### Problem 1:

```
Ouestion 1 -
     dat:
           mean [-0.009481 -0.008284 -0.009672]
           variance [[.9983 .0001687 .001237]
                        [.0001687 1.003 .001553]
                        [.001237 .001553 1.005]]
     dat1:
           mean [0.9905 1.992 2.990]
                      [[.9983 .0001687 .001237]
           variance
                        [.0001687 1.003 .001553]
                        [.001237 .001553 1.005]]
     dat2:
           mean [9.905 5.975 2.990]
           variance [[99.83 .005061 .01237]
                        [.005061 9.031 .004658]
                        [.01237 .004658 1.005]]
     dat3:
           mean [11.26 3.532 -1.886]
           variance [[49.15 44.62 6.870]
                        [44.62 58.64 7.514]
                        [6.870 7.514 2.067]]
```

### Question 2 -

The direction of maximum variance for dat2, from the eigenvector, is along the x-axis (the first dimension, which was multipled by 10). This makes sense since we adjusted variances by multiplying dat1 by the diag[ $10 \ 3 \ 1$ ] vector.

The direction of max variance for dat3, from its eigenvector, is approaching the  $1^{\rm st}$  row of the rotation matrix R. This makes sense since we rotated our dataset using the R matrix.

## Question 3 -

The first principal component of dat3 is [0.6651, 0.7427, -0.0770]. Yes this is what would be expected since the original data was rotated, which directly affects the covariance of the data, the principal component(s) would tend towards this rotation matrix.

#### Ouestion 4 -

The mean and variance from dat are as expected, since the data was generated using N(0,1), the mean should be around 0 the diagonals of the covariance matrix around 1.

The manipulation of dat to get dat1 would only change the means, by 1, 2 and 3 respectively which is what we confirmed, and variances would remain unchanged.

The manipulation of dat1 to dat2, by multiplying by diag[10 3 1] impacts the variance and we confirmed this with our covariance matrix. The variance matrix should be approximately [100 9 1], which is confirmed in our dat2 covariance matrix. As the number increases the variance will approach the [100 9 1] variances.

### Matt Hall Homework 3

Rotating dat2 to obtain dat3 generates expected results. Calculating the eigenvalues/vectors shows that the principal components will tend towards this rotation matrix as the number of samples is increased.

### Problem 2:

Average Accuracy: 74.79% Std Dev of Accuracy: 2.456

In order to get the 3 principal components, the eigenvalues were calculated from the training data covariance matrix. The eigenvectors corresponding to the 3 largest eigenvalues were selected as the principal components.

For the final run the 3 components were:

1 [0.002445 -0.02436 0.02302 0.07141 0.1672 0.001913 -0.9827 0.003658]

2 [-0.09163 -0.9746 -0.1275 -0.1460 -0.04565 0.04682 0.002648 -0.001121]

3 [-0.01265 -0.1263 0.9293 0.1637 -0.2857 0.1084 -0.01164 0.0009828]

### Problem 3:

# Problem 4:

Resulting 'a' vector: [1, 3, 1, -1, 3, -5]

```
Average Accuracy: 71.80%
Std Dev of Accuracy: 1.782
Optimal projection:
[-0.1401 \ -0.04205 \ 0.01861 \ -0.008783 \ 0.0009270 \ -0.08736 \ -0.9849 \ -0.02385]
Problem 5:
(a)
Want to minimize training error.
Training error will be zero if:
      \{a.transpose() * yi > 0 for all yi in c1
      {a.transpose() * yi < 0 for all yi in c2</pre>
After normalization training error will be zero if:
      {a.transpose() * yi > 0 for all yi in cl
     {a.transpose() * (-yi) > 0 for all yi in c2
so, we want to find a vector `a` such that a.transpose() * yi > 0 for all
yi.
(b)
```