31)}_{n \times d} & G^{(32)}_{n \times 1} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{w} \\ \delta \end{bmatrix} \preceq \mathbf{h}^{(3)}_{n \times 1} \iff -X\mathbf{w} - \delta \cdot \mathbf{1}_n \preceq -\mathbf{y}$$
$$G^{(31)}_{n \times d} \cdot \mathbf{w} + G^{(32)}_{n \times 1} \cdot \delta = -X\mathbf{w} - \delta \cdot \mathbf{1}_n \preceq -\mathbf{y} = \mathbf{h}^{(3)}_{n \times 1}$$

So,

$$G_{n\times d}^{(31)} = -X$$

 $G_{n\times d}^{(32)} = -\mathbf{1}_{n\times 1}$
 $G_{n\times (d+1)}^{(3)} = \begin{bmatrix} -X & -\mathbf{1}_{n\times 1} \end{bmatrix}$
 $h_{n\times 1}^{(3)} = -\mathbf{y}$

(b.5) (2%) Based on your derivations in (b), implement a Python function

$$\mathbf{w} = \min \operatorname{minimizeLinf}(X, y)$$

that returns a $d \times 1$ vector of weights/parameters **w** corresponding to the solution of minimum L_{∞} loss.

$$\mathbf{w} = \operatorname{argmin}_{w \in \mathbb{R}^d} ||X\mathbf{w} - \mathbf{y}||$$

Based on our derivations in (b), we result in

$$\mathbf{c} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix} \in \mathbb{R}^{d+1}$$

$$\mathbf{u} = \begin{bmatrix} \mathbf{w} \\ \delta \end{bmatrix} \in \mathbb{R}^{d+1}$$

$$G = \begin{bmatrix} \mathbf{0}_{1 \times d} & -1 \\ X & -\mathbf{1}_n \\ -X & -\mathbf{1}_n \end{bmatrix} \in \mathbb{R}^{(2n+1) \times (d+1)}$$

$$\mathbf{h} = \begin{bmatrix} 0 \\ \mathbf{y} \\ -\mathbf{y} \end{bmatrix} \in \mathbb{R}^{2n+1}$$

$$\mathbf{s.t.}$$

$$G \cdot \mathbf{u} \leq \mathbf{h}$$

$$(2n+1) \times (d+1) \cdot (d+1) \times 1 \leq \mathbf{h}$$

$$(2n+1) \times (d+1) \cdot (d+1) \times 1 \leq \mathbf{h}$$

Please see A1codes.py for full implementation.

- (c) (2%) Synthetic Regression Problem
 In this part, you will evaluate your implemented algorithms on a synthetic dataset.
 - (c.1) (1%) Implement a Python function

that returns a 2 x 2 matrix train loss of average training losses and a 2 x 2 matrix test loss of average test losses (See Table 1 and Table 2 below.) It repeats 100 runs as follows

Please see **A1codes.py** for full details.

(c.2) (1%) Looking at your tables from above, analyze the results and discuss any findings you may have and the possible reason behind them.