Binary Logistic Regression

Dataset preparation:

1. Use dataset(dataset.csv).
2. Randomly Split the dataset into Training (70%), Validation (15%) and Test (15%) set

Train (update):

1. **for** each sample, ***X*** = *[x1, x2, … , xn]* **in** TRAINING set:
2. concatenate 1 and turn it into ***X'*** = *[x1, x2, …, xn, 1]*
3. randomly initialize θ = [θ1,θ2, …, θ(n+1)] within 0 to 1
   // θ1, θ2, …: weights, θ (n+1): bias
4. *max_iter* = 500, *lr* = 0.01
5. *history* = list()
6. **for** itr **in** [1, *max_iter*]:
7. *TJ=0* // total cost
8. **for** each sample, ***X'***, in TRAINING set:
9. *z = X'.* $\boldsymbol{\theta}$ // use np.dot function
10. *h* = sigmoid(*z*) // sigmoid available in python
11. *J = - y log (h) - (1-y) log (1-h)* // *h* = pred label, *y* = true label
12. *TJ=TJ+J*
13. ***dv*** = *X'. (h-y)* // dim(*dv*)=n+1
14. θ = θ - *dv* * *lr* // dim( )=n+1, *lr* = learning rate
15. *TJ = TJ / N_train* // *N_train* = #training samples
16. append *TJ* into *history* // average loss

Validation:

1. *correct* = 0
2. **for** each sample ***V'*** in the **VALIDATION** set:
3. *z = V'.* $\boldsymbol{\theta}$
4. *h* = sigmoid(*z*)
5. **if** *h >= 0.5* *h = 1*
6. **else**: *h = 0*
7. **if** *h == y:* *correct = correct + 1*
8. *val_acc = correct * 100 / N_val* // *N_val* = #validation samples

- [ ] Calculate validation accuracy (*val_acc*) for *lr* = 0.1, 0.01, 0.001 and 0.0001 (*max_iter* = 500)
- [ ] Make a table with 2 columns: learning rate *lr* and *val_acc*
- [ ] Now, take the *lr* with maximum *val_acc*
- [ ] Calculate *test accuracy* for *max_iter* = 500 and the **chosen *lr*** in the previous step
- [ ] Plot the train_loss (history) vs epoch (iteration) graph

Instruction

- Submit a .ipynb file and a report (report template) .pdf file.
- **DO NOT USE LIBRARIES SUCH AS: "Sklearn", "Scikit learning" or "pandas" for this assignment. You can use pandas only for reading the csv file.**
- **Copying will result in -100% penalty**

Marks Distribution

(1) Dataset loading, train-val-test split: 2
(2) Training code: 8
(3) Validation/ test code: 5
(4) l.r. and val_acc table: 2.5
(5) train_loss vs epoch graph plot for the best l.r.: 2.5
Task (2)-(5) have to be done without using sklearn like libraries.
Your marks will fully depend on your viva and understanding.

Resources

[Logistic Regression Explained](#)
[Logistic Regression](#)

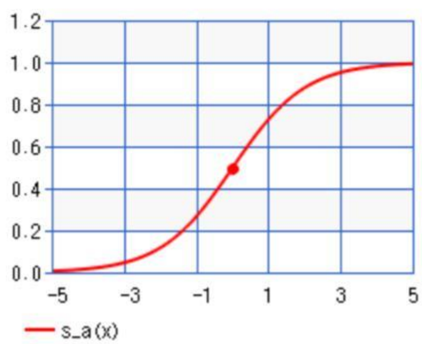
Labels = 0 or 1 ⇒ binary classification

How to predict?

Let, sample 1 of dataset, X_1 = [x1, x2, x3, 1]

Weights, = [1, 2, 3, **4**] **4 is called bias**

Model/Prediction equation: ***z = X. = x1. 1 + x2. 3 + x3. 3 + 4***. We update weights so that z can correctly predict the label of X_1, but its value can be very big (>1) or very small (<0).



Solution: use activation function sigmoid
sigmoid(z) = 1/(1 + −)

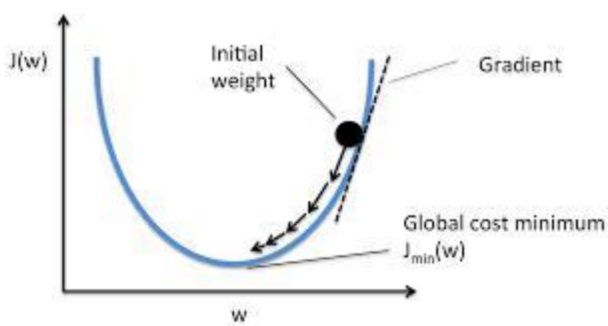
So, ***h = sigmoid(z) is the predicted label of X1***

How to update weights?

Gradient descent optimization

Log loss function: J( ) = - y log(h) - (1-y) log(1-h) , y is the true label and h is the predicted label

The closer h is to y, the lesser the loss.



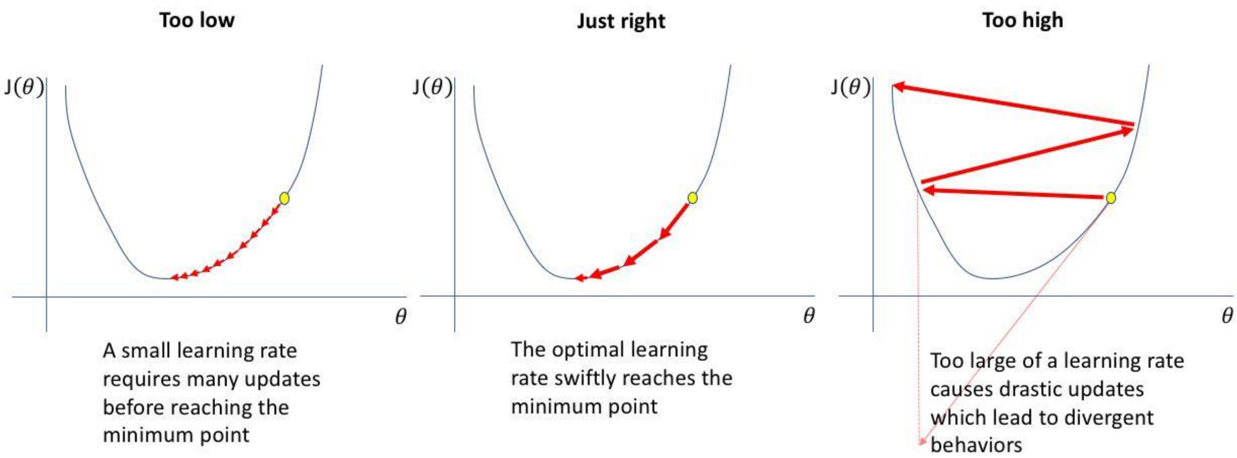
dv = Derivative of J( ) = **Gradient** = X(h-y)

If gradient +ve, we should decrease weights, else if gradient -ve, we should increase weights. So, update = - dv

However, weights may oscillate without reaching our desired value. Solution:

introduce learning rate lr **(0<lr<1) e.g. 0.01, 0.001, 0.0001**

= - dv * lr



Weights are updated using the training set.

How to choose the value of lr?

Hyperparameter tuning using validation set.