Machine Learning

Assignment 3

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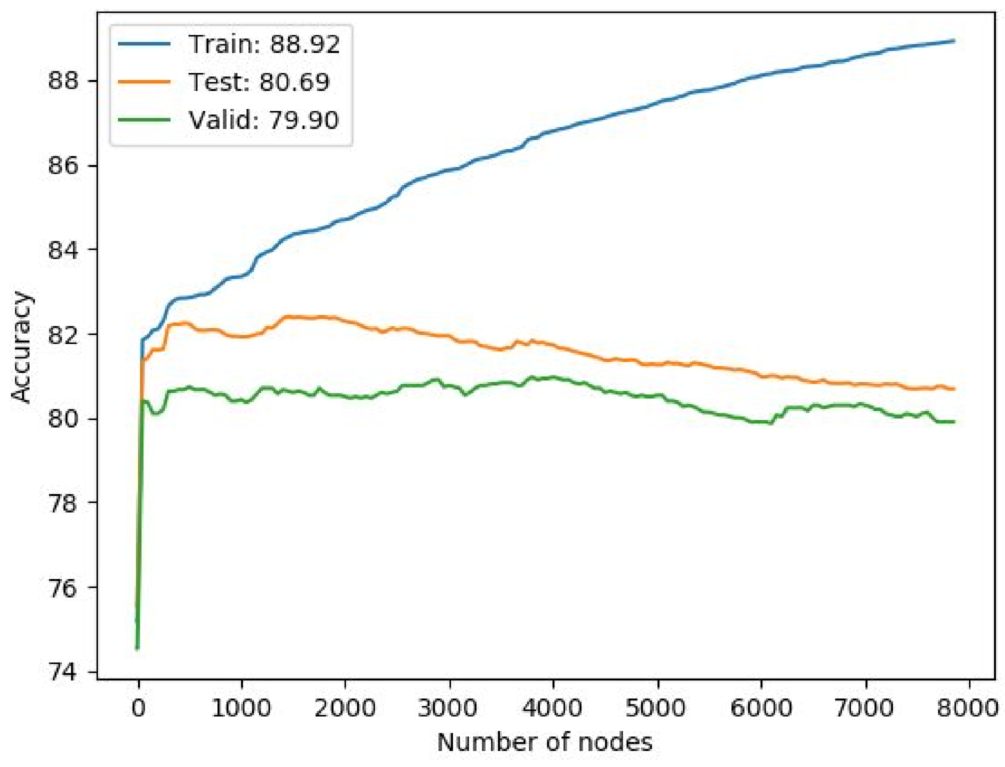
2017MCS2076

Q1: Decision Trees

a.)

Decision tree accuracy as number of nodes grow



A tree with just a single decision node predicting majority class (0) results in an accuracy of ~75%.

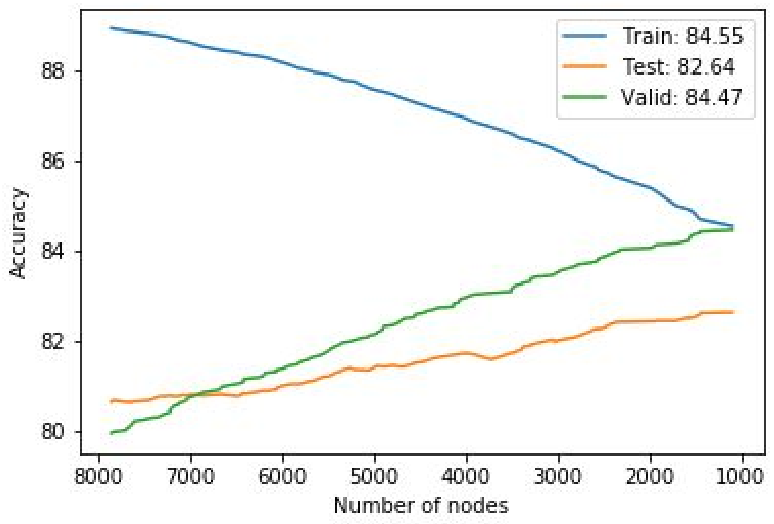
As we can see from the graph, as number of nodes increase, Training accuracy increases but Test / Validation accuracies decrease - a typical case of Overfitting.

The decision tree generated is of height 11 with total node count of 7902.

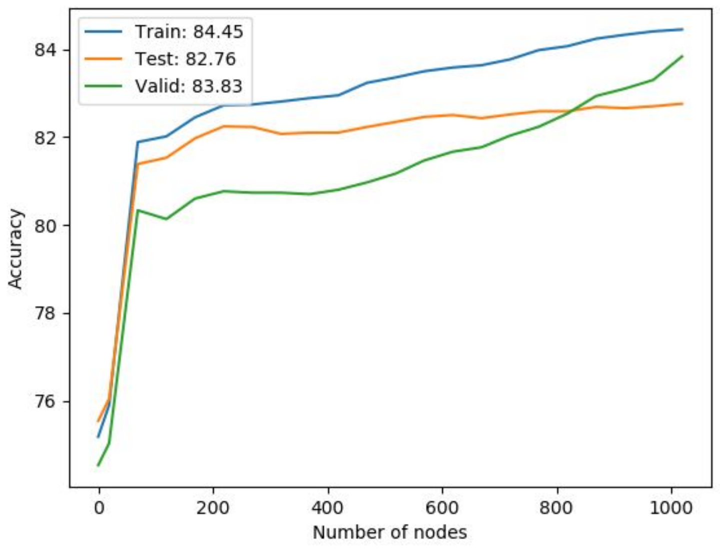
b.)

Post pruning the tree

We prune a node (and the entire subtree rooted at it) if pruning it increases the accuracy on validation data. While pruning, accuracies on all 3 datasets is calculated, resulting in following plot:



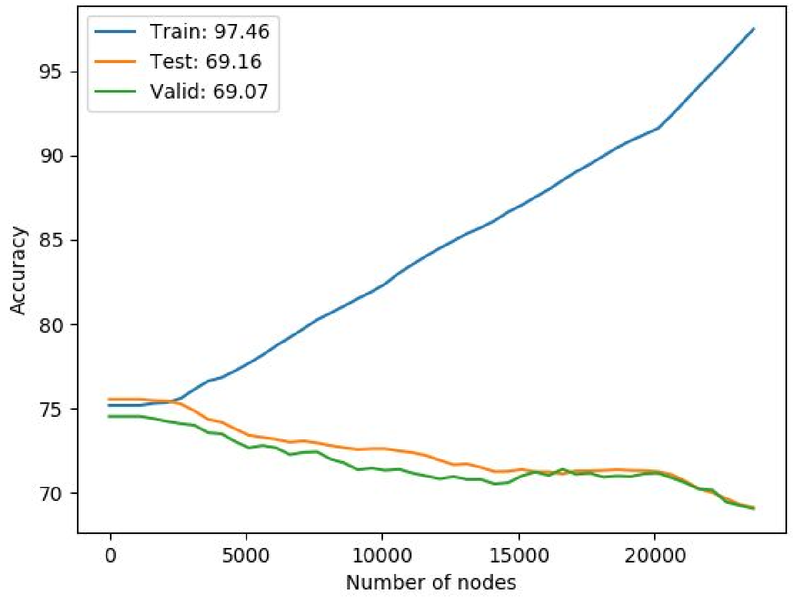
This shows how validation and test accuracies increase from 81% to 84%, while the others decrease. Pruning keeps the height of the tree same (11) while decreases the number of nodes from 7902 to 1069.



c.)

Using dynamic medians (without pruning)

When not computing the medians dynamically (of only the data that coming to a node) we find that the following plot is generated:



This depicts how badly this algorithm overfits the data. The observed tree is of height 16 and has 24116 nodes.

Numerical Attributes that are split maximum times on a path, and their corresponding thresholds:

age 7 times: [38.0, 46.0, 56.0, 57.0, 62.0, 64.0, 65.0]

fnlwgt 15 times: [178615.0, 117681.0, 80665.5, 46729.0, 62176.0, 71770.0, 67248.5, 64922.0, 63577.0, 62898.5, 62485.0, 62346.0, 62374.0, 62385.0, 62438.0]

edun 3 times: [9.0, 9.5, 11.5]

d.)

scikit-learn’s Decision Tree

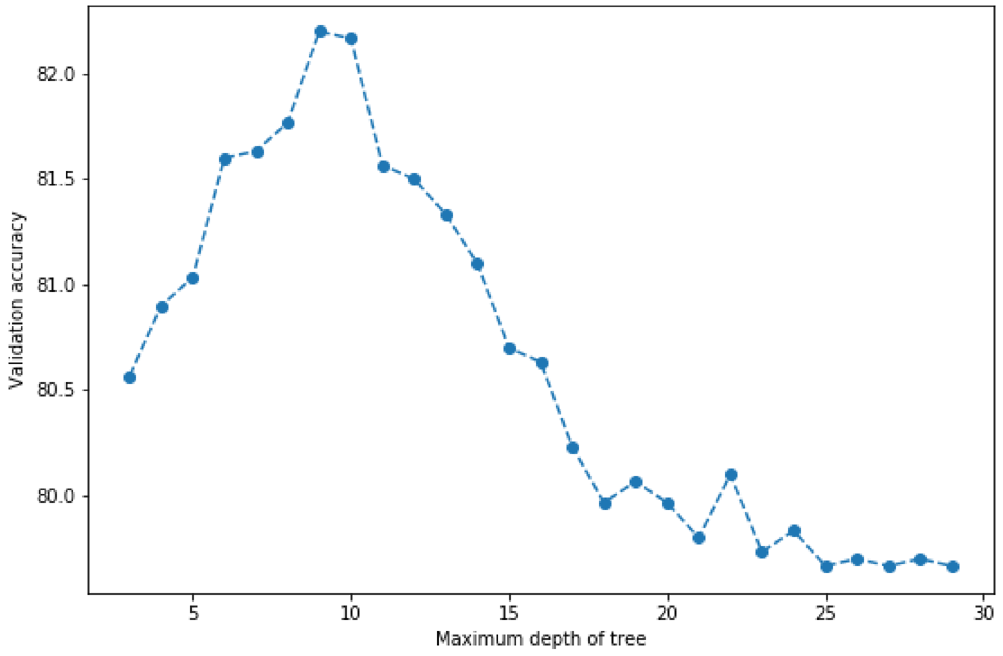
With the default parameters:

max_depth=None, min_samples_split=2, min_samples_leaf=1

Validation Acc: 79.6%, Tree Depth: 29, Number of Nodes: 7667

Effect of varying **max_depth**:

Best depth: 9, with accuracy of 82.2 %



Running a grid search on the parameters to find the best ones, yields:

Best set of parameters: max_depth = 12, min_samples_leaf = 10, min_samples_split = 60 with an accuracy of 83 %

e.)

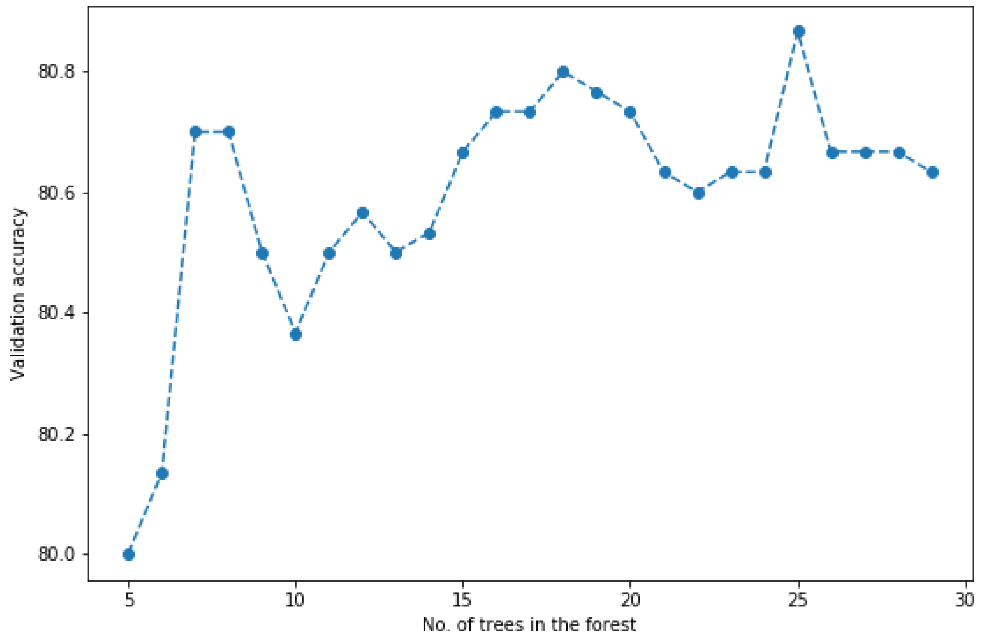
scikit-learn’s Random Forests

With the default parameters:

n_estimators=10, Bootstrap=True, max_features=14

Validation Acc: 80.3%

Effect of varying **n_estimators:**



Running a grid search on the parameters to find the best ones, yields:

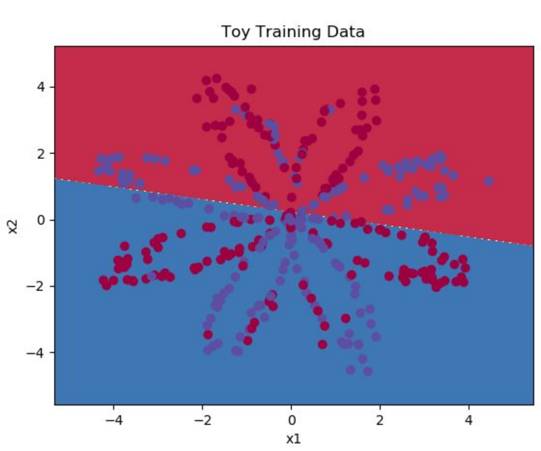
bootstrap = True, max_depth = 12, max_features = 4, n_estimators = 22

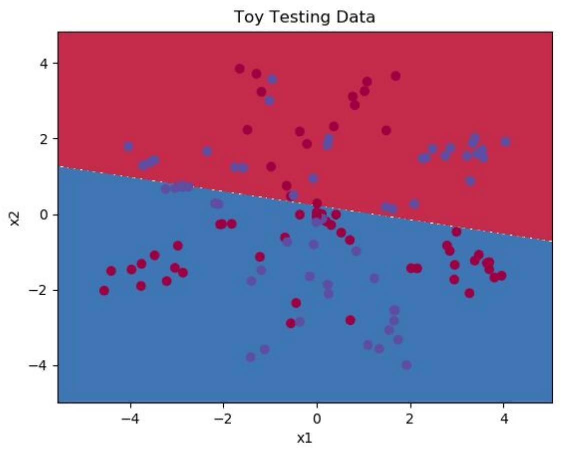
Which resulted in an accuracy of: 82.6 %

Q2: Neural Networks

b.) **Toy Data**

i.) sklearn's Logistic Learner

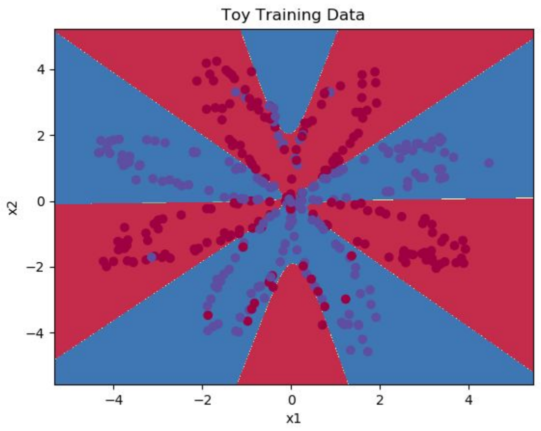


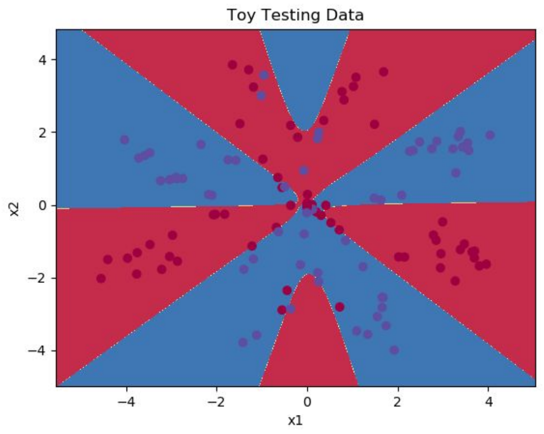


Training Accuracy: 45.8%

Testing Accuracy: 38.3%

ii.) Single Hidden Layer with 5 neurons





Training Accuracy: 90%

Testing Accuracy: 83.3%

We observe that, while logistic regression (which is a linear classifier) was unable to classify the data, because the data is inherently non linear. Neural Networks do a pretty good job of classifying the data correctly.

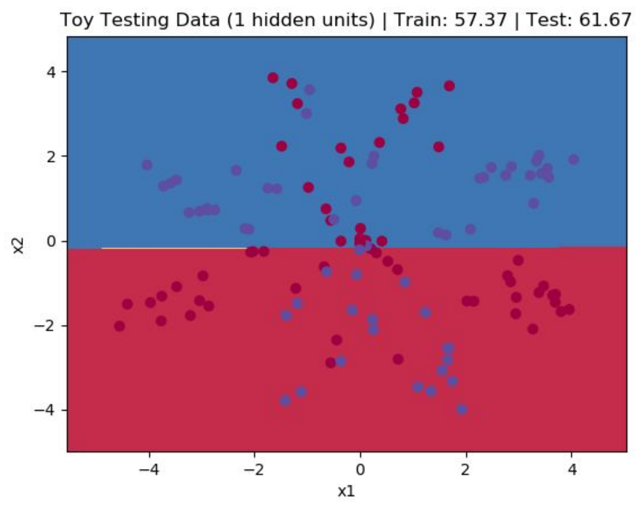
iii.) Effect of increasing neurons in hidden layer

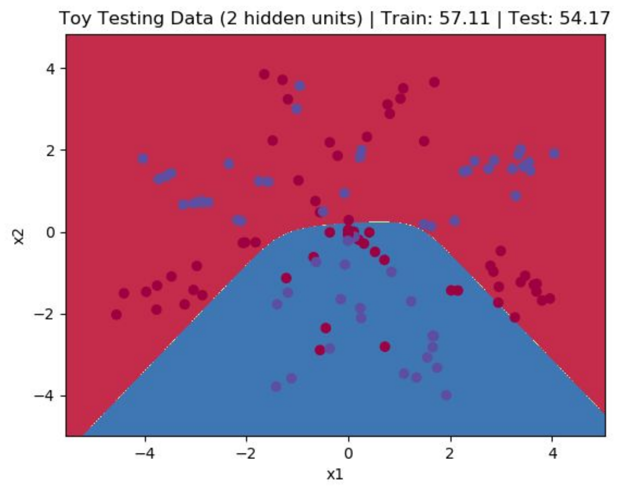
Stopping criteria was a maximum of 6000 epochs or an error threshold of 10**-6, whichever

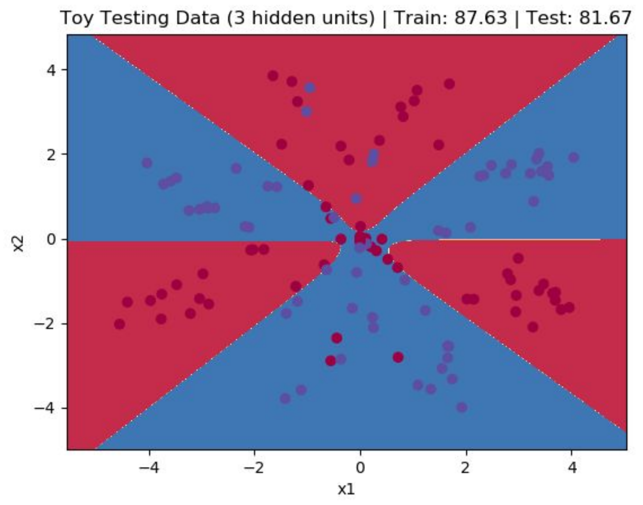
Neurons	Training Accuracy	Testing Accuracy	Stopping
1	57.36	61.66	Epochs: 835 / 6000 Avg. Error: 0.12380
2	57.10	54.16	Epoch: 2788 / 6000 Avg. Error: 0.11008
3	87.63	81.66	Epoch: 6000 / 6000 Avg. Error: 0.05430
5	88.68	82.50	Epoch: 6000 / 6000 Avg. Error: 0.05003
10	88.42	82.50	Epoch: 6000 / 6000 Error: 0.04949
20	87.89	82.50	Epoch: 6000 / 6000 Error: 0.04913
40	88.15	82.50	Epoch: 6000 / 6000 Error: 0.05053

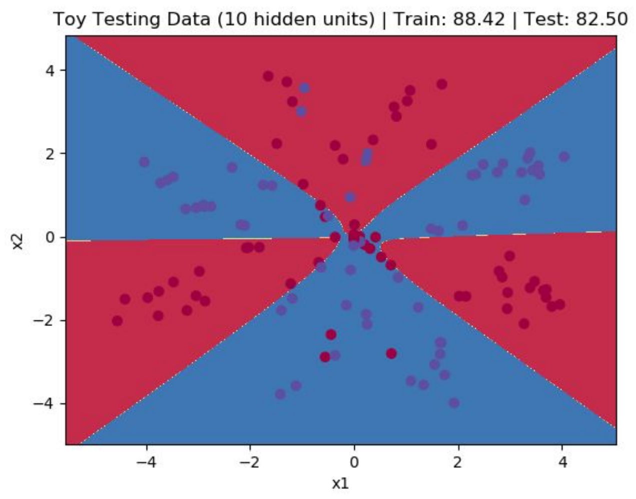
As the number of neurons in the hidden layers are increased, the network starts to learn the idiosyncrasies of the data and begins to overfit, as a result of which the decision boundaries become tighter and may not generalize well on future data.

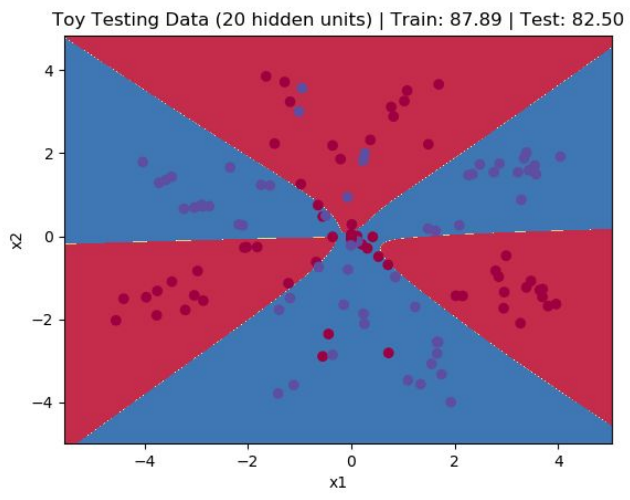
The optimal number of neurons seem to be 5.

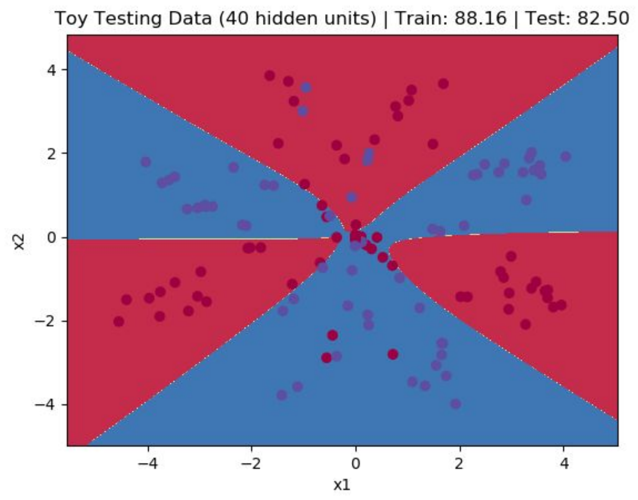

Toy Testing Data (1 hidden units) | Train: 57.37 | Test: 61.67
x1
x2


Toy Testing Data (2 hidden units) | Train: 57.11 | Test: 54.17
x1
x2


Toy Testing Data (3 hidden units) | Train: 87.63 | Test: 81.67
x1
x2


Toy Testing Data (10 hidden units) | Train: 88.42 | Test: 82.50
x1
x2

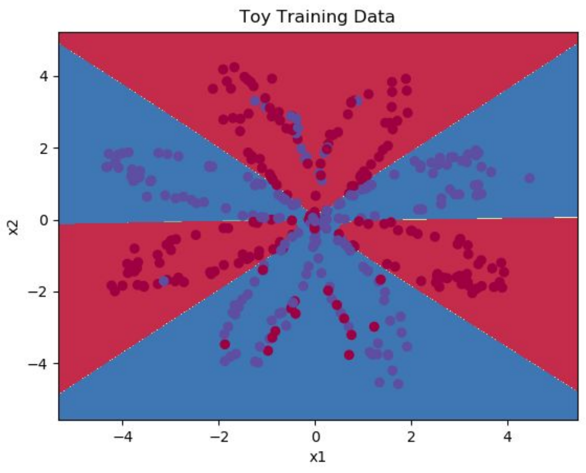

Toy Testing Data (20 hidden units) | Train: 87.89 | Test: 82.50
x1
x2

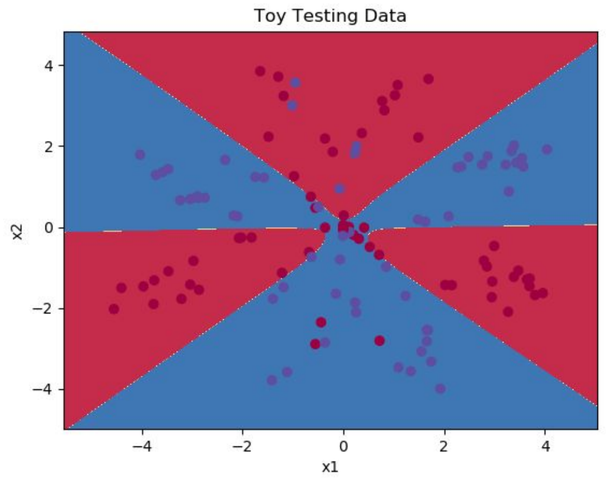

Toy Testing Data (40 hidden units) | Train: 88.16 | Test: 82.50
x1
x2

v.) Network with Two hidden layers of 5 - 5 neurons each.

After a maximum of 5000 epochs, the accuracy is:

Training Accuracy 87.89% and Testing Accuracy 83.33%





We observe that this is certainly better than the previous cases, where there wasn't a lot of change in the accuracies.

c.) MNIST Handwritten Digits recognition - Only 6 & 8

i.) libsvm & single perceptron

SVM with linear kernel and C = 1 results in:

Training Accuracy = 99.87% (9987/10000)
Testing Accuracy = 98.8333% (3558/3600)

Since linear SVM is able to do such a good job at classification, it shows that the data is inherently linear and we expect a single perceptron to be good enough too.

Single Perceptron results in:

Training Accuracy = 99.64%
Testing Accuracy = 99.13%

This takes 70 epochs to converge to a final absolute error of 20.72 (with threshold 10^{-4}.)

ii.) A network with 100 neurons in hidden layer

The stopping criteria used was the change in average error <= 10^{-4} (it was not converging on 10^{-5} even after 100 epochs.)

Training Accuracy 99.75%
Testing Accuracy 99.14%

This runs for a maximum of 100 epochs resulting in a final absolute error of 15.38 (with threshold 10^{-4}.)

iii.) Effect of ReLU activation unit in hidden layers

The accuracies obtained when we use ReLU are:

Training Accuracy 99.97
Testing Accuracy 99.5277777778

After a maximum of 100 epochs, the total absolute error is 2.00629.

Even though there is not a marked improvement in accuracy, we observe that the network converges faster than it did before, after only epochs, this is perhaps because of the fact that it is simpler (faster) to compute and its gradient does not saturate (always stays 1 for positive input.)