Final Project: Tensorflow and Neural Network Report

Name: Shraddha Manchekar

UID: 004945217

Q4: Tensorflow

C:\Users\shraddha_m26\Desktop\Stats Programming\Assignments\Final_submit>python TF.py

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Accuracy: 0.9682

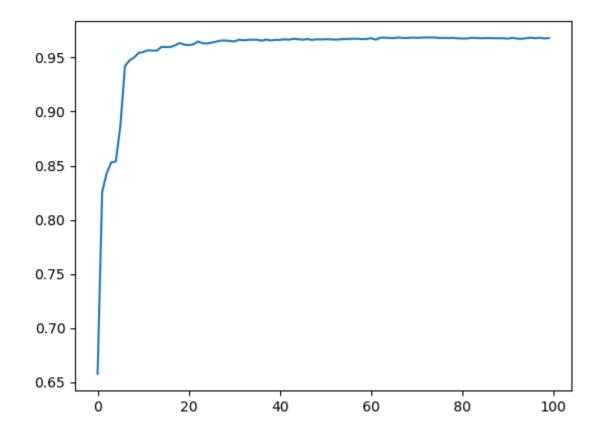
Epoch: 98

Accuracy: 0.9676

Epoch: 99

Accuracy: 0.968

0.968



Q3:

2-layer Neural Network using relu and sigmoid activation function:

C:\Users\shraddha_m26\Desktop\Stats Programming\Assignments\Final>python 2_layer_nn.py

Training Accuracy at Iteration 0: 0.459259259259

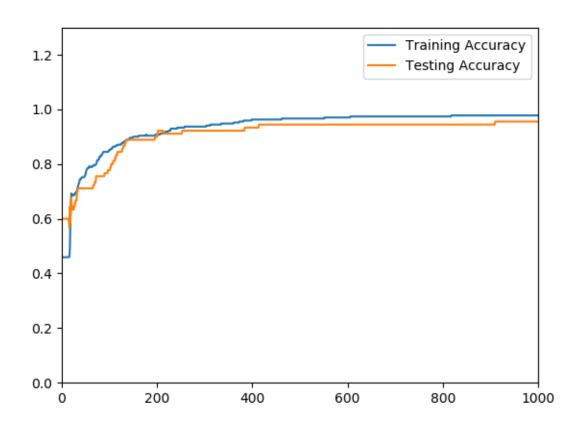
Testing Accuracy at Iteration 0: 0.6

Training Accuracy at Iteration 50: 0.762962962963
Testing Accuracy at Iteration 50: 0.71111111111
Training Accuracy at Iteration 100: 0.851851851852
Testing Accuracy at Iteration 100: 0.7777777778

Training Accuracy at Iteration 150: 0.9

Testing Accuracy at Iteration 200: 0.9

 Testing Accuracy at Iteration 450: 0.94444444444 Training Accuracy at Iteration 500: 0.96666666667 Testing Accuracy at Iteration 500: 0.944444444444 Training Accuracy at Iteration 550: 0.96666666667 Testing Accuracy at Iteration 550: 0.944444444444 Training Accuracy at Iteration 600: 0.97037037037 Testing Accuracy at Iteration 600: 0.944444444444 Training Accuracy at Iteration 650: 0.974074074074 Testing Accuracy at Iteration 650: 0.94444444444 Training Accuracy at Iteration 700: 0.974074074 Testing Accuracy at Iteration 700: 0.944444444444 Training Accuracy at Iteration 750: 0.974074074074 Testing Accuracy at Iteration 750: 0.94444444444 Training Accuracy at Iteration 800: 0.974074074 Testing Accuracy at Iteration 800: 0.944444444444 Training Accuracy at Iteration 850: 0.9777777778 Testing Accuracy at Iteration 850: 0.94444444444 Training Accuracy at Iteration 900: 0.9777777778 Testing Accuracy at Iteration 900: 0.944444444444 Training Accuracy at Iteration 950: 0.9777777778 Testing Accuracy at Iteration 950: 0.95555555556



Observation: Neural network is a non-linear classifier, as the hidden layers introduce complexity. Neural networks are also heavily parametric. As seen from the graph, neural networks converge last,

but reliably reach the correct beta values, often local minimas. However, neural networks are prone to overfitting. The algorithm is complex, hence, it takes the most amount of time to converge.

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C:\Users\shraddha_m26\Desktop\Stats Programming\Assignments\Final>python svm.py Training Accuracy:

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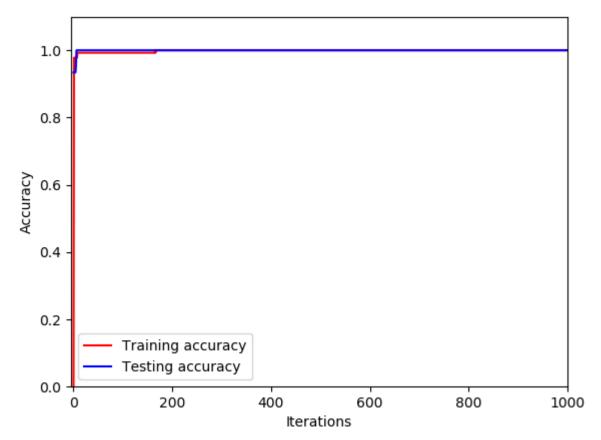
Testing Accuracy:

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Observation: SVM (support vector machine) constructs a hyperplane or set of hyperplanes in a highor infinite-dimensional space, which can be used for classification, regression, or other tasks like outlier detection. SVM uses the closest points in different classes as "support vectors" to estimate a convex, yet optimal hyperplane separating the classes. SVM has a regularization parameter that avoids over fitting. As seen from the graph, SVM avoids over fitting and provides excellent results for the test accuracy. SVMs are resilient to noise and take the least time to train.

Adaboost:

C:\Users\shraddha_m26\Desktop\Stats Programming\Assignments\Final>python svm.py Training Accuracy:

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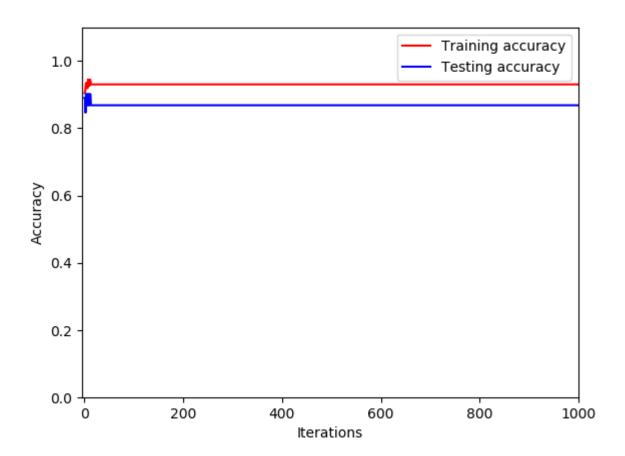
Testing Accuracy:

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Observation: Adaboost combines the output of the other learning algorithms ('weak learners') into a weighted sum that represents the final output of the boosted classifier. Adaboost can handle sparse dataset and hence, can work with weak classifiers. But, it shows some variations after it reaches peak classification correctness. AdaBoost can be sensitive to noisy data and outliers. As seen from the graph, Adaboost reaches an effective solution quickly, but in subsequent iterations, it becomes sensitive to noise. Adaboost is the least accurate for the given dataset. It should be used when there is a class imbalance in the dataset.