Binary Logistic Regression

Dataset preparation:

1. Use dataset `diabetes`. Code for loading dataset into 2D python list: [here]
2. Randomly Split the dataset into Training (70%), Validation (15%) and Test (15%) set

Train (update **ϴ**):

1. **for** each sample, **X** = $[x1, x2, \ldots, xn]$ **in** TRAINING set:
2.   concatenate 1 and turn it into **X'** = $[x1, x2, \ldots, xn, 1]$
3. randomly initialize **ϴ** = [**ϴ**1, **ϴ**2, ..., **ϴ**(n+1)] within 0 to 1
   // **ϴ**1, **ϴ**2, ...: 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' . ***ϴ*** // 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(***ϴ***)=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'.***ϴ***
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**
- **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_CRR.pdf

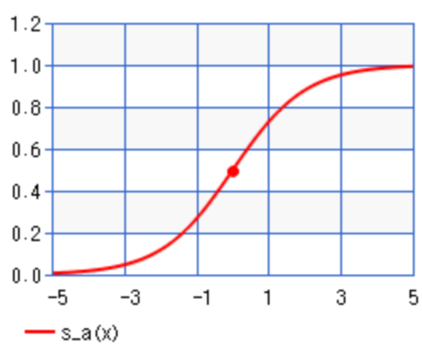
Labels = 0 or 1 ⇒ binary classification

How to predict?

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

Weights, **θ** = [**θ**1, **θ**2, **θ**3, **θ4**]   **θ4 is called bias**

Model/Prediction equation: ***z = X.θ = x1. θ1 + x2.θ3 + x3. θ3 + θ4***. We update weights **θ** 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) = $1/(1 + e^{-z})$

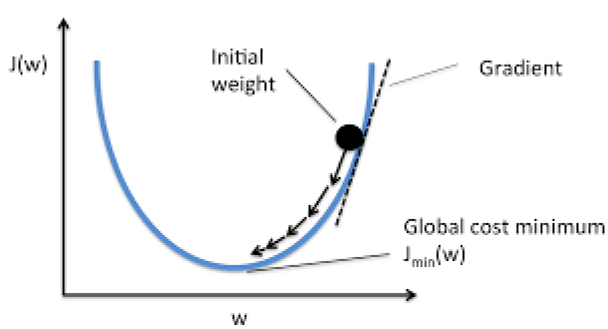
So, *h = sigmoid(z) is the predicted label of X1*

How to update weights?

Gradient descent optimization

Log loss function: J(**θ**) = - 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.



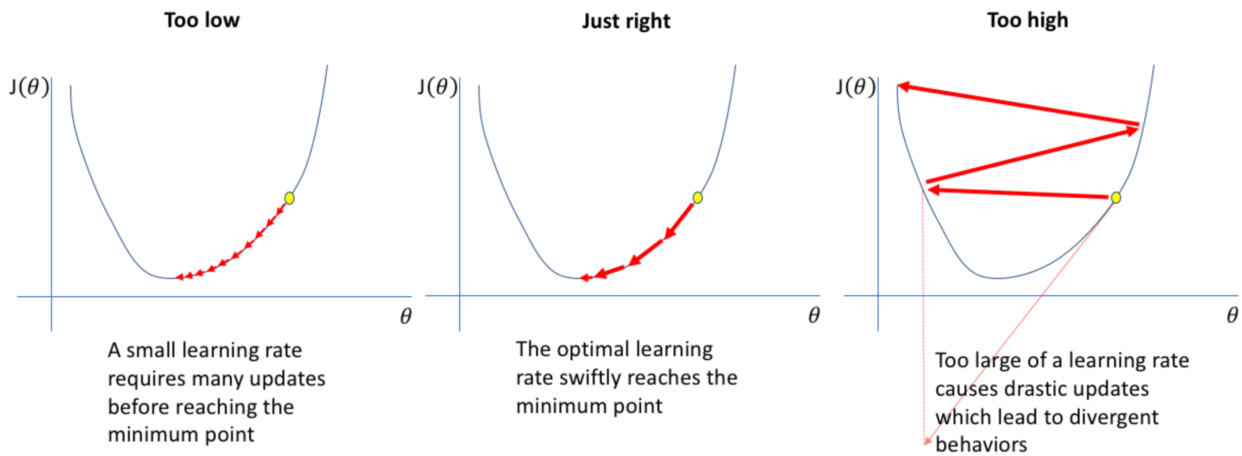
dv = Derivative of J(**θ**) = **Gradient** = X(h-y)

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

$\theta = \theta - dv * lr$



Weights are updated using the training set.

How to choose the value of lr?

Hyperparameter tuning using validation set.