

EEE 591 Machine Learning with deployment to FPGA

HOMEWORK 4
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1.

Least square cost function:

$$g(W) = \frac{1}{P} \sum_{p=1}^P (b + X_p^T W - Y_p)^2$$

first derivative is:

$$\begin{aligned} d g(W) / d w &= \frac{d}{d w} \frac{1}{P} \sum_{p=1}^P (b + X_p^T W - Y_p)^2 \\ &= 2 \cdot \frac{1}{P} \sum_{p=1}^P (X_p^T W - Y_p) X_p^T. \end{aligned}$$

Second derivative is given by:

$$\begin{aligned} &= \frac{d}{d w} \cdot 2 \cdot \frac{1}{P} \sum_{p=1}^P X_p (X_p^T W - Y_p). \\ &= 2 \cdot \frac{1}{P} X_p (X_p^T) + 0 \\ &= 2 \cdot \frac{1}{P} (X_p \cdot X_p^T) \end{aligned}$$

2.

Sigmoid function:

$$S(x) = \frac{1}{1+e^{-x}}$$

Differentiate the equation:

$$\begin{aligned} dS/dx &= \frac{d}{dx} \frac{1}{1+e^{-x}} \\ &= (-1 \cdot \frac{d}{dx} (1+e^{-x}) + 0) / (1+e^{-x})^2 \\ &= -1 (0 + (-1) \cdot e^{-x}) / (1+e^{-x})^2 \\ &= e^{-x} / (1+e^{-x})^2 \\ &= \frac{e^{-x}}{(1+e^{-x})^2} \end{aligned}$$

Rationalizing:

$$= \frac{1}{(1 + e^{-x})} \cdot \frac{e^{-x}}{(1 + e^{-x})}$$

$$= \frac{1}{(1 + e^{-x})} \cdot 1 - \frac{1}{(1 + e^{-x})}$$

$$V\sigma(t) = \sigma(t)(1 - \sigma(t))$$

3.

Cross Entropy Cost function:

$$g(W) = \frac{1}{p} \cdot \sum_{p=1}^p -y_p \log(\sigma(X_p^T w)) - (1 - y_p) \log(1 - \sigma(X_p^T w))$$

$$dg/d(W) = \frac{1}{p} \cdot \sum_{p=1}^p -0 \cdot \log(\sigma(X_p^T w)) - y_p \cdot \frac{1}{\sigma(X_p^T w)} \cdot \sigma(X_p^T) - \frac{1}{1 - \sigma(X_p^T w)} \cdot \sigma(X_p^T) - y_p \cdot \frac{1}{1 - \sigma(X_p^T w)} \cdot \sigma(X_p^T)$$

$$= \frac{1}{p} \cdot \sum_{p=1}^p -y_p \cdot \frac{1}{\sigma(X_p^T w)} \cdot \sigma(X_p^T) - \frac{1}{1 - \sigma(X_p^T w)} \cdot \sigma(X_p^T) + y_p \cdot \frac{1}{1 - \sigma(X_p^T w)} \cdot \sigma(X_p^T)$$

$$= \frac{1}{p} \cdot \sum_{p=1}^p -y_p \cdot \frac{1}{\sigma(X_p^T w)} \cdot \sigma(X_p^T) + y_p \cdot \frac{1}{1 - \sigma(X_p^T w)} \cdot \sigma(X_p^T) - \frac{1}{1 - \sigma(X_p^T w)} \cdot \sigma(X_p^T)$$

$$= \frac{1}{p} \cdot \sum_{p=1}^p \left(X_p^T (y_p - \sigma(X_p^T w)) \right) \cdot \frac{1 - \sigma(X_p^T w)}{1 - \sigma(X_p^T w)}$$

$$= \frac{1}{p} \cdot \sum_{p=1}^p \left(X_p^T (y_p - \sigma(X_p^T w)) \right)$$

Question 4.

Question 4
Multiclass
Learning rate is 0.1
Train_errors are 1.0
Test_errors are 3.0
Testing accuracy = 0.9333333333333333
Training accuracy = 0.9904761904761905

Most Highly Correlated

	FirstVariable	SecondVariable	Correlation
0	petal length (cm)	petal width (cm)	0.962865
1	sepal length (cm)	petal length (cm)	0.871754
2	sepal length (cm)	petal width (cm)	0.817941
3	sepal width (cm)	petal length (cm)	-0.428440
4	sepal width (cm)	petal width (cm)	-0.366126
5	sepal length (cm)	sepal width (cm)	-0.117570
6	sepal length (cm)	sepal length (cm)	0.000000
7	sepal width (cm)	sepal length (cm)	-0.000000
8	sepal width (cm)	sepal width (cm)	0.000000
9	petal length (cm)	sepal length (cm)	0.000000
10	petal length (cm)	sepal width (cm)	-0.000000
11	petal length (cm)	petal length (cm)	0.000000
12	petal width (cm)	sepal length (cm)	0.000000
13	petal width (cm)	sepal width (cm)	-0.000000
14	petal width (cm)	petal length (cm)	0.000000
15	petal width (cm)	petal width (cm)	0.000000

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

Question 5
Canned algorithm Logistic Regression
Training Accuracy is 0.9809523809523809
Testing Accuracy is 0.9777777777777777

5.

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Canned Algorithm is better than the normal one with more accuracy , can be varied by changing the hyper parameters.

```
In [1]: from sklearn import datasets
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from matplotlib import pyplot as plt

iris = datasets.load_iris()
X = iris.data[:,0:4]
Y = iris.target

# Compact Notation
m = np.size(Y)
Ones = np.ones(m,dtype=int)
X_compact = np.column_stack((Ones,X))

X_train,X_test,Y_train,Y_test = train_test_split(X_compact,Y,test_size=0.3,random_state=0)

# One hot Encoding
targets = np.array(Y_train).reshape(-1)
Y_train_one= np.eye(3)[targets]

targets = np.array(Y_test).reshape(-1)
Y_test_one= np.eye(3)[targets]

converged=False
W = np.ones((5,3))
alpha=0.1
iterations=0
Training_error=[]
Testing_error=[]

def sigmoid(X,W):
    return 1/(1 + np.exp(-(np.dot(X.T,W))))

while not converged:
    U = - 1/m * np.dot(X_train.T,(Y_train_one - sigmoid(X_train.T,W)))
    W_new = W - alpha * U
    epsilon=np.abs(W_new-W)
    W = np.copy(W_new)

    converged=(np.abs(epsilon) < 0.0001).all()
    if iterations>4000:
        converged = True

    Y_train_pred=np.dot(X_train,W)
    Y_train_pred1=np.argmax(Y_train_pred,axis=1)
    Train_error = np.sum((Y_train != Y_train_pred1)/np.size(Y_train))

    Y_test_pred=np.dot(X_test,W)
    Y_test_pred1=np.argmax(Y_test_pred,axis=1)
    Test_error = np.sum((Y_test != Y_test_pred1)/np.size(Y_test))

    Training_error.append(Train_error)
    Testing_error.append(Test_error)

    iterations+=1
print('Question 4')
print('Multiclass')
print('Learning rate is 0.1')
print('Train_errors are ', Train_error*np.size(Y_train))
print('Test_errors are ', Test_error*np.size(Y_test))
print("Testing accuracy =",(np.size(Y_test) - Test_error*np.size(Y_test))/np.size(Y_test))
print("Training accuracy =",(np.size(Y_train) - Train_error*np.size(Y_train))/np.size(Y_train))

def mosthighlycorrelated(mydataframe, numtoreport):
    cormatrix = mydataframe.corr()
    cormatrix *= np.tri(*cormatrix.values.shape, k=-1).T
    cormatrix = cormatrix.stack()
    cormatrix = cormatrix.reindex(cormatrix.abs().sort_values(ascending=False).index).reset_index()
    cormatrix.columns = ["FirstVariable", "SecondVariable", "Correlation"]
    return cormatrix.head(numtoreport)

irisp = pd.DataFrame(iris.data,columns=iris.feature_names)

print("\nMost Highly Correlated")
print(mosthighlycorrelated(irisp,50))
print('\n',irisp.head())

print('\n Question 5')
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression(random_state=0,solver='lbfgs', max_iter=2000).fit(X_train,Y_train)
print("Canned algorithm Logistic Regression")
print("Training Accuracy is ",clf.score(X_train, Y_train))
print("Testing Accuracy is ",clf.score(X_test, Y_test))
```

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In []: