Machine Learning CS 726, Fall 2011 *Christoph Schulze, Michael Whidby, and Kotaro Hara*

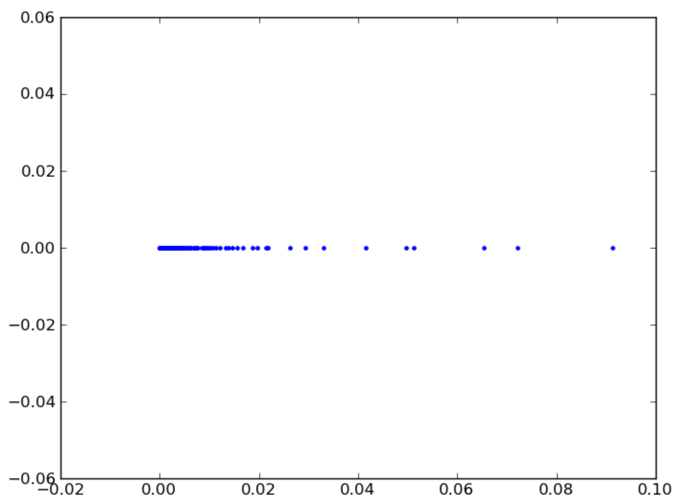
Project 3: Basic classification

WU1

Two eigen vectors both pass through the origin, perpendicular to each other. However, depending on your random data, slopes will vary.

WU2

Figure 1: wu2



To account for 90% variance, we have to include 82 eigenvectors. To account for 95% variance, we have to include 136 eigenvectors.

WU3

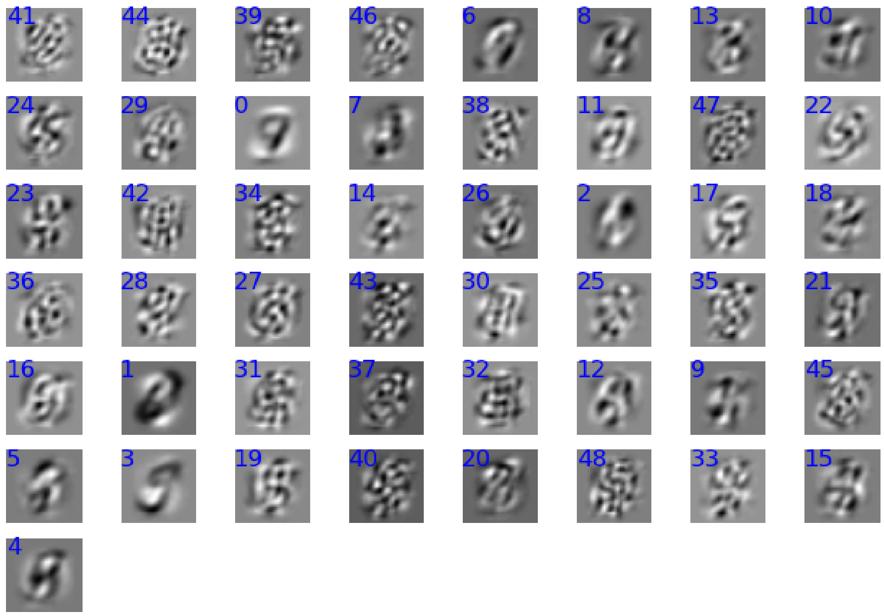
No, they do not look like digits.

WU4

Vanilla PCA will find this data difficult because variance of all directions are similar, which means that eigenvectors can point in any direction.

Large eigenvalues means there is no correlation between any of the axis.

Figure 2: wu3



WU5

PCA did not do what we want it to do :'(In addition to the reasons listed in WU4, vanilla PCA did not do what we wanted to do because the data is not linearly separable.

WU6

Eignevalues here is [0.08228617 0.05882765], which is significantly smaller than the eigenvalues for linear: [6.00010675 5.57361851]

WU7

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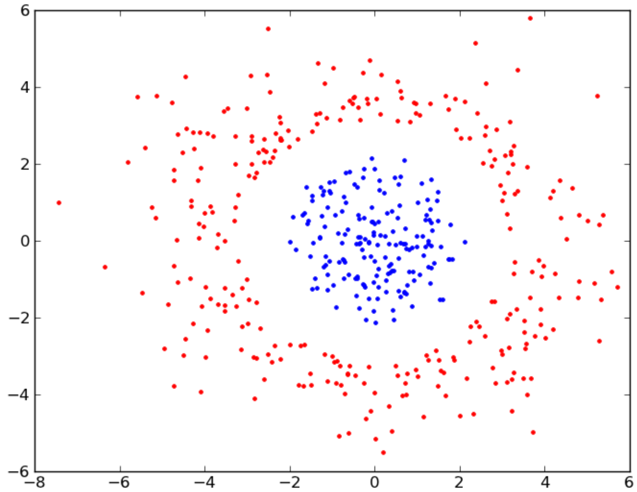
linear: evals [ 6.00010675  5.57361851]
poly2: [ 60.36960773  57.61047579]
poly3: [ 2316.48011949  2139.88680252]
rbf0_2: evals [ 0.15469386  0.10178237]
rbf0_5: evals [ 0.1194342   0.06754455]
rbf2: evals [ 0.05293176  0.04460633]
rbf5: evals [ 0.02906865  0.02521906]
```

Figure 3: wu4



WU8

WU9

WU10

Figure 4: wu5

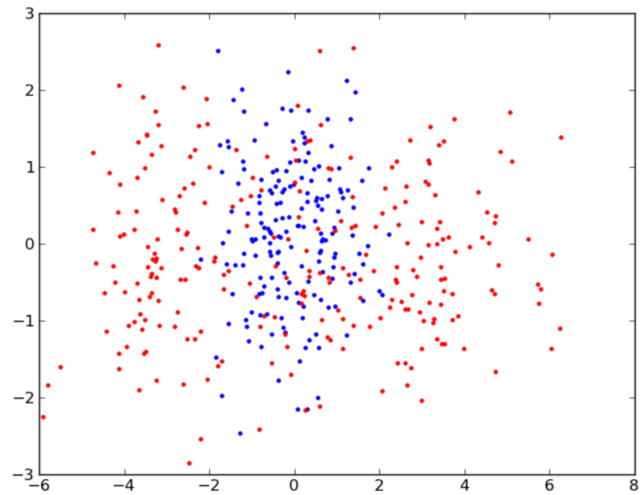


Figure 5: wu6

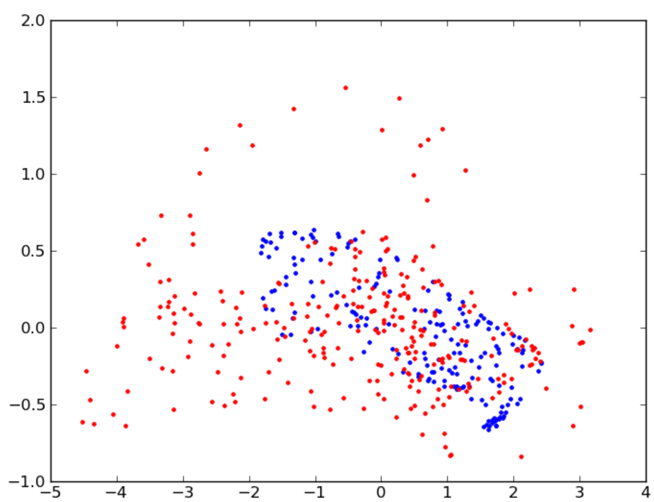


Figure 6: wu7 linear

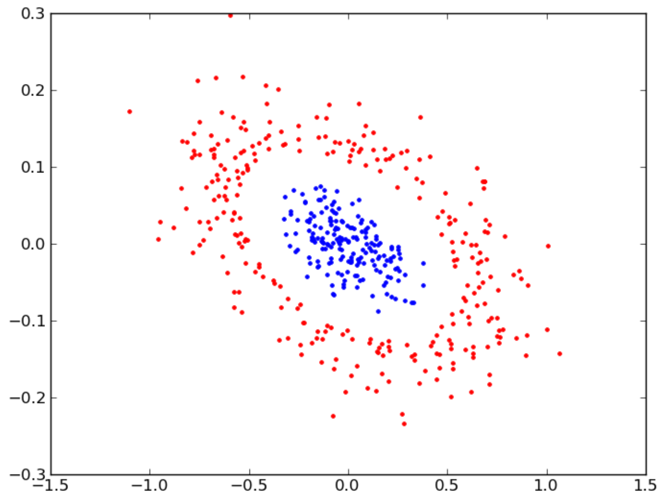


Figure 7: wu7 poly2

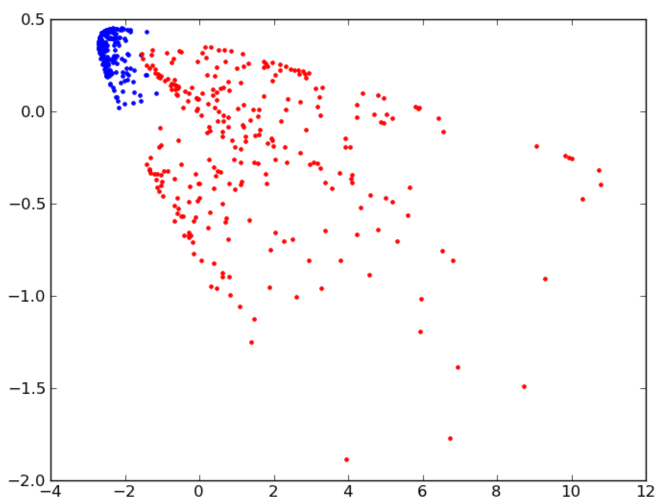


Figure 8: wu7 poly3

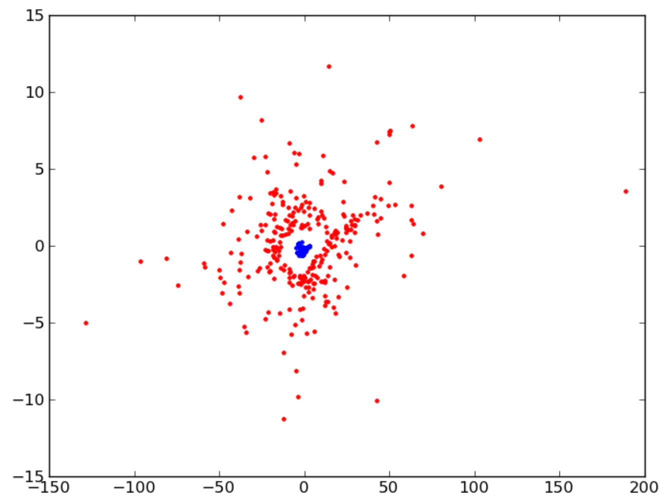


Figure 9: wu7 rbf0.2

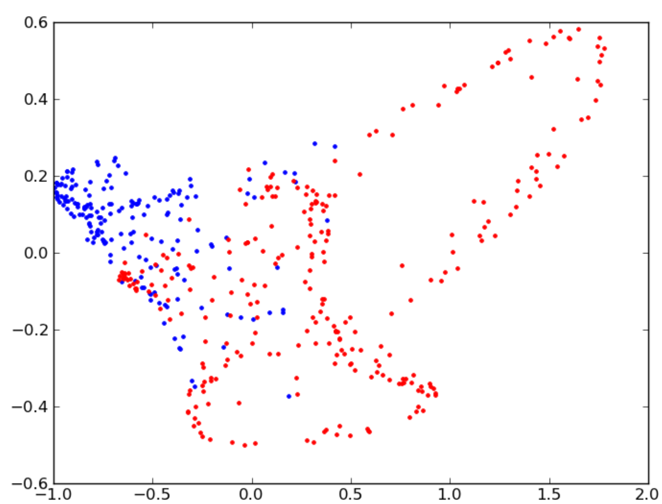


Figure 10: wu7 rbf0.5

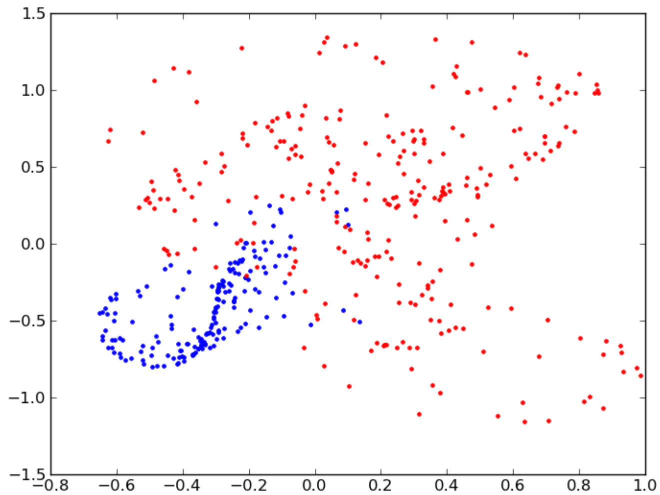


Figure 11: wu7 rbf1

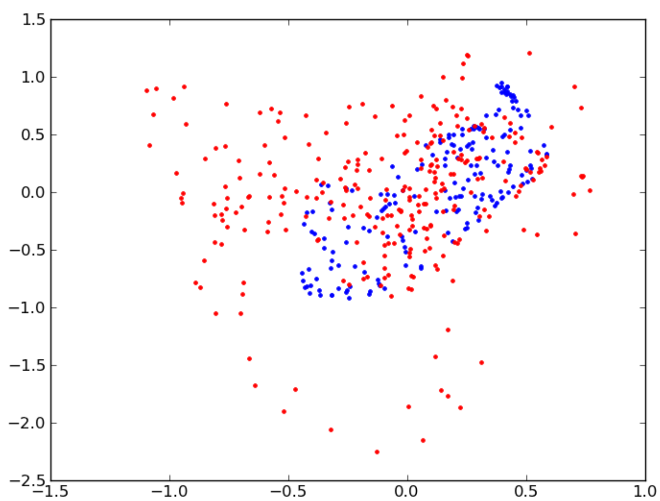


Figure 12: wu7 rbf2

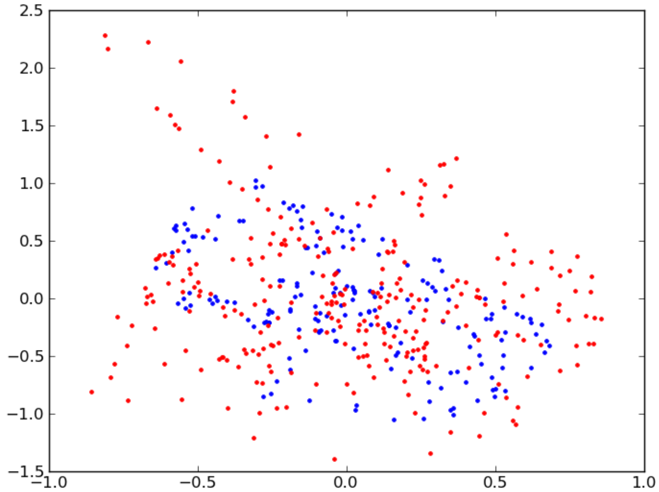


Figure 13: wu7 rbf5