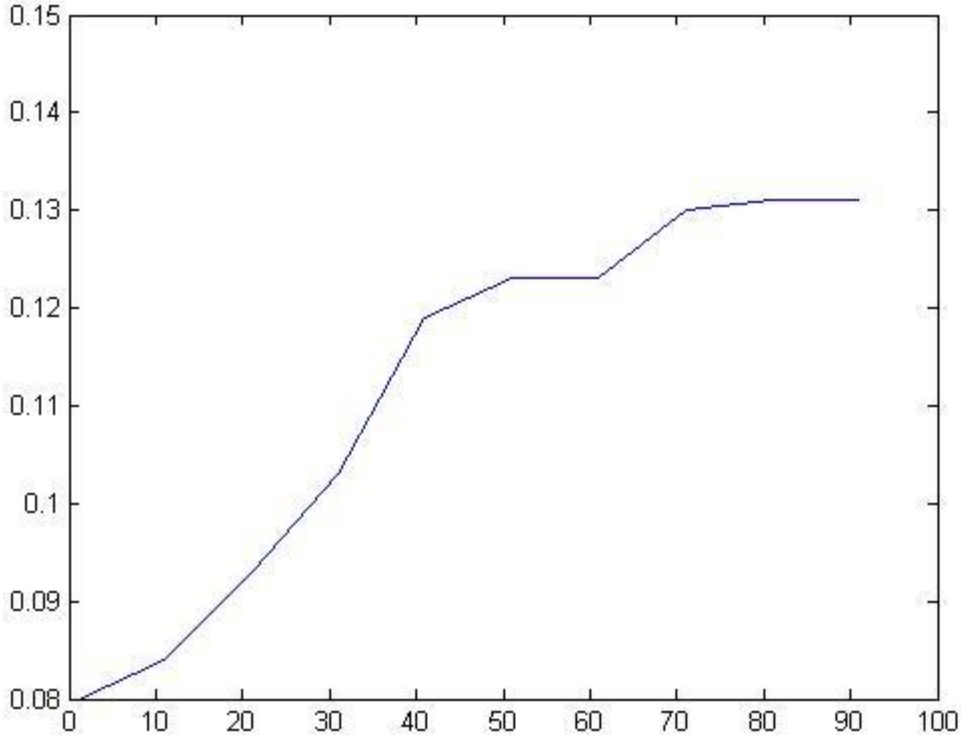
CS 365 Artificial Intelligent Assignment 1

PART 1



X axis represents the value of k

Y axis represents the (%value of error/10)

Observation: As we plot the error vs k value we see that % value of error decreases with increase in k. This may be due to fact that as k increases volume of support set increases which may cause intersection b/w support set of different digits and thus may increase in error. But if we increase data set then same value of k will cover less volume so we may take higher value of k.

Min error rate achieved = 8% for values of k b/w 3-5.

Part 2

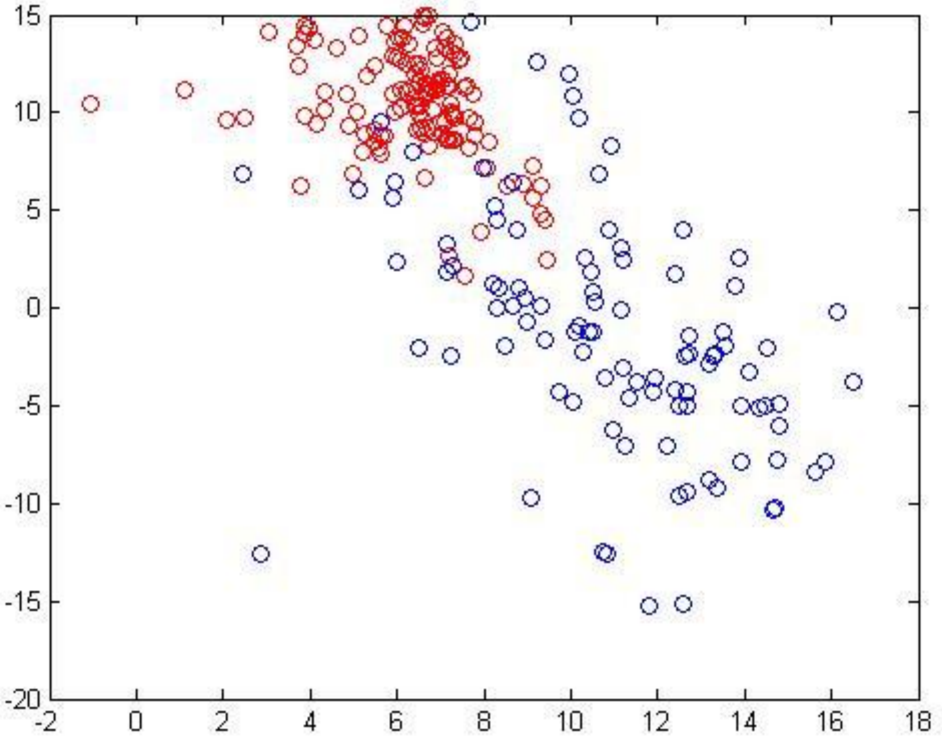
Isomap is one of several widely used low-dimensional embedding methods, where geodesic distances on a weighted graph are incorporated with the classical scaling (metric multidimensional scaling). Isomap is used for computing a quasi-isometric, low-dimensional embedding of a set of high-dimensional data points. The algorithm provides a simple method for estimating the intrinsic geometry of a data manifold based on a rough estimate of each data point's neighbors on the manifold. Isomap is highly efficient and generally applicable to a broad range of data sources and dimensionalities.

Isomap is one representative of isometric mapping methods, and extends metric multidimensional scaling (MDS) by incorporating the geodesic distances imposed by a weighted graph. To be specific, the classical scaling of metric MDS performs low-dimensional embedding based on the pairwise distance between data points, which is generally measured using straight-line Euclidean distance. Isomap is distinguished by its use of the geodesic distance induced by a neighborhood graph embedded in the classical scaling. This is done to incorporate manifold structure in the resulting embedding. Isomap defines the geodesic distance to be the sum of edge weights along the shortest path between two nodes (computed using Dijkstra's algorithm, for example). The top *n* eigenvectors of the geodesicdistance matrix, represent the coordinates in the new *n*-dimensional Euclidean space.

Isomap using Euclidean distance:

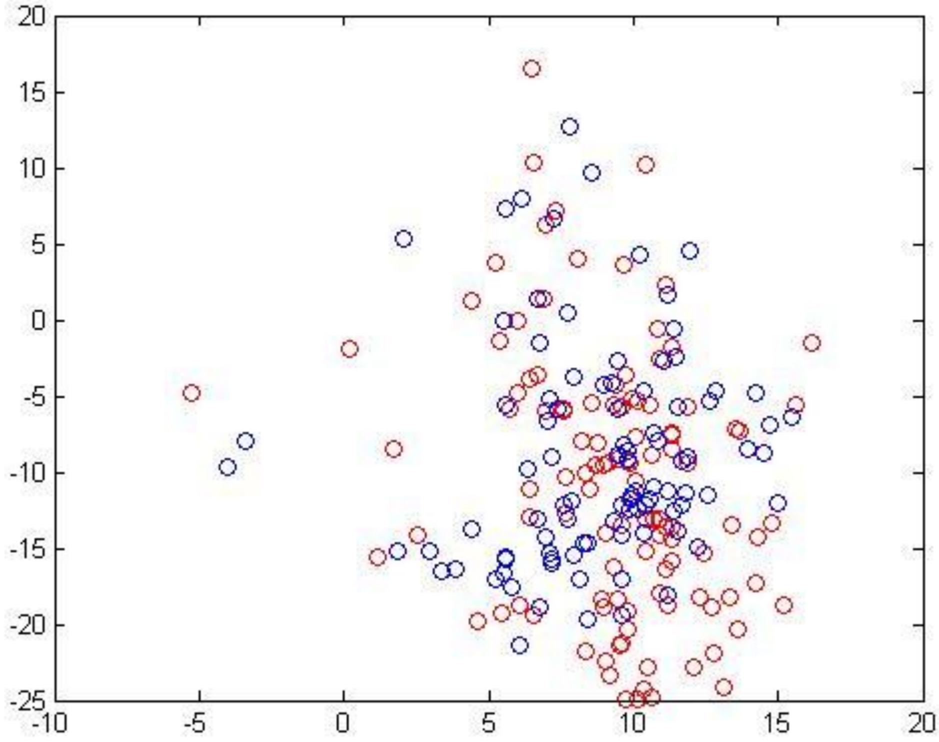
Isomap for digit 1 and 7

(red represents 1 and blue represents 7)



Isomap for four and nine

(red represents 4 and blue represents 9)

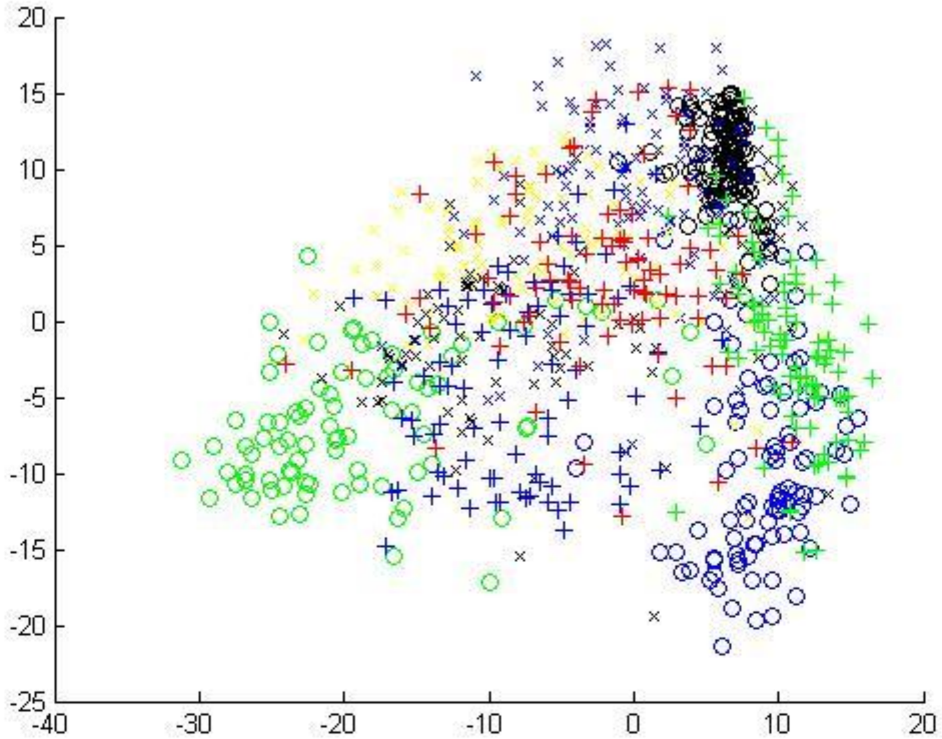


Isomap for all the digits

(Digit :representation in graph

0 : Green circle; 1 : Black circle; 2 : Black x; 3 :Yellow x;

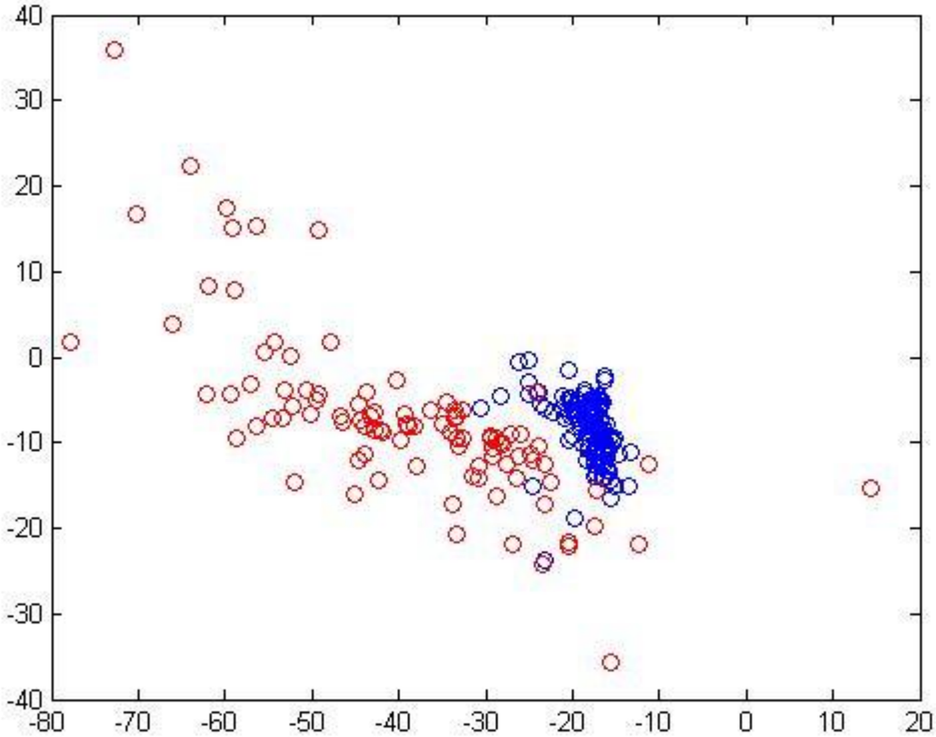
5 : Black x; 6 : Blue +; 7 : Green +; 8 : Red +; 9 : Blue circle)



Isomap using Tangent distance:

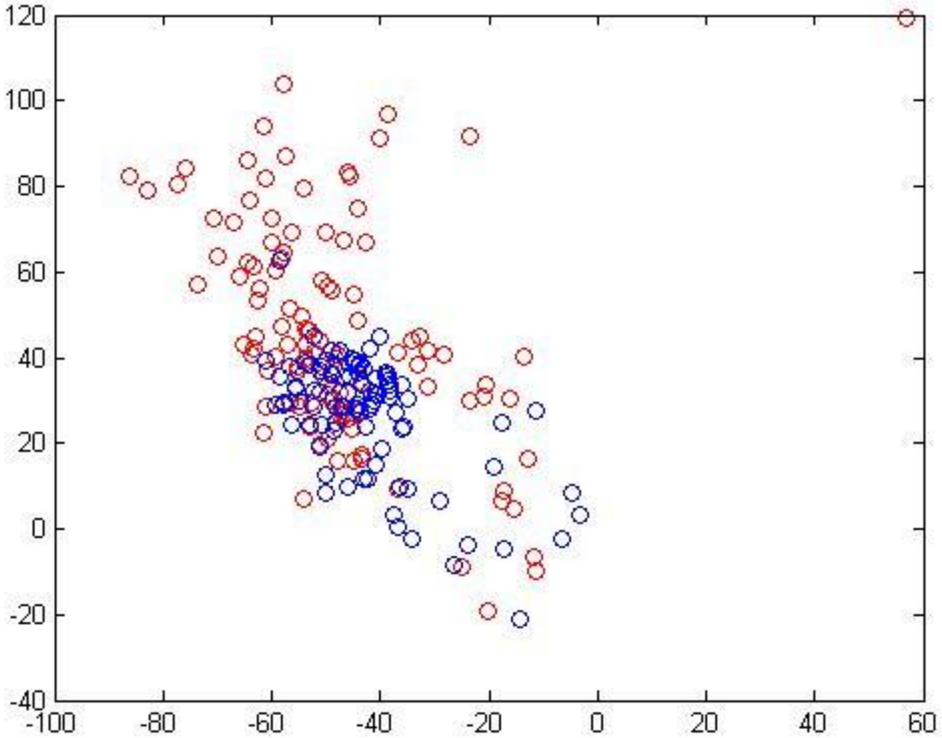
Isomap for digit 1 and 7

(red represents 7 and blue represents 1)



Isomap for four and nine

(red represents 4 and blue represents 9)

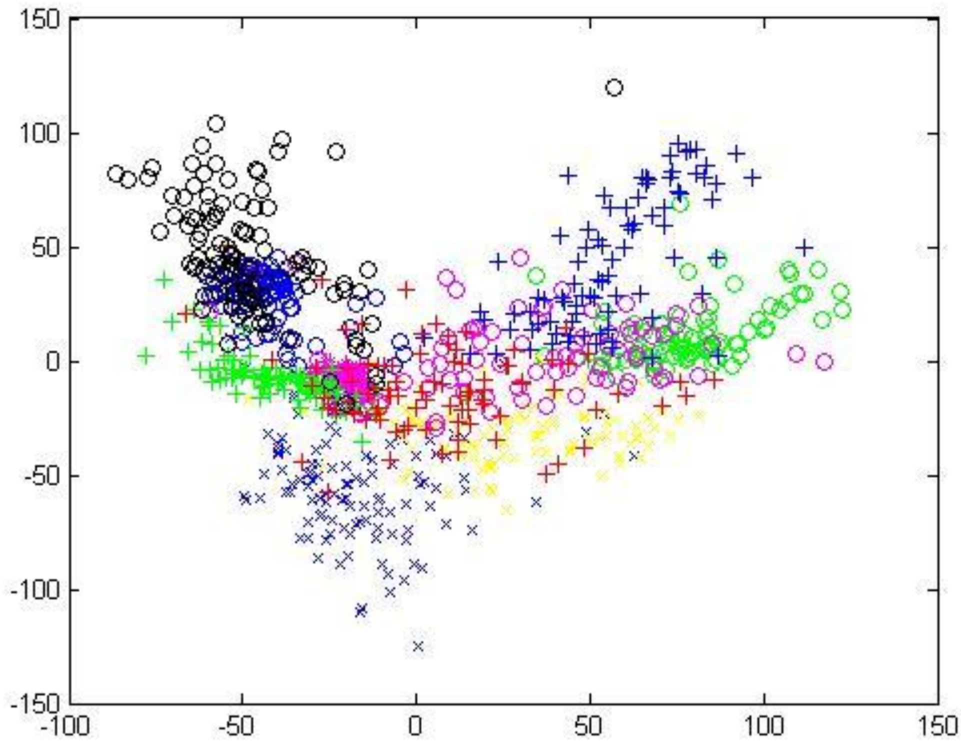


Isomap for all the digits

(Digit :representation in graph

0 : Green circle; 1 : Magenta *; 2 : Black x; 3 :Yellow x; 4 : Black circle

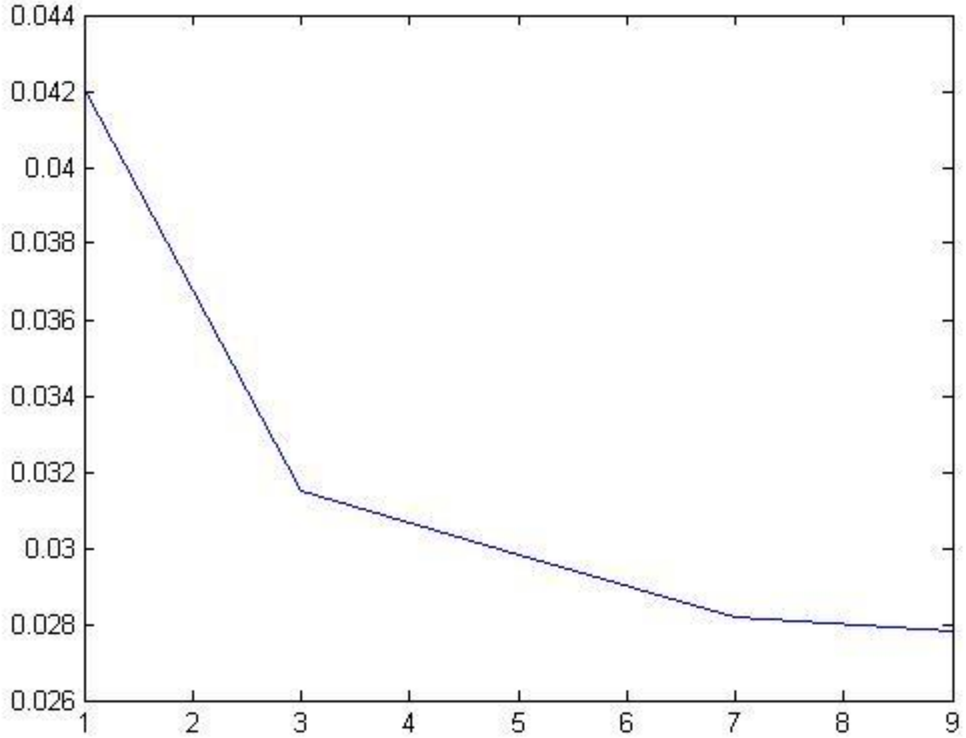
5 : Magenta circle; 6 : Blue +; 7 : Green +; 8 : Red +; 9 : Blue circle)



Observations: As isomap tries to projects multi dimension data in two dimension it gives separable decision regions for some of the Digits but not for all the digits. As isomap is not able to create much clearer regions for all the digits it seems for more clear boundaries our decision region should be of more dimensions. Also it seems from above observation that tangent distance gives better decision regions for some of the digits in above case.

Part 3:

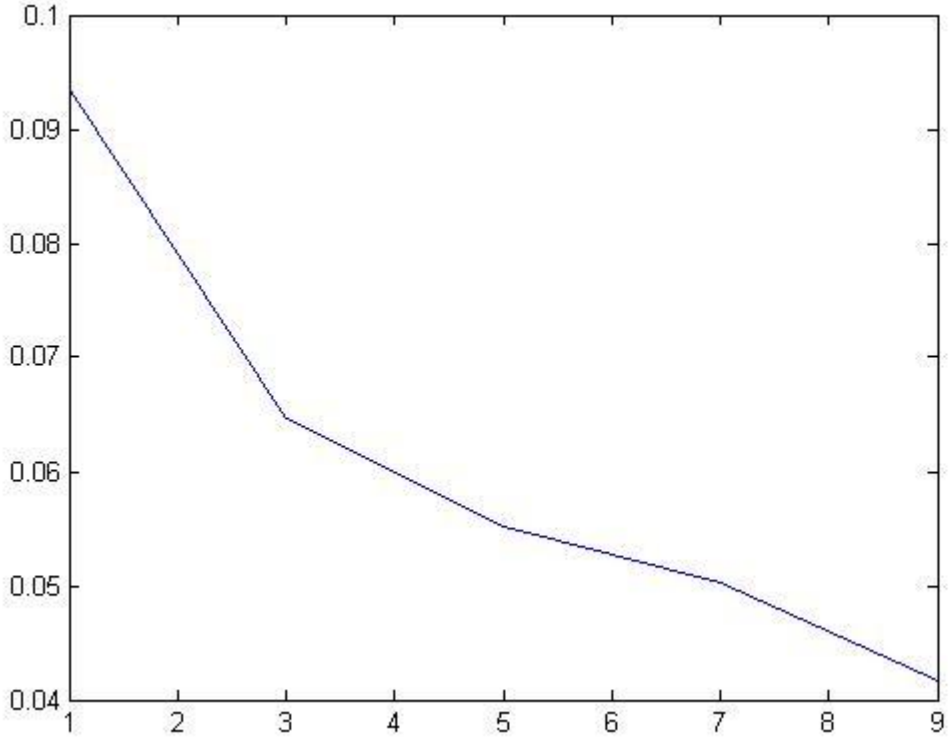
Error rate variation for Deep Belief Networks



Learn rate vs Error rate graph

As we increase the learning rate the error will reduce for same no. of epochs

But we can’t increase it to much as it may overshoot the optimal point.



epoch vs error rate graph

as we increase the epochs error rate decreases

Error variation with epoch , Batch size , Architecture

Epochs	Batch Size	Avg. Reconstruction Error
1	100	65.6
1	150	71.6
5	100	44.25
5	150	45.8