

Linear regression implementation

a) Read data:

train.txt, test.txt \rightarrow Each column is a feature except last column, which is label

$X \rightarrow$ load feature columns in ~~matx~~ matrix X

$t \rightarrow$ load label column in t

In case of simple LR: $X = \begin{bmatrix} 3032 \\ 2078 \\ 2400 \\ \vdots \end{bmatrix}$, $t = \begin{bmatrix} 525k \\ 230k \\ 87k \\ \vdots \end{bmatrix}$

b) Standardize features:

mean \rightarrow find mean of each feature (column) and store it in mean

std \rightarrow find standard deviation of each feature (column) and store it in std

standardize features in X by subtracting their mean and dividing by their standard deviation: $s = (X - \text{mean}) / \text{std}$

For simple LR: $X = \begin{bmatrix} 3032 \\ 2078 \\ 2400 \\ \vdots \end{bmatrix}$

lets say mean of 1st feature/column in X , $\text{mean} = [2528]$

" " standard deviation of 1st feature/column of X ,
 $\text{std} = [238]$

Then, $s = (X - \text{mean}) / \text{std} = \begin{bmatrix} \frac{3032 - 2528}{238} \\ \frac{2078 - 2528}{238} \\ \frac{2400 - 2528}{238} \\ \vdots \end{bmatrix}$

c) Implement GD in 'train' function to compute w .

For simple LR: $w = [w_0 \ w_1]$.

Each ^{epoch} update of GD: $w = w - \text{eta} \cdot \text{grad}$

where ~~grad~~ $\text{grad} = \begin{bmatrix} \frac{\partial J(w)}{\partial w_0} & \frac{\partial J(w)}{\partial w_1} \end{bmatrix}$ computed using 'compute_v' ^{gradient}

Run GD for 200 epochs ~~with~~ with $\text{eta} = 0.1$ ^{derivatives of cost function}

d) Use 'compute-gradient' function to compute ~~grad~~

$\text{grad} = \begin{bmatrix} \frac{\partial J(w)}{\partial w_0} & \frac{\partial J(w)}{\partial w_1} \end{bmatrix}$, where ~~grad~~ is

For simple LR:

$\Rightarrow X$ should have bias features added as first column:

$$X = \begin{bmatrix} 1 & 3032 \\ 1 & 2078 \\ 1 & 2400 \\ \vdots & \vdots \end{bmatrix} \rightarrow \underline{50 \times 2}$$

~~$\Rightarrow w^T X$ should be $= [w_0 \ w_1] * \underline{50 \times 2}$~~ $\underline{50 \times 2}$

$$\Rightarrow w^T X \text{ should be } = [w_0 \ w_1] * \begin{bmatrix} 1 & 3032 \\ 1 & 2078 \\ \vdots & \vdots \end{bmatrix} = \begin{bmatrix} w_0 & w_1 \cdot 3032 \\ w_0 & w_1 \cdot 2078 \\ \vdots & \vdots \end{bmatrix}$$

\Rightarrow Given $w^T X$, Obtain $[L - t]$ s.t.

$$L = \begin{bmatrix} w_0 + w_1 \cdot 3032 \\ w_0 + w_1 \cdot 2078 \\ w_0 + w_1 \cdot 2400 \\ \vdots \end{bmatrix} \quad \text{labels} \quad \text{and } t = \begin{bmatrix} t_1 \\ t_2 \\ t_3 \\ \vdots \end{bmatrix}$$

$\underline{50 \times 1} \qquad \underline{50 \times 1}$

$$\therefore [L - t] = \begin{bmatrix} w_0 + w_1 \cdot 3032 - t_1 \\ w_0 + w_1 \cdot 2078 - t_2 \\ \vdots \end{bmatrix} \rightarrow \underline{50 \times 1}$$

$$\frac{\partial}{\partial w_j} J(w)$$

$$\Rightarrow \text{Given } \text{grad}_N = \frac{1}{N} \sum_{i=1}^N (h_w(x^{(i)}) - y^{(i)}) \cdot x_j^{(i)} \text{ for } j=0, 1$$

$$\Rightarrow \text{In vectorized form, } \text{grad} = \left[\frac{\partial}{\partial w_0} J(w) \quad \frac{\partial}{\partial w_1} J(w) \right] = \frac{1}{N} (X.T \cdot [L - t])$$

$$\Rightarrow \text{Here, } X.T = \begin{bmatrix} 1 & 1 & 1 & \dots \\ 3032 & 2078 & 2400 & \dots \end{bmatrix}$$

$$2 \times 50$$

$$\Rightarrow X.T \cdot [L - t] = \begin{bmatrix} 1 & 1 & \dots \\ 3032 & 2078 & \dots \end{bmatrix} \cdot \begin{bmatrix} w_0 + w_1 \cdot 3032 - t_1 \\ w_0 + w_1 \cdot 2078 - t_2 \\ \vdots \end{bmatrix}$$

$$2 \times 50$$

$$50 \times 1$$

$$= \begin{bmatrix} 1(w_0 + w_1 \cdot 3032 - t_1) + 1(w_0 + w_1 \cdot 2078 - t_2) + \dots \\ 3032(w_0 + w_1 \cdot 3032 - t_1) + 2078(w_0 + w_1 \cdot 2078 - t_2) + \dots \end{bmatrix}$$

$$2 \times 1$$

$\Rightarrow N = \text{number of training examples}$

gradient

\therefore Obtain and return vectorized form of grad in 'compute_grad' function.

e) Compute cost function $J(w)$ in 'compute_cost' function.

$$\Rightarrow J(w) = \frac{1}{2N} \sum_{i=1}^N (h_w(x^{(i)}) - y^{(i)})^2$$

For simple LR: obtain

$$\Rightarrow \text{Find}_N [L - t] = \begin{bmatrix} w_0 + w_1 \cdot 3032 - t_1 \\ w_0 + w_1 \cdot 2078 - t_2 \\ \vdots \end{bmatrix} \rightarrow 50 \times 1$$

\Rightarrow Then find $s = \text{sum of all values in } [L - t]$. Find s^2 .

$\therefore J(w)$ is given by $= \frac{1}{2N} \cdot s^2$

⇒ Then obtain s^2 sum of squared values in $[L-t]$

$$\Rightarrow s^2 = (w_0 + w_1 \cdot 3032 - t_1)^2 + (w_0 + w_1 \cdot 2078 - t_2)^2 + \dots$$

⇒ Given s^2 , $J(w) = \frac{1}{2N} \cdot s^2$
obtain

⇒ Return $J(w)$

e. Use the 'compute_rmse' function to compute and return root mean square error of dataset

⇒ Compute and return RMSE as square root of $J(w)$ computed above.

f. In the main method, standardize the training and test data, X_{train} and X_{test} . Then add a column of ones as the first column of training and test data. The column of ones are the bias features.

For simple LR: $X_{train} = \begin{bmatrix} 3032 \\ 2074 \\ \vdots \end{bmatrix}$, after adding bias v features, $X_{train} = \begin{bmatrix} 1 & 3032 \\ 1 & 2074 \\ \vdots & \vdots \end{bmatrix}$

3. Implement the steps above for the multiple LR problem where there are 3 data features corresponding to the first 3 columns and the labels " " " last column in the dataset.

4. BONUS [SGD], Implement SGD using the 'train_sgd' function to solve the simple and multiple LR problems. In each epoch of SGD:

⇒ $w = w - \text{eta} \cdot \text{grad}$ is computed for a single training example

⇒ Iterate ^{above} over all training examples.