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QUESTION 1

```
% Please download the ?rawdata.mat? data file attached in this
 homework (click the link to get the
% file). The rawdata matrix in this data file represents 512 vectors
 in a 1024-dimensional vector
% space. This data set is generated so that the vectors actually
 reside in a much-lower dimensional
% subspace: More specifically, the data that lives in a low-
dimensional subspace and then a certain
% amount of noise are added ? so the data in rawdata is just
 approximately low-dimensional.
% Begin by writing a function to zero-mean the data. That is, write a
 function that shifts the
% vectors so that the mean of the data in each dimension is zero. Use
 it to zero-mean rawdata.
% Use a different name, as you will still need the non-zero-mean
 version of rawdata in the future.
```

ANSWER 1

```
load 'rawdata.mat';
raw_zero =
 reshape(zscore(rawdata(:)),size(rawdata,1),size(rawdata,2)); %Calculates
 the zero mean of the raw data
```

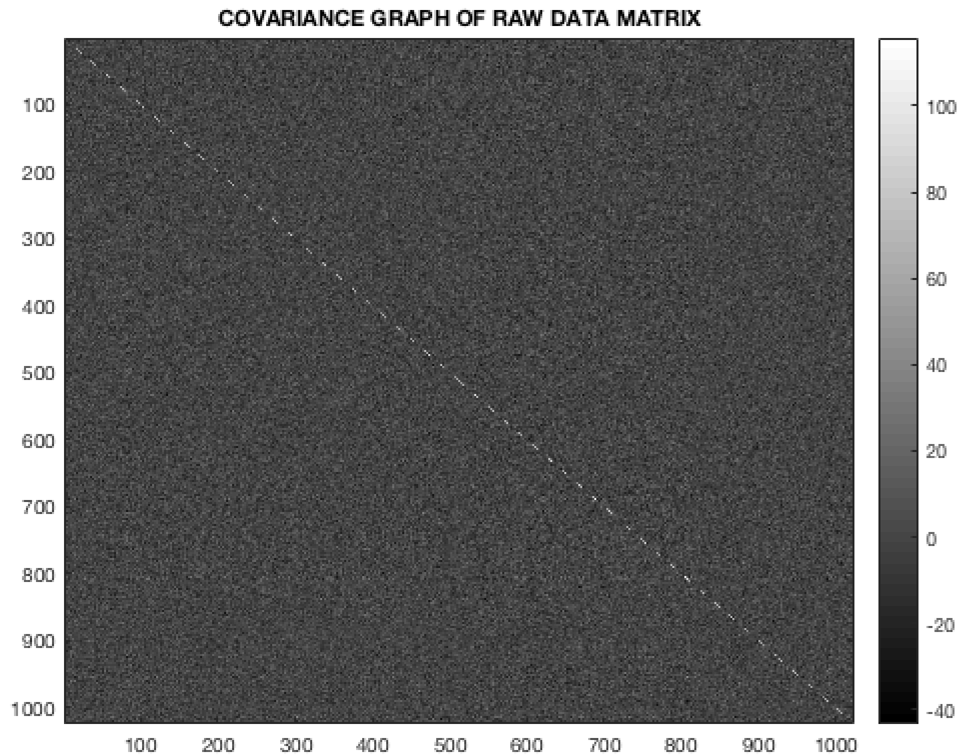
QUESTION 2

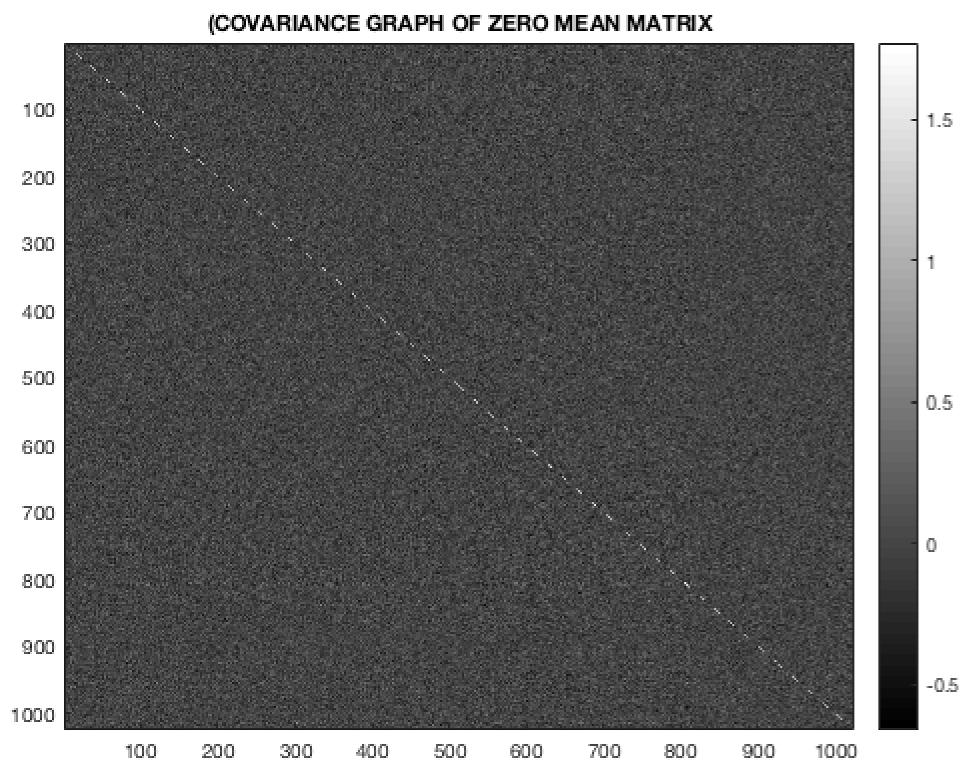
```
% Compute the covariance matrix for both rawdata and its zero-mean
 version. You may use the
```

```
% MATLAB function cov. Plot the matrices and their difference to
 demonstrate that zero-meaning
% the data does not affect the covariance. (Pro tips: Use imagesc to
 display the matrix and it will
% scale the color map appropriately. Use colormap gray to get a color
 map that gives a smooth
% variation in color with value. Use colorbar to place a scale next to
 the image.)
```

ANSWER 2

```
cov_rawdata = cov(rawdata);       %Covariance of the raw data
cov_raw_zero = cov(raw_zero);     %Covariance of the zero mean data
figure(1);
imagesc(cov_rawdata);             %Plotting the covariance raw data
colorbar;
colormap 'gray';
title('COVARIANCE GRAPH OF RAW DATA MATRIX');
figure(2);
imagesc(cov_raw_zero);            %Plotting the covariance zero mean
 data
colorbar;
colormap 'gray';
title('(COVARIANCE GRAPH OF ZERO MEAN MATRIX');
figure(3);
imagesc(cov_rawdata-cov_raw_zero); %Plotting the covariance of the
 Difference
colorbar;
colormap 'gray';
title('COVARIANCE GRAPH OF THE DIFFERENCE BETWEEN RAW DATA AND ZERO
 MEAN');
```


COVARIANCE GRAPH OF RAW DATA MATRIX
100
200
300
400
500
600
700
800
900
1000
100
200
300
400
500
600
700
800
900
1000
100
80
60
40
20
0
-20
-40


(COVARIANCE GRAPH OF ZERO MEAN MATRIX
100
200
300
400
500
600
700
800
900
1000
100
200
300
400
500
600
700
800
900
1000
1.5
1
0.5
0
-0.5

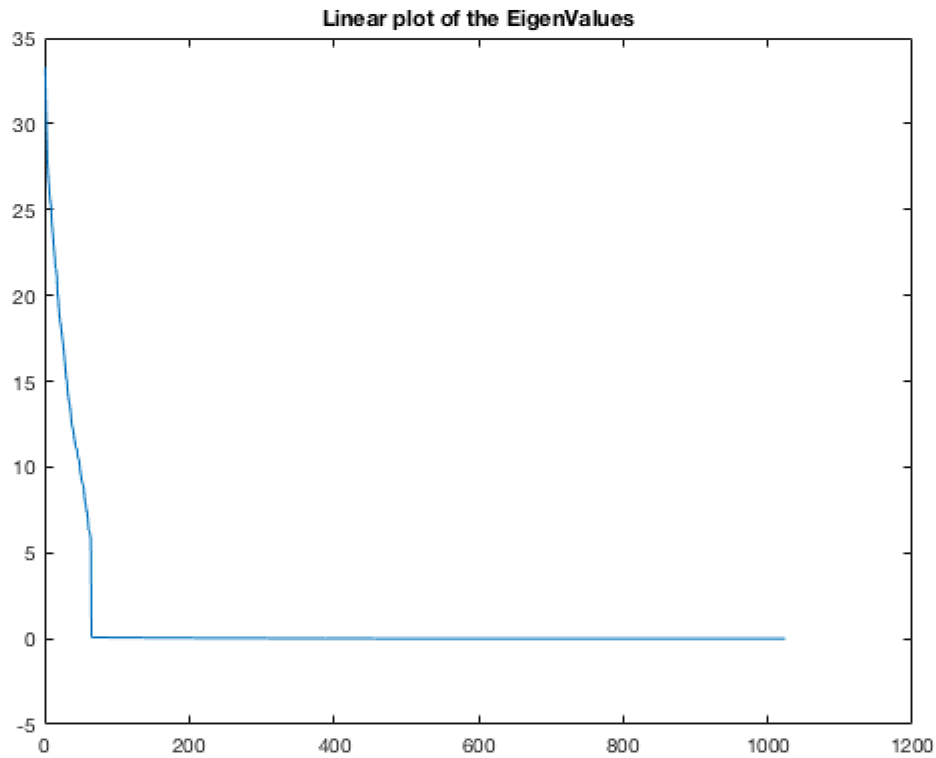
QUESTION 3

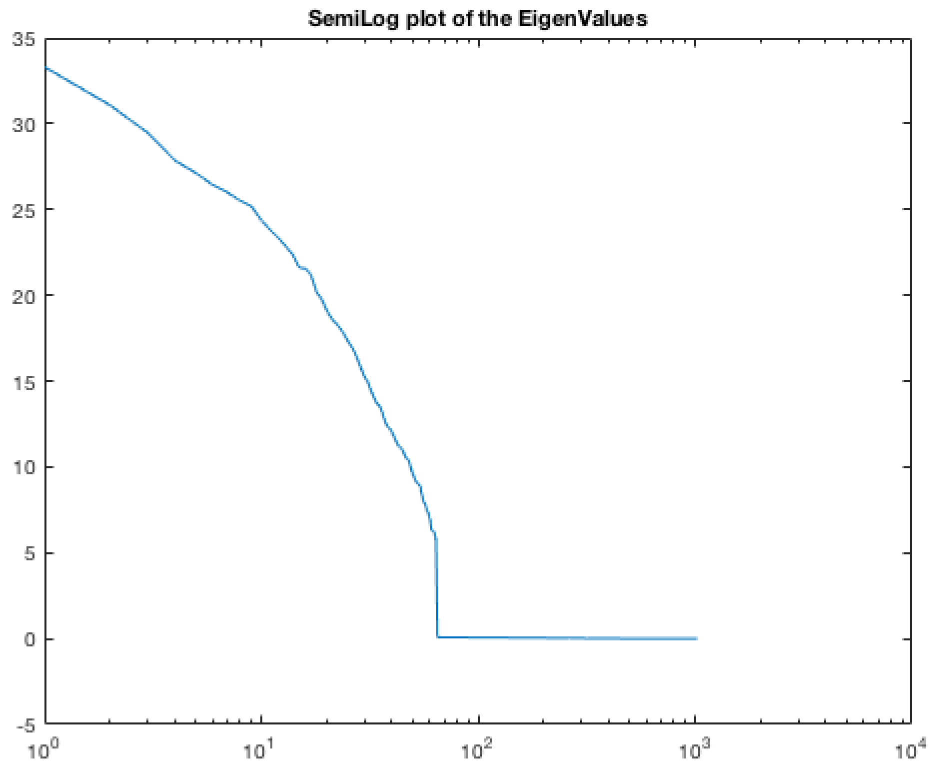
```
% Compute the principal components by finding the eigen-decomposition
 of your zero-mean covariance
% matrix. Use the MATLAB function eig. Sort the eigenvalues from
 largest to smallest (and
% sort the eigenvectors as well). (Pro tip: Use the [vals index] =
 sort(numbers, ?descend?)
% version of the sort command to get a sorted list of indices that you
 can use to sort the eigenvectors.).
% Make two plots of the eigenvalues (linear and semilog). Use this
 information to infer
% the dimension of the low-dimensional subspace that the data
 approximately resides in.
```

ANSWER3

```
[E_zeromean_var_vec,E_zeromean_var_val] = eig(cov_raw_zero);  %Finding
 out the Eigen Vlaues and Eigen Vectors
E_diag = diag(E_zeromean_var_val);
E_val_sorted = sort(E_diag,'descend');                          %Sorting
 the Eigen Values in Descending Order
A = size(E_zeromean_var_vec);
[B A] = sort(E_zeromean_var_vec,'descend');                     %Sorting
 the Eigen Vectors in Descending Order
```

```
figure(4);
plot(E_val_sorted);
title('Linear plot of the EigenValues');
  %Plotting the sorted Eigen Values
figure(5);
semilogx(E_val_sorted);
title('SemiLog plot of the EigenValues');
  %Plotting the sorted Eigen Vectors
```



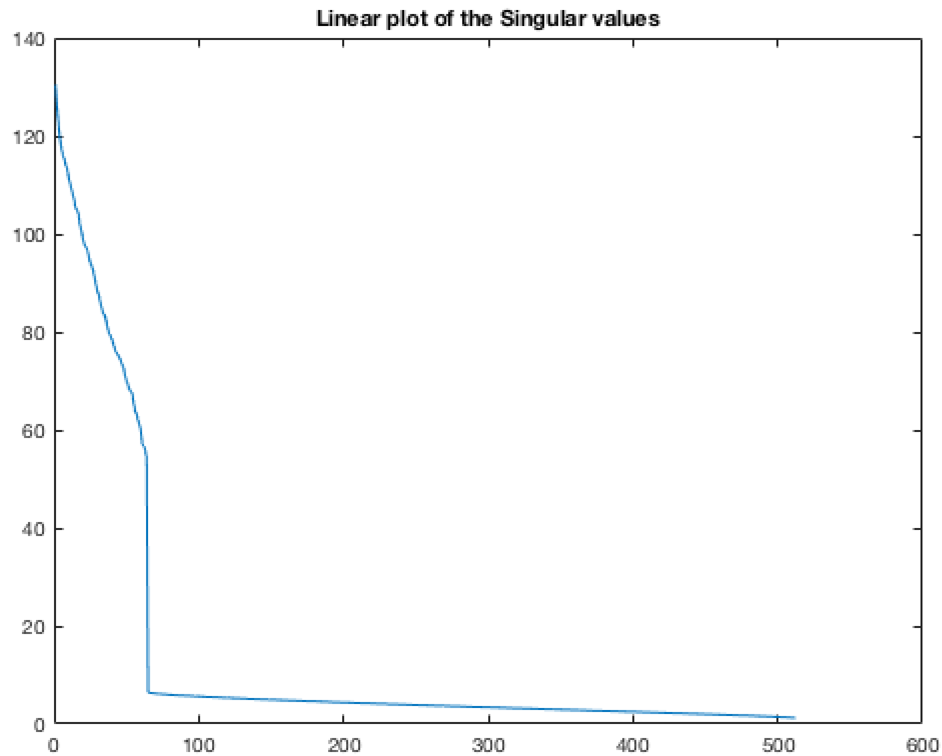


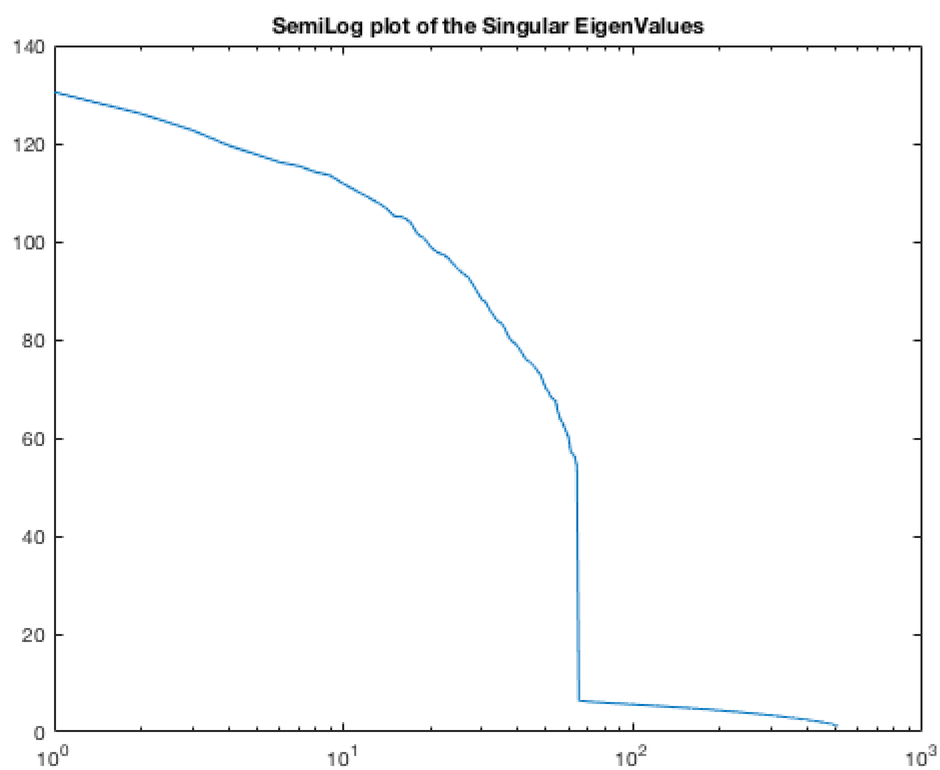
QUESTION 4

```
% Now we ere going to compute the principal components via singular-
value decomposition (SVD).
% Use the MATLAB svd command to decompose the zero-mean data into U,
 S, and V matrices.
% Make two plots of the singular values (linear and semilog). Use this
 information to infer the
% dimension of the low-dimensional subspace that the data
 approximately resides in. Compare
% with the answer you found earlier.
```

ANSWER 4

```
[U,E_singular,V] = svd(raw_zero);                             %Singular
 Value Decomposition of raw zero data
E_singular_diag = diag(E_singular);
figure(6);
plot(E_singular_diag);
  %Plotting(LINEAR) the singular value from SVD
title('Linear plot of the Singular values');
figure(7);
semilogx(E_singular_diag);
  %Plotting(SEMILOG) the singular value from SVD
title('SemiLog plot of the Singular EigenValues');
```


Linear plot of the Singular values
140
120
100
80
60
40
20
0
0
100
200
300
400
500
600

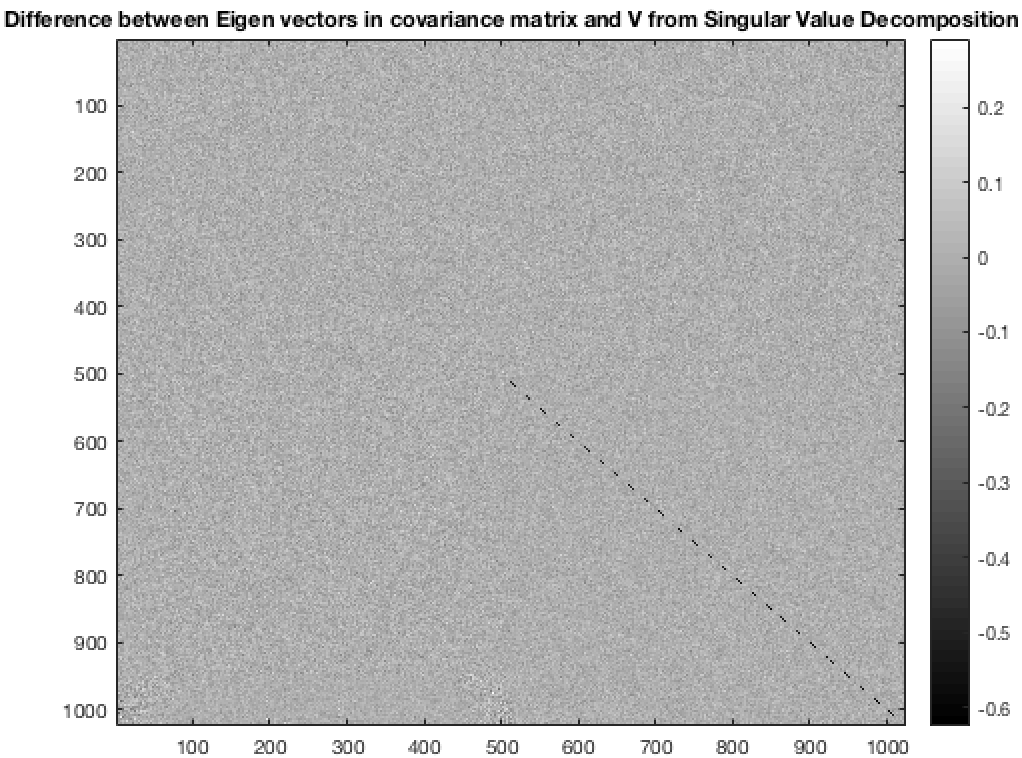

SemiLog plot of the Singular EigenValues
140
120
100
80
60
40
20
0
10^0
10^1
10^2
10^3

QUESTION 5

```
% Compare the principal components found by taking the eigenvectors of
 the covariance matrix
% (in Subproblem 3) with the ones found in the matrix V of the SVD (in
 Subproblem 4). Plot the
% difference of the two matrices. Comment on the differences.
```

ANSWER 5

```
figure(8);
imagesc(E_zeromean_var_vec-V);               %Plotting the Difference
 between the zero mean variance and V from SVD
colorbar;
colormap 'gray';
title('Difference between Eigen vectors in covariance matrix and V
 from Singular Value Decomposition');
```



QUESTION 6

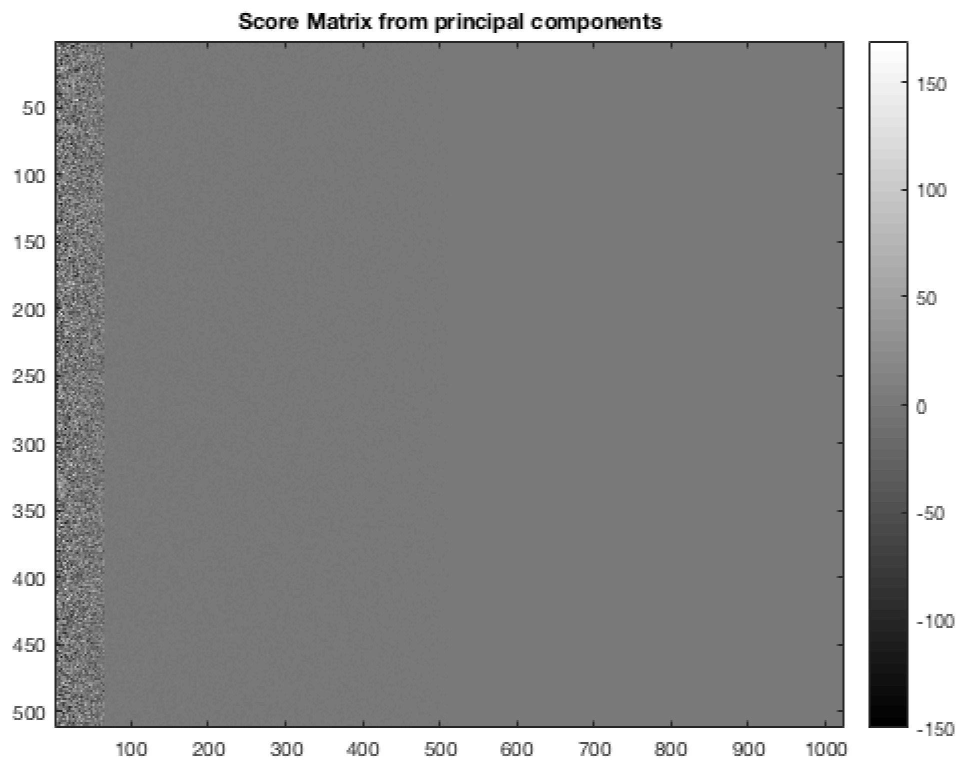
```
% Now we are going to use the MATLAB function princomp to compute the
 principal components.
% This time, use the non-zero-meaned data (princomp takes care of that
 detail for you). Plot the
```

```
% score matrix returned by princomp. This matrix gives the expansion
 coefficients for the data in
% the principal component basis. Comment on the structure you see.
```

ANSWER 6

```
[Coeff_raw_data,Score_raw_data] = princomp(rawdata);   %Doing the PCA
 of the raw data
figure(9);
imagesc(Score_raw_data);                                %Plotting the
 score from tbe PCA
colorbar;
colormap gray;
title('Score Matrix from principal components');
% Have to comment on the structure
```

Warning: princomp will be removed in a future release. Use pca instead.



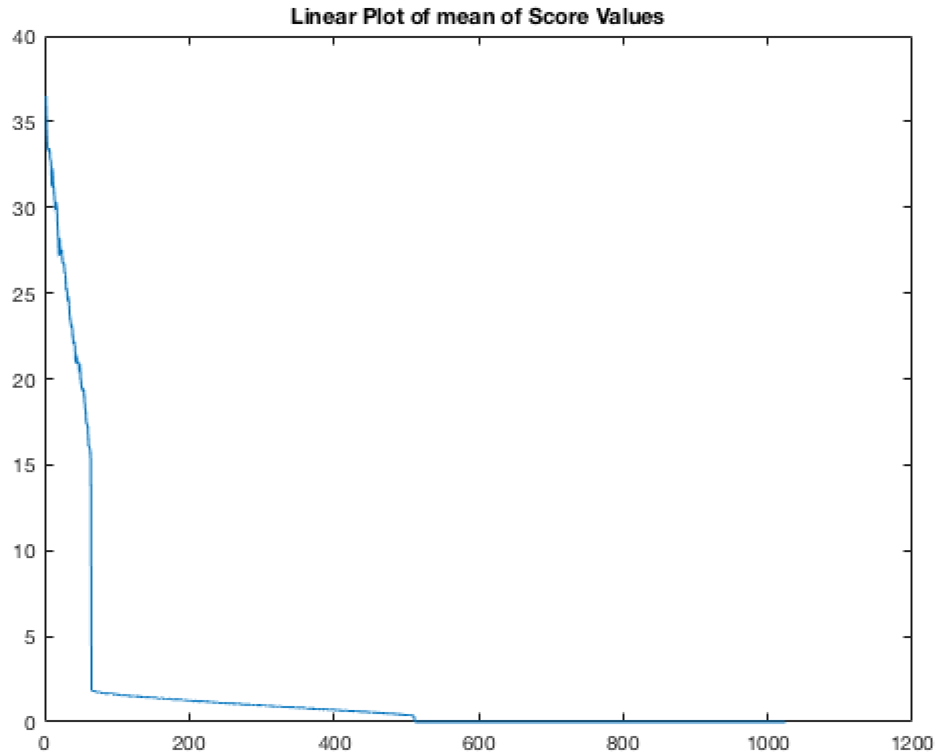
QUESTION 7

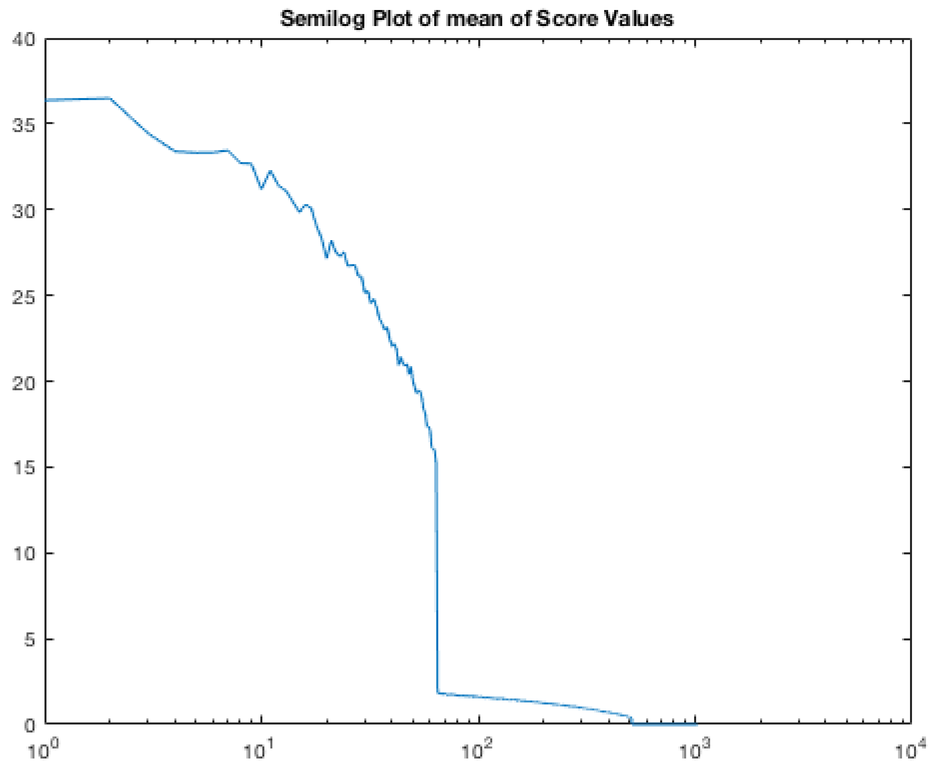
```
% Following up on the lead from the subproblem above, compute the mean
 of the absolute value of
% the elements in each column of score. Make two plots of this
 information (linear and semilog).
```

```
% Use this information to infer the dimension of the low-dimensional
 subspace that the data
% approximately resides in.
```

ANSWER 7

```
Score_abs = abs(Score_raw_data);
Score_mean = mean(Score_abs);                          %Mean of the score
 raw data
figure(10);
plot(Score_mean);                                      %Plotting(LINEAR)
 of the score mean
title('Linear Plot of mean of Score Values');
figure(11);
semilogx(Score_mean);                                  %Plotting(SEMILOG)
 of the score mean
title('Semilog Plot of mean of Score Values');
```





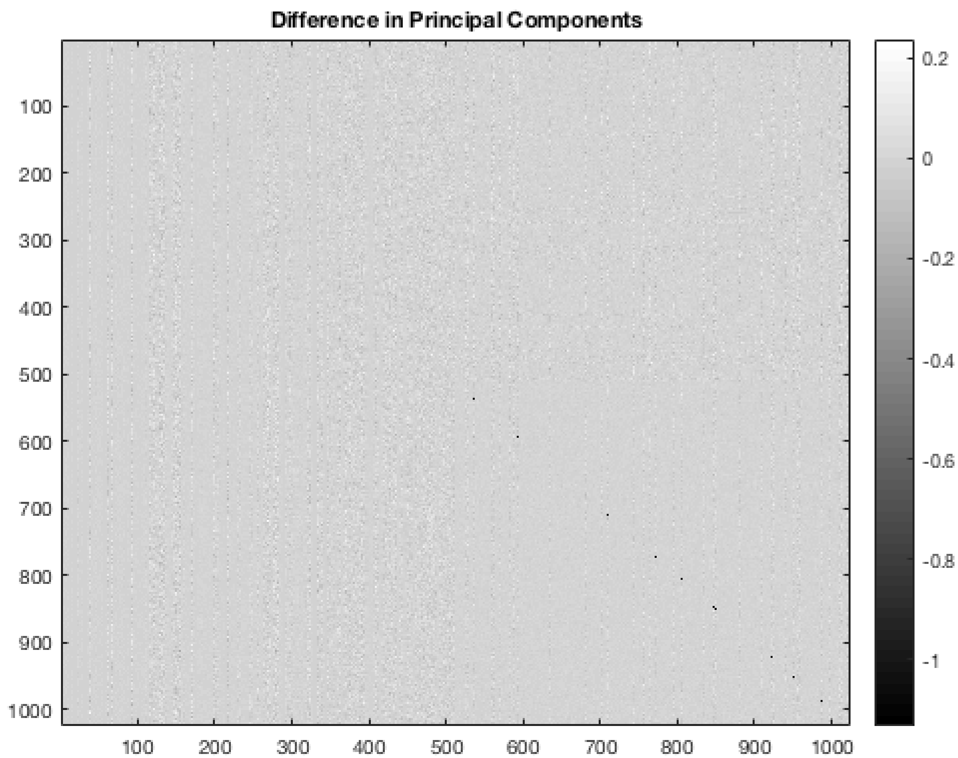
QUESTION 8

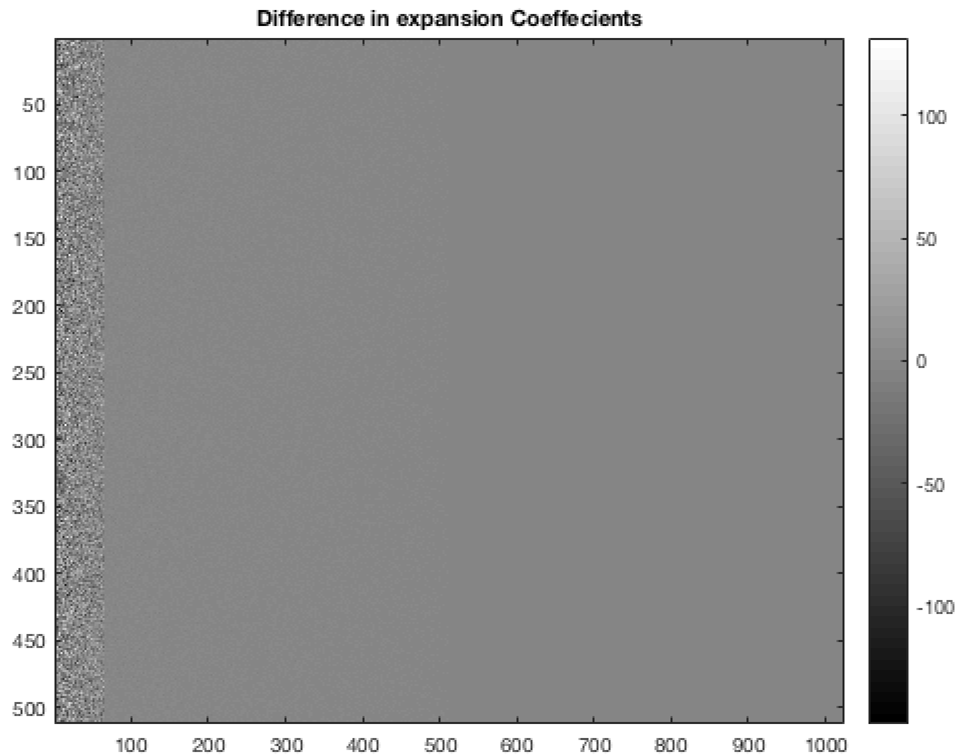
```
% Now compare the principal components found via svd and princomp.
 Plot the difference of the
% two matrices. Now compare the difference in the expansion
 coefficients. In the svd version, this
% will be the product US. Compute the difference of the two matrices.
 Comment on the results.
```

ANSWER 8

```
Signum_V = sign(V(1,:));
Signum_Coeff_raw_data = sign(Coeff_raw_data(1,:));
Signum_common = repmat(Signum_V.*Signum_Coeff_raw_data,[1024,1]);
V_final = Signum_common.*V;
figure(12);
imagesc(V_final - Coeff_raw_data);
title('Difference in Principal Components');
colorbar;
colormap 'gray';
SVD_princomp = U*E_singular;
PCA_princomp = Score_raw_data;
Signum_SVD_princomp = sign(SVD_princomp(1,:));
Signum_PCA_princomp = sign(PCA_princomp(1,:));
Signum_common_2 = Signum_SVD_princomp.*Signum_PCA_princomp;
```

```
SVD_princomp_final = Signum_common_2.*SVD_princomp;
figure(13);
imagesc(SVD_princomp_final - PCA_princomp);
title('Difference in expansion Coeffecients');
colorbar;
colormap 'gray';
```





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