1. Problem 1
   1. Hinge Loss: . 0-1 Loss:

LogReg Loss: In terms of the functions, hinge and logistic loss are both convex when plotted on the unified graph.

* 1. A point not on the boundary is not a support vector, and it does not affect the decision boundary. However, LogReg uses all data points so the loss function takes all points into account.

1. Problem 2
   1. Using the singular value decomposition of **A**, we have

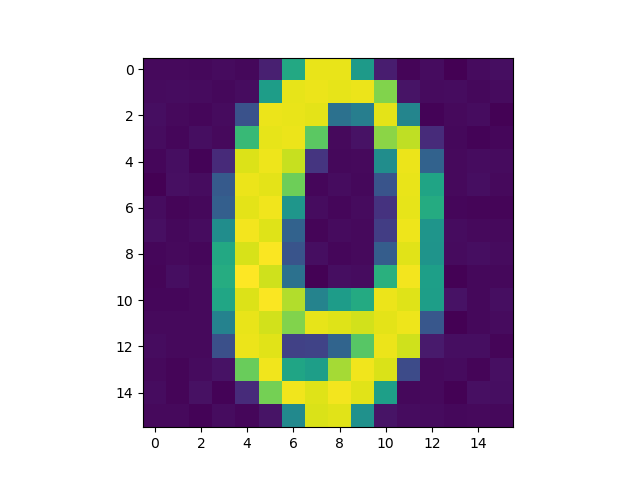
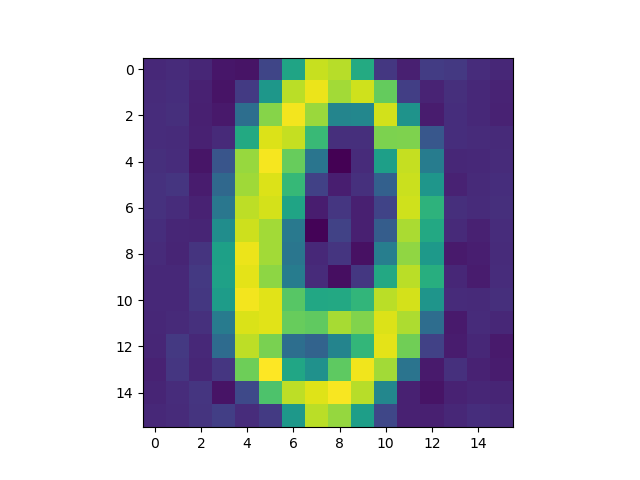
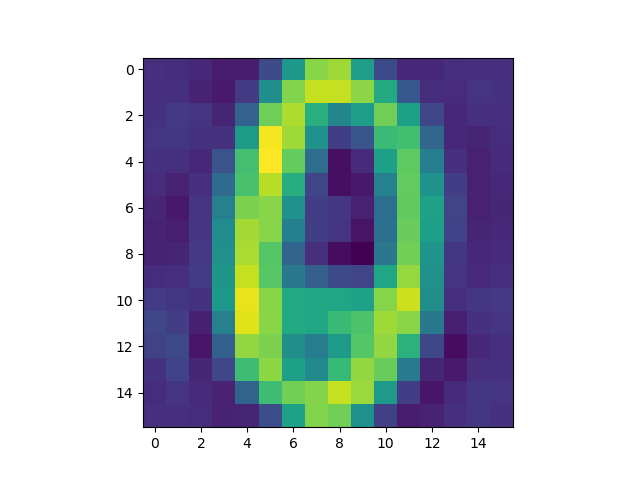
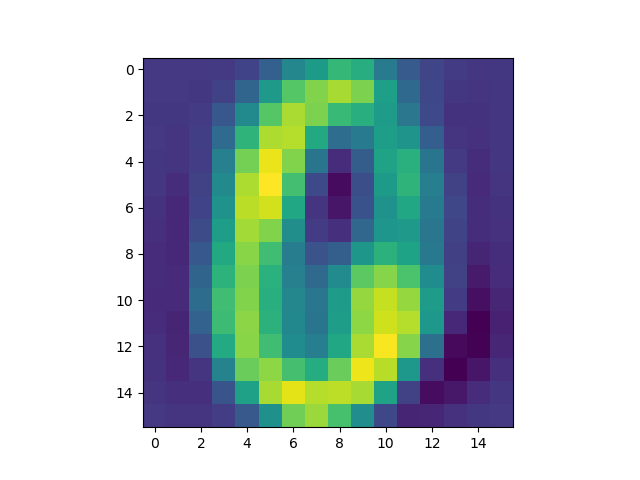
=**.** Thus, the columns of **U** are the eigenvectors of .

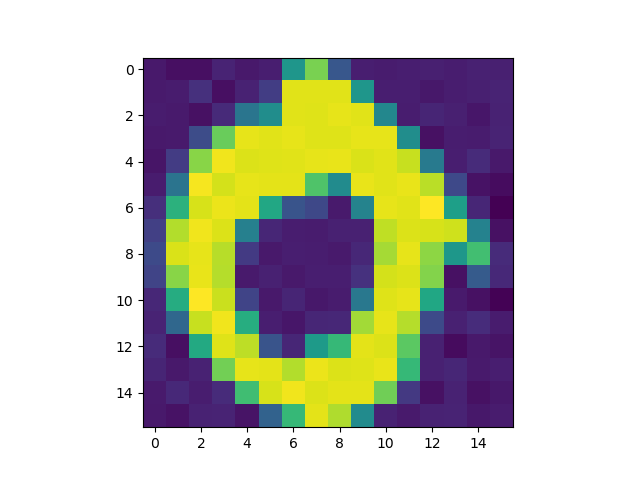
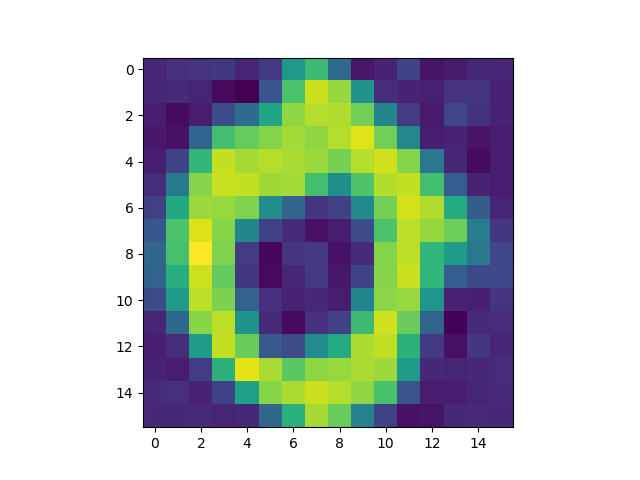
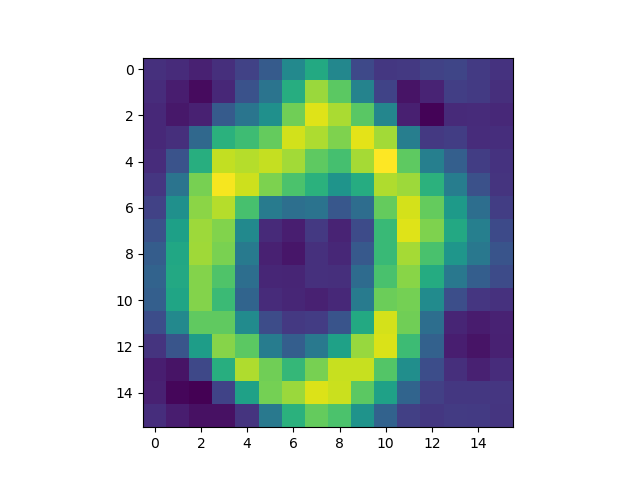
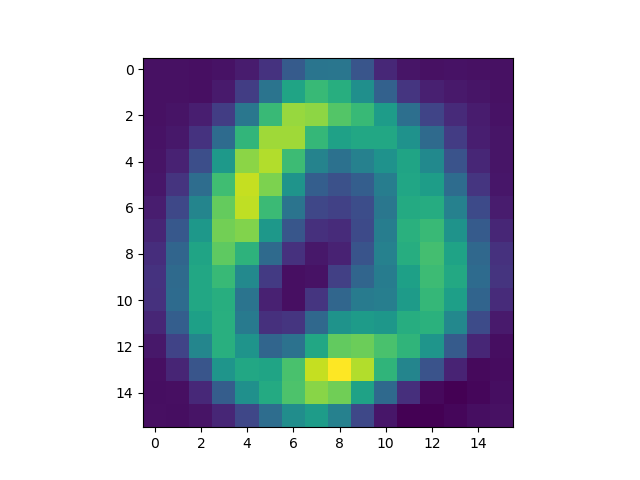
* 1. Similarly, =. Thus, the columns of **V** are the eigenvectors of .

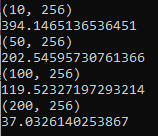
1. We have a symmetric matrix in our eigen-decomposition, therefore
2. To calculate PCA, we first have to center our matrix X. This is done by the formula: **.** We then subtract this from X. **.** From here, we can compute the covariance matrix and use eigenvalues and eigenvectors. but this would be difficult for large p. Therefore, we instead take the singular value decomposition. . We can then get the projected features . The minimum reconstruction error property is as follows: . You get the reconstruction by the formula

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1. On separate paper!
2. Here are the images from the reconstructions at k=10,50,100, and 200 respectively on both images:





Program execution gives us the following error values: 

We can observe that as we preserve more components of our data, we have lower reconstruction error. This is because when k is higher, there is lower dimensionality reduction.