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HW02  
Stat W4240  
Section 2

## Homework 2

### Problem #1

#### Part a)

```
> colMeans(set1,na.rm=TRUE)
      x1      x2      x3      x4      x5
6.049104 -8.277221 4.665532 7.914270 62.138753
> rowMeans(set1,na.rm=TRUE)
[1] -0.1277116 20.8162864 -8.8984358 25.5999204 -9.7472153 64.0626702 22.0392371 23.3914888 31.7598224 -13.8680290 43.8318898 6.5478369 14.1665143 16.1945993
[15] 29.6357898 11.0316832 -2.5453007 8.6124471 33.8364419 24.9647839 34.8385372 34.1951748 25.8869897 -0.4545730 9.0418836 21.4051827 3.2291136 35.5748021
[29] 21.1031545 6.5535668 3.7478608 18.9230712 -9.2447158 6.3811655 16.8358750 7.9628124 16.6264489 16.7027735 -34.4147885 0.4138282 12.6572899 35.4589880
[43] 17.3456417 17.2383651 0.5124620 -24.7073649 17.1498949 52.3665782 9.6993053 0.3079195 15.6758568 -13.3093667 8.2062088 34.8247664 12.1909900 -3.1939531
[57] -5.4779341 10.7689107 36.2253846 19.5034554 8.9492321 4.4008921 14.3901288 14.7207124 27.9510161 -14.3617846 39.3331820 24.0356530 -6.7256757 -4.2948679
[71] 27.1881673 47.2951022 19.1932996 23.5607379 7.6480638 18.1517706 16.9872267 -46.6660940 7.2223867 28.8378401 6.5043155 26.5206768 -2.4442159 15.3802055
[85] 16.1739005 26.1705488 20.1409435 63.2646829 9.1977728 29.2026018 1.2105932 21.2145724 -8.4896595 19.0639963 20.9767512 3.5962333 22.3461063 0.7145014
[99] 6.3080005 64.8829556
```

This matrix has 5 columns and 100 rows, and we can see that the column and row means vary in both magnitude and sign. The second column has a negative mean, while the fifth column's mean is significantly larger than those of the other columns. Among the rows, there are more positive row means than negative ones.

#### Part b)

```
> set1_emp
      x1      x2      x3      x4      x5
x1  1.0000000 -0.9328319  0.9903675  0.9229496  0.8391148
x2 -0.9328319  1.0000000 -0.9641852 -0.7226496 -0.9787417
x3  0.9903675 -0.9641852  1.0000000  0.8733612  0.8921875
x4  0.9229496 -0.7226496  0.8733612  1.0000000  0.5657457
x5  0.8391148 -0.9787417  0.8921875  0.5657457  1.0000000
```

The diagonal values of the covariance matrix are all 1, while the off-diagonal values are symmetric around the main diagonal. Thus, we know that the covariance matrix is symmetric and standardized.

#### Part c)

```
> eigen(set1_emp)
$values
[1] 4.486912e+00 5.087101e-01 4.368873e-03 8.952428e-06 5.481364e-07

$vectors
      [,1]      [,2]      [,3]      [,4]      [,5]
[1,] 0.4673470 -0.19431684 -0.42408896 0.7368413 0.14505575
[2,] -0.4596583 -0.31879336 0.25264423 0.2026734 0.76300680
[3,] 0.4711378 -0.04048796 0.85611177 0.1967856 -0.06883262
[4,] 0.4064079 -0.71331462 -0.12223569 -0.5420731 0.13126328
[5,] 0.4279751 0.59173874 -0.09192674 -0.2888262 0.61221849
```

We know that the left eigenvectors are transposes of the right eigenvectors of the transposed covariance matrix. In this case, our left and right eigenvectors are the same since our covariance matrix is symmetric.

#### Part d)

```
> set1_pca$scores
```

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
x1	0.9171061	-0.058803201	-2.038744e-03	6.118564e-06	1.221961e-10
x2	-3.2422362	0.007687044	9.159998e-05	4.785668e-07	9.545031e-12
x3	0.9365474	0.018887709	3.482194e-03	1.813234e-06	3.599721e-11
x4	0.6355725	-0.314161290	-5.228455e-04	-4.897621e-06	-9.769873e-11
x5	0.7530102	0.346389738	-1.012205e-03	-3.512744e-06	-7.003975e-11

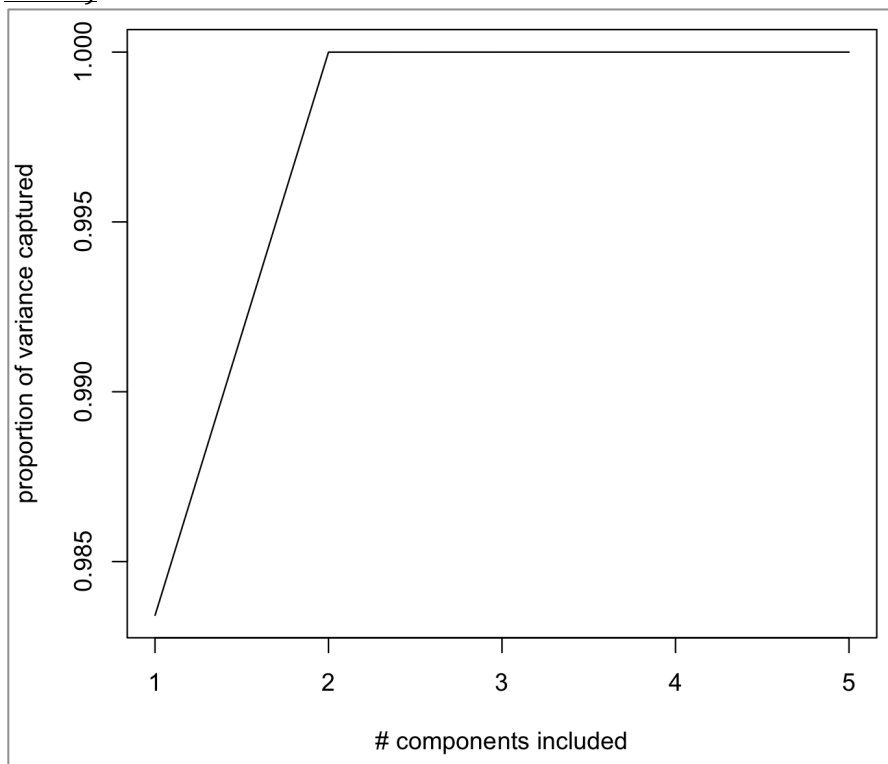
```
> set1_pca$loadings
```

Loadings:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
x1	0.461	-0.209	-0.424	0.735	0.154
x2	-0.469	-0.304	0.253	0.194	0.765
x3	0.469		0.856	0.198	
x4	0.384	-0.726	-0.121	-0.544	0.125
x5	0.446	0.578		-0.296	0.609

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
SS loadings	1.0	1.0	1.0	1.0	1.0
Proportion Var	0.2	0.2	0.2	0.2	0.2
Cumulative Var	0.2	0.4	0.6	0.8	1.0

#### Part e)



We should include 2 components, as additional components beyond the first two contribute very insignificantly toward the proportion of variance captured.

Part f)

```
> set2_pca$scores
```

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
[1,]	-0.5143948	-1.5502331	0.007730112	0.0007486009	-8.770762e-15
[2,]	1.9261814	0.7596842	-0.028036107	0.0012971909	-1.487699e-14
[3,]	1.8510330	-0.2785482	-0.027645240	-0.0015602335	1.726397e-14
[4,]	-2.9793826	0.5349135	-0.045528501	-0.0002362324	1.887379e-15
[5,]	-0.2834370	0.5341836	0.093479737	-0.0002493259	3.996803e-15

Part g)

Coordinates of the projection in the original space:

```
> Y
```

	x1	x2	x3	x4	x5
1	1.6021865	0.04605328	1.0635890	-0.5996748	-4.0227381
2	-1.2877658	-4.14192024	-1.1392189	1.7976776	-18.8652256
3	-3.2729844	6.43439645	-2.5496028	-7.6101484	-29.9975327
4	0.9713501	0.74796859	0.4469463	-3.5978859	0.6046244
5	0.8458003	-2.76899602	1.2421640	-0.2266484	21.2489825

Euclidean distance:

```
> sqrt(sum((Y-set1_centered))^2)
```

```
[1] 46.39402
```

Part h)

```
> as.vector(errors)
```

```
[1] 1.838789e-01 6.410107e-01 4.796689e-02 9.753955e-04 9.249128e-09
```

The errors are all positive, though very small, for the 5 new points. The direction of the error for the 5 new points is likely perpendicular to the direction of the projections in the original space since this generates the smallest possible error.

## Problem #2

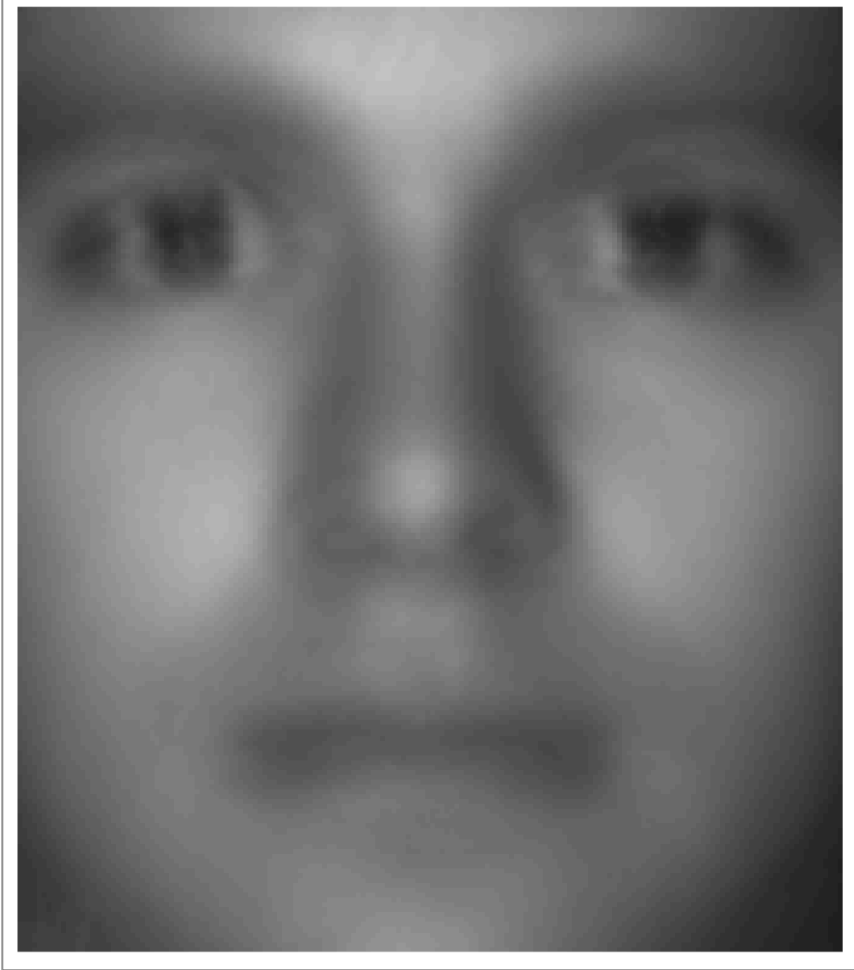
Part a)

```
> dim(faces_matrix)
```

```
[1] 152 32256
```

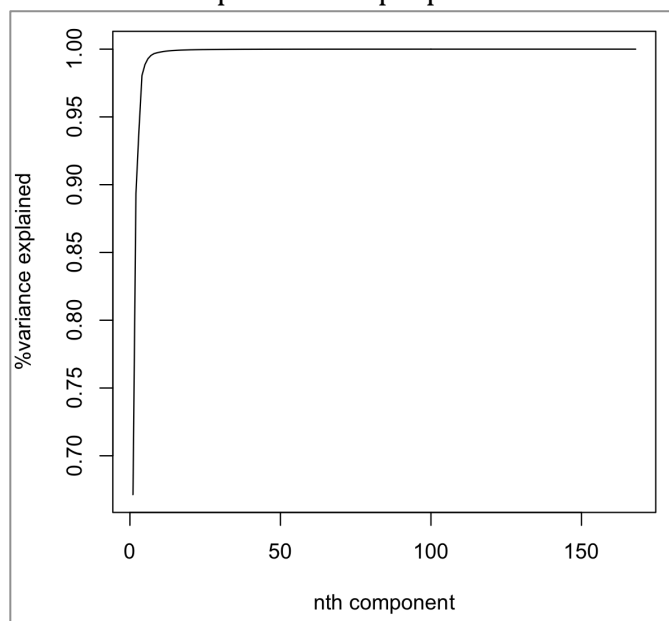
This matrix is 152 rows by 32,256 columns, where each row represents a different picture.

Part b)



Part c)

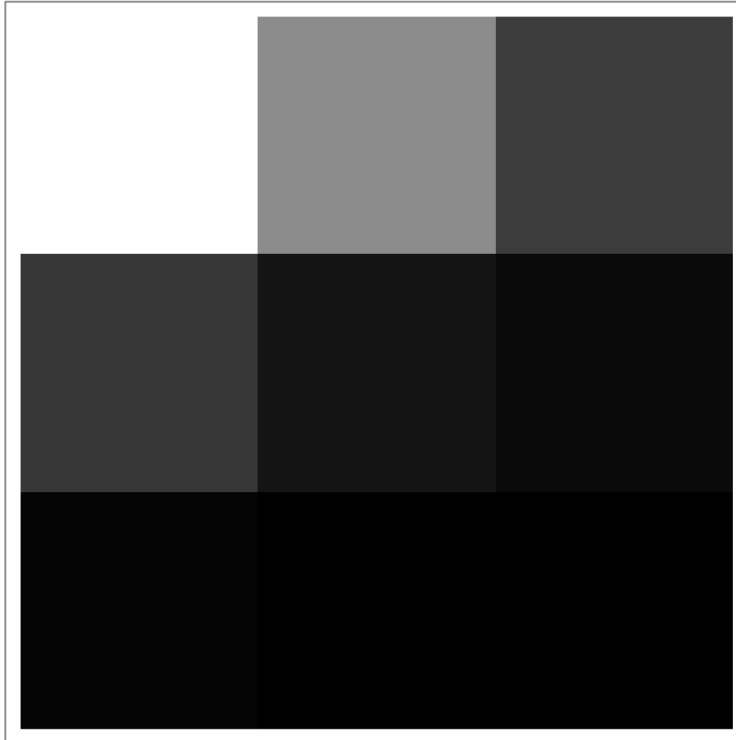
Number of components vs. proportion of variance explained:



## Principal components:

```
> summary(means_pca)
Importance of components:
PC1    PC2    PC3    PC4    PC5    PC6    PC7    PC8    PC9    PC10   PC11   PC12   PC13   PC14   PC15   PC16   PC17   PC18   PC19
Standard deviation  1.1039  0.6352  0.29058 0.27083 0.1213 0.08869 0.06581 0.04903 0.03369 0.02938 0.02659 0.02456 0.02047 0.01833 0.01585 0.01506 0.01329 0.01200 0.01116
Proportion of Variance 0.6714 0.2223 0.04652 0.04041 0.0081 0.00433 0.00239 0.00132 0.00063 0.00048 0.00039 0.00033 0.00023 0.00019 0.00014 0.00012 0.00010 0.00008 0.00007
Cumulative Proportion 0.6714 0.8936 0.94013 0.98054 0.9886 0.99298 0.99536 0.99669 0.99731 0.99779 0.99818 0.99851 0.99874 0.99892 0.99906 0.99919 0.99929 0.99936 0.99943
PC20   PC21   PC22   PC23   PC24   PC25   PC26   PC27   PC28   PC29   PC30   PC31   PC32   PC33   PC34   PC35   PC36
Standard deviation 0.01072 0.01023 0.00927 0.008325 0.007995 0.007051 0.006429 0.00622 0.005875 0.005736 0.00525 0.004931 0.004796 0.004665 0.004587 0.004437 0.004139
Proportion of Variance 0.00006 0.00006 0.00005 0.000040 0.000040 0.000030 0.000020 0.00002 0.000020 0.000020 0.000020 0.000020 0.000010 0.000010 0.000010 0.000010 0.000010
Cumulative Proportion 0.99950 0.99955 0.99960 0.999640 0.999680 0.999700 0.999730 0.99975 0.999770 0.999780 0.99980 0.999810 0.999820 0.999840 0.999850 0.999860 0.999870
PC37    PC38    PC39    PC40    PC41    PC42    PC43    PC44    PC45    PC46    PC47    PC48    PC49    PC50    PC51    PC52    PC53
Standard deviation 0.004082 0.003806 0.003662 0.003574 0.003204 0.003109 0.00303 0.002938 0.002913 0.002884 0.002715 0.002624 0.002549 0.002383 0.002341 0.002298 0.00218
Proportion of Variance 0.000010 0.000010 0.000010 0.000010 0.000010 0.000010 0.00001 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.00000
Cumulative Proportion 0.999880 0.999890 0.999890 0.999900 0.999910 0.999910 0.99992 0.999920 0.999930 0.999930 0.999940 0.999940 0.999940 0.999940 0.999950 0.999950 0.99995
PC54    PC55    PC56    PC57    PC58    PC59    PC60    PC61    PC62    PC63    PC64    PC65    PC66    PC67    PC68    PC69    PC70
Standard deviation 0.002152 0.002063 0.002028 0.001947 0.001922 0.00185 0.001844 0.001766 0.001697 0.00166 0.001607 0.001577 0.001508 0.001494 0.001412 0.001384 0.001342
Proportion of Variance 0.000000 0.000000 0.000000 0.000000 0.000000 0.00000 0.000000 0.000000 0.000000 0.00000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.00000
Cumulative Proportion 0.999960 0.999960 0.999960 0.999960 0.999960 0.99997 0.999970 0.999970 0.999970 0.99997 0.999970 0.999980 0.999980 0.999980 0.999980 0.999980 0.999980
PC71    PC72    PC73    PC74    PC75    PC76    PC77    PC78    PC79    PC80    PC81    PC82    PC83    PC84    PC85    PC86
Standard deviation 0.001312 0.001299 0.001286 0.001258 0.001209 0.001145 0.001108 0.001086 0.001055 0.0009972 0.0009898 0.0009629 0.0009522 0.0009308 0.0009174 0.0008839
Proportion of Variance 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
Cumulative Proportion 0.999980 0.999980 0.999980 0.999990 0.999990 0.999990 0.999990 0.999990 0.999990 0.999990 0.999990 0.999990 0.999990 0.999990 0.999990 0.999990
PC87    PC88    PC89    PC90    PC91    PC92    PC93    PC94    PC95    PC96    PC97    PC98    PC99    PC100   PC101
Standard deviation 0.0008578 0.0008239 0.0008154 0.0007983 0.0007717 0.0007569 0.0007339 0.0006941 0.000669 0.0006639 0.0006531 0.0006334 0.0006244 0.0005997 0.0005917
Proportion of Variance 0.0000000 0.0000000 0.0000000 0.0000000 0.0000000 0.0000000 0.0000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
Cumulative Proportion 0.9999900 0.9999900 0.9999900 0.9999900 0.9999900 0.9999900 0.9999900 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000
PC102   PC103   PC104   PC105   PC106   PC107   PC108   PC109   PC110   PC111   PC112   PC113   PC114   PC115   PC116
Standard deviation 0.0005641 0.0005506 0.0005441 0.0005311 0.0005133 0.0004959 0.0004883 0.0004798 0.0004686 0.0004619 0.0004459 0.0004353 0.0004239 0.0004101 0.0003975
Proportion of Variance 0.0000000 0.0000000 0.0000000 0.0000000 0.0000000 0.0000000 0.0000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
Cumulative Proportion 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000
PC117   PC118   PC119   PC120   PC121   PC122   PC123   PC124   PC125   PC126   PC127   PC128   PC129   PC130   PC131
Standard deviation 0.0003962 0.0003827 0.0003791 0.0003677 0.0003623 0.000349 0.0003318 0.0003284 0.0003239 0.0003092 0.000304 0.0002988 0.0002957 0.0002815 0.0002751
Proportion of Variance 0.0000000 0.0000000 0.0000000 0.0000000 0.0000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
Cumulative Proportion 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000
PC132   PC133   PC134   PC135   PC136   PC137   PC138   PC139   PC140   PC141   PC142   PC143   PC144   PC145   PC146
Standard deviation 0.0002649 0.0002562 0.0002436 0.0002379 0.0002334 0.000232 0.0002172 0.0002093 0.0001982 0.0001925 0.0001922 0.0001838 0.0001715 0.0001671 0.0001651
Proportion of Variance 0.0000000 0.0000000 0.0000000 0.0000000 0.0000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
Cumulative Proportion 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000
PC147   PC148   PC149   PC150   PC151   PC152   PC153   PC154   PC155   PC156   PC157   PC158   PC159   PC160   PC161
Standard deviation 0.0001594 0.000153 0.0001516 0.0001494 0.0001369 0.000134 0.0001306 0.000124 0.0001141 0.0001114 0.0001009 9.791e-05 8.512e-05 8.312e-05 8.153e-05
Proportion of Variance 0.0000000 0.000000 0.0000000 0.0000000 0.0000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000e+00 0.000e+00 0.000e+00 0.000e+00
Cumulative Proportion 1.0000000 1.000000 1.0000000 1.0000000 1.0000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000e+00 1.000e+00 1.000e+00 1.000e+00
PC162   PC163   PC164   PC165   PC166   PC167   PC168
Standard deviation 7.794e-05 7.374e-05 6.306e-05 5.782e-05 5.198e-05 4.563e-05 3.076e-05
Proportion of Variance 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00
Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.000e+00
```

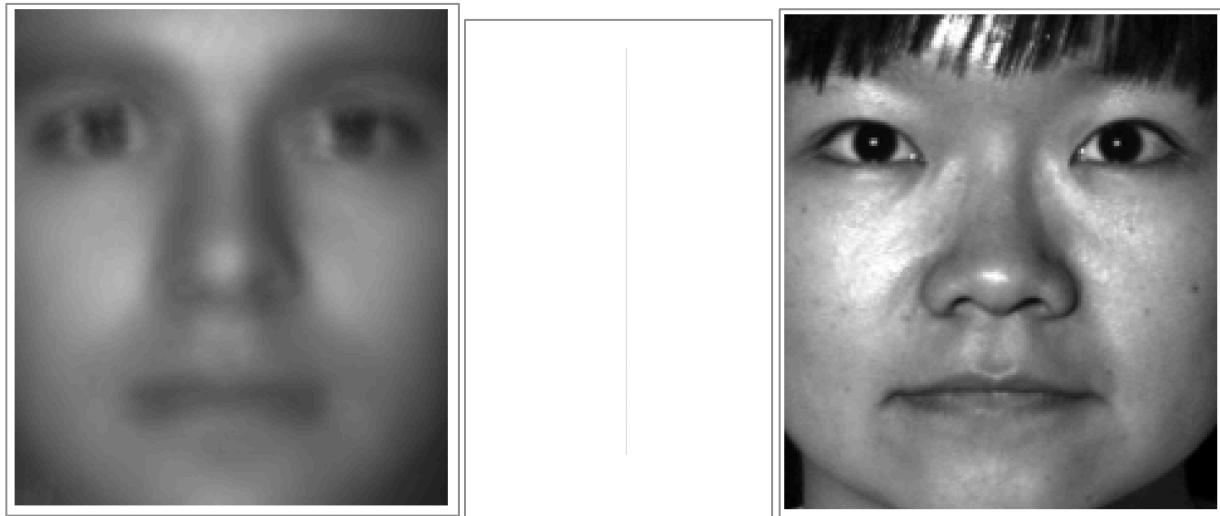
## Part d)



The eigenfaces take on the standard ranges of pixmap class objects of 0 to 1, where 1 represents white and 0 represents black. These eigenfaces represent eigenvectors of our covariance matrix of faces, or more generally the principal components of a distribution of

faces. We generated our principal components in part c, and these form a basis for the images of all of the faces.

Part e)



Unfortunately, we failed to generate the 5x5 plot, as our code only produced an image of a vertical grey line (see middle image above). However, we understand that by adding eigenfaces in the following manner...

$\text{mean\_face} + \text{score}[1] * \text{loading}[1] + \dots + \text{score}[m] * \text{loading}[m]$

...we slowly transform our mean face into the face of Subject 5. It would likely take us a fairly substantial number of eigenvectors (at least about 80~100) for us to be able to recognize the person.

Part f)

```
> dim(new_matrix)
[1] 148 32256
```

Removing subject 1 leaves us with a new matrix of faces of dimension 148 by 32256. We also successfully run `prcomp()` to obtain new principal components (see below).

summary(new_pca)																			
Importance of components:																			
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15	PC16	PC17	PC18	PC19
Standard deviation	15.5266	7.2094	6.15662	5.99079	5.57408	5.31375	4.94628	4.23696	3.65965	3.44747	3.25434	3.17436	3.02384	2.91959	2.78488	2.64503	2.58397	2.50496	2.35343
Proportion of Variance	0.3678	0.0793	0.05783	0.05476	0.04741	0.04308	0.03733	0.02739	0.02044	0.01813	0.01616	0.01537	0.01395	0.01301	0.01183	0.01067	0.01019	0.00957	0.00845
Cumulative Proportion	0.3678	0.4471	0.50497	0.55973	0.60714	0.65022	0.68755	0.71494	0.73538	0.75351	0.76967	0.78504	0.79900	0.81200	0.82383	0.83451	0.84470	0.85427	0.86272
	PC20	PC21	PC22	PC23	PC24	PC25	PC26	PC27	PC28	PC29	PC30	PC31	PC32	PC33	PC34	PC35	PC36	PC37	PC38
Standard deviation	2.23564	2.17815	2.11883	2.08600	1.96834	1.93196	1.86006	1.83588	1.81298	1.76646	1.70521	1.64866	1.6394	1.58417	1.49621	1.46367	1.43663	1.38629	1.30114
Proportion of Variance	0.00763	0.00724	0.00685	0.00664	0.00591	0.00569	0.00528	0.00514	0.00502	0.00476	0.00444	0.00415	0.0041	0.00383	0.00342	0.00327	0.00315	0.00293	0.00258
Cumulative Proportion	0.87035	0.87759	0.88444	0.89108	0.89699	0.90268	0.90796	0.91310	0.91812	0.92288	0.92732	0.93146	0.9356	0.93939	0.94281	0.94608	0.94923	0.95216	0.95474
	PC39	PC40	PC41	PC42	PC43	PC44	PC45	PC46	PC47	PC48	PC49	PC50	PC51	PC52	PC53	PC54	PC55	PC56	PC57
Standard deviation	1.26920	1.19783	1.1732	1.05725	1.03599	0.96921	0.92505	0.90463	0.90216	0.87494	0.86756	0.83367	0.82290	0.79682	0.77706	0.76083	0.73611	0.73041	0.72038
Proportion of Variance	0.00246	0.00219	0.0021	0.00171	0.00164	0.00143	0.00131	0.00125	0.00124	0.00117	0.00115	0.00106	0.00103	0.00097	0.00092	0.00088	0.00083	0.00081	0.00079
Cumulative Proportion	0.95720	0.95939	0.9615	0.96320	0.96483	0.96627	0.96757	0.96882	0.97006	0.97123	0.97238	0.97344	0.97447	0.97544	0.97636	0.97725	0.97807	0.97889	0.97968
	PC58	PC59	PC60	PC61	PC62	PC63	PC64	PC65	PC66	PC67	PC68	PC69	PC70	PC71	PC72	PC73	PC74	PC75	PC76
Standard deviation	0.71667	0.69545	0.68247	0.66793	0.65500	0.65219	0.63927	0.61782	0.60503	0.58738	0.5732	0.56603	0.53497	0.53026	0.52260	0.5092	0.49680	0.49485	0.49008
Proportion of Variance	0.00078	0.00074	0.00071	0.00068	0.00065	0.00065	0.00062	0.00058	0.00056	0.00053	0.0005	0.00049	0.00044	0.00043	0.00042	0.0004	0.00038	0.00037	0.00037
Cumulative Proportion	0.98046	0.98120	0.98191	0.98259	0.98325	0.98390	0.98452	0.98510	0.98566	0.98619	0.9867	0.98718	0.98761	0.98804	0.98846	0.9889	0.98923	0.98961	0.98997
	PC77	PC78	PC79	PC80	PC81	PC82	PC83	PC84	PC85	PC86	PC87	PC88	PC89	PC90	PC91	PC92	PC93	PC94	PC95
Standard deviation	0.48523	0.47223	0.46992	0.46132	0.45510	0.44976	0.4454	0.43751	0.42826	0.41397	0.41002	0.40595	0.39723	0.39520	0.38811	0.38240	0.37561	0.37085	0.3649
Proportion of Variance	0.00036	0.00034	0.00034	0.00032	0.00032	0.00031	0.0003	0.00029	0.00028	0.00026	0.00026	0.00025	0.00024	0.00024	0.00023	0.00022	0.00022	0.00021	0.0002
Cumulative Proportion	0.99033	0.99067	0.99101	0.99133	0.99165	0.99196	0.9923	0.99255	0.99283	0.99309	0.99335	0.99360	0.99384	0.99408	0.99431	0.99453	0.99475	0.99496	0.9952
	PC96	PC97	PC98	PC99	PC100	PC101	PC102	PC103	PC104	PC105	PC106	PC107	PC108	PC109	PC110	PC111	PC112	PC113	PC114
Standard deviation	0.3602	0.35378	0.35102	0.34900	0.34080	0.33564	0.33374	0.32756	0.32285	0.31477	0.31069	0.30445	0.30025	0.29722	0.29136	0.28753	0.28450	0.27622	0.27216
Proportion of Variance	0.00002	0.00019	0.00019	0.00019	0.00018	0.00017	0.00017	0.00016	0.00016	0.00015	0.00015	0.00014	0.00014	0.00013	0.00013	0.00013	0.00012	0.00012	0.00011
Cumulative Proportion	0.9954	0.99555	0.99574	0.99592	0.99610	0.99627	0.99644	0.99661	0.99677	0.99692	0.99706	0.99721	0.99734	0.99748	0.99761	0.99773	0.99786	0.99797	0.99809
	PC115	PC116	PC117	PC118	PC119	PC120	PC121	PC122	PC123	PC124	PC125	PC126	PC127	PC128	PC129	PC130	PC131	PC132	PC133
Standard deviation	0.26435	0.2588	0.2528	0.23946	0.23648	0.23472	0.23028	0.22461	0.22059	0.21242	0.20712	0.20087	0.19981	0.19643	0.19199	0.18712	0.18534	0.18175	0.17965
Proportion of Variance	0.00011	0.0001	0.0001	0.00009	0.00009	0.00008	0.00008	0.00008	0.00007	0.00007	0.00007	0.00006	0.00006	0.00006	0.00006	0.00005	0.00005	0.00005	0.00005
Cumulative Proportion	0.99819	0.9983	0.9984	0.99848	0.99857	0.99865	0.99873	0.99881	0.99888	0.99895	0.99902	0.99908	0.99914	0.99920	0.99925	0.99931	0.99936	0.99941	0.99946
	PC134	PC135	PC136	PC137	PC138	PC139	PC140	PC141	PC142	PC143	PC144	PC145	PC146	PC147	PC148				
Standard deviation	0.17872	0.17647	0.17424	0.16913	0.16850	0.16412	0.16049	0.15878	0.15595	0.15142	0.14694	0.14053	0.13782	0.13431	0.1234e-14				
Proportion of Variance	0.00005	0.00005	0.00005	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003				
Cumulative Proportion	0.99951	0.99956	0.99960	0.99965	0.99969	0.99973	0.99977	0.99981	0.99985	0.99988	0.99991	0.99994	0.99997	1.00000	1.0000e+00				

Unfortunately, we were unable to generate a reconstructed image, though we understand that we are using the eigenfaces of the remaining images to reconstruct subject 1's image. We know that the reconstructed image will look somewhat like the original image since we are eliminating data on the other subjects' faces from the mean face which thus allows us to approximate the image of subject 1.

## Code

```
#####
# Kevin Gong
# STAT W4240
# Homework 2 , Problem 1
# 2/19/14
#

#####

#####
# Setup
#####

# make sure R is in the proper working directory
# note that this will be a different path for every machine
setwd("~/Dropbox/SIPA/Data Mining/HW2")

# first include the relevant libraries
# note that a loading error might mean that you have to
# install the package into your R distribution.  From the
# command line, type install.packages("pixmap")
library(pdist)

#####
# Problem 1a
#####

set1 = read.csv(file="hw02_q1_p1.csv")
head(set1)
colMeans(set1,na.rm=TRUE)
rowMeans(set1,na.rm=TRUE)

#####
# Problem 1b
#####

set1_centered = scale(set1, center=TRUE)
set1_emp = cov(set1_centered)
set1_emp

#####
# Problem 1c
#####

eigen(set1_emp)

#####
# Problem 1d
#####

set1_pca = princomp(set1_emp)
set1_pca$scores
set1_pca$loadings

#####
# Problem 1e ??
#####
```



```

set1_pca$sdev^2/sum(set1_pca$sdev^2)

cumsum(set1_pca$sdev^2/sum(set1_pca$sdev^2))

plot(cumsum(set1_pca$sdev^2/sum(set1_pca$sdev^2)),type='l',xlab="# components included",
     ylab="proportion of variance captured")

#####
# Problem 1f
#####

set2 = read.csv(file="hw02_q1_p2.csv")
set2_centered = scale(set2, center=TRUE)
set2_pca = princomp(set2_centered)
set2_pca$scores

#####
# Problem 1g
#####

W = set1_pca$loadings[,1:2]
X = set2_centered[1:5,1:5]
Y = X*t(W)
#euclidean distances
sqrt(sum((Y-set1_centered))^2)
pdist(Y,set1_centered)
dist(Y,set1_centered)

#####
# Problem 1h
#####

errors = set2_pca$sdev-set1_pca$sdev
as.vector(errors)

#####
# Kevin Gong
# STAT W4240
# Homework 2 , Problem 2
# 2/19/14
#

#####

#####
# Setup
#####

```

```

# make sure R is in the proper working directory
# note that this will be a different path for every machine
setwd("~/Dropbox/SIPA/Data Mining/HW2")

# first include the relevant libraries
# note that a loading error might mean that you have to
# install the package into your R distribution. From the
# command line, type install.packages("pixmap")
library(pixmap)

#####
# Problem 2a
#####

# the list of pictures
dir_list_1 = dir(path="CroppedYale/",all.files=FALSE)
view_list = c( 'P00A+000E+00' , 'P00A+005E+10' , 'P00A+005E-10' , 'P00A+010E+00' )

# preallocate an empty list
this_face_row = vector()
# initialize an empty matrix of faces data
faces_matrix = vector()
pic_list = c(
  01,02,03,04,05,06,07,08,09,10,11,12,13,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,
  34,35,36,37,38,39)

#generating a matrix of photos of the 4 desired views

for (i in 1:38) {

placeholder_matrix <- NULL

for (j in 1:4) {
  filename= sprintf("CroppedYale/%s/%s_%s.pgm",dir_list_1[i],dir_list_1[i],view_list[j])
  print(filename)
  face=read.pnm(file=filename)
  pic_data <-getChannels(face)
  pic_data_vec <- as.vector(pic_data)
  placeholder_matrix=rbind(placeholder_matrix,pic_data_vec)
}
faces_matrix=rbind(faces_matrix,placeholder_matrix)
}

dim(faces_matrix)

#####
# Problem 2b
#####

#computing the mean of the faces
faces.matrix_v2=as.matrix(faces_matrix)
means_col=colMeans(faces.matrix_v2)
means_mat=as.matrix(means_col)

#reshape this matrix into 192x168
means_mat_ref=matrix(means_mat,192,168)

#double check dimensions to make sure it worked
dim(means_mat_ref)

```

```

#generate image of mean face
means_face=pixmapGrey(means_mat_ref)
plot(means_face)

#save image of mean face
filename = 'hw02_02b.png'
dev.copy(device=png, file=filename, height=600, width=800)
dev.off()

#####
# Problem 2c
#####

means_pca = prcomp(means_mat_ref)
summary(means_pca)
plot(summary(means_pca)$importance[3,], type="l", ylab="%variance explained", xlab="nth
component")
means_pca$x

#####
# Problem 2d
#####

eigenfaces_matrix = matrix(summary(means_pca)$sdev[1:9], 3,3, byrow=TRUE)
eigenfaces_matrix
eigenfaces = pixmapGrey(eigenfaces_matrix)
plot(eigenfaces)

#####
# Problem 2e
#####

summary(means_pca)$loadings
means_pca

means_prin = princomp(means_mat_ref)
means_prin$loadings[1,]
means_prin$scores[,1]

dim(means_pca)

yaleB05 P00A+010E+00.pgm
face_05 = read.pnm(file = "CroppedYale/yaleB05/yaleB05_P00A+010E+00.pgm")
plot(face_05)

final_matrix=NULL
p=1

for(i in 1:5){
  face_row=NULL
  for(j in 1:5){
    if(i==1 && j==1){
      z=as.vector(means_mat_ref)
      #z=rbind(z,z)
    }
    else {
      means_mat=means_mat_ref+((as.matrix(means_pca$x[,p]))%*%t(as.matrix(means_pca$x[p,])))
      mean_face_t=t(means_mat)
      p=p+1
    }
  }
}

```

```

        face_vec=as.vector(mean_face_t)
        z=cbind(z, face_vec)
    }
}
final_matrix=rbind(final,z)
}

```

```

faces = pixmapGrey(final_matrix)
plot(faces)

```

```

as.matrix(means_pca$x[,1])
t(as.matrix(means_pca[1,]))
loadings(means_pca)

```

```

head(means_pca)

```

```

dim(means_pca$x)

```

```

#####
# Problem 2e
#####

```

```

new_matrix = faces_matrix[5:152,]
dim(new_matrix)
new_pca = prcomp(new_matrix)
summary(new_pca)

```

```

final_matrix2=NULL
p=1

```

```

for(i in 1:5){
face_row=NULL
for(j in 1:5){

if(i==1 && j==1){
    z=as.vector(means_mat_ref)
    #z=rbind(z,z)
}
else {
    means_mat=new_matrix+((as.matrix(new_pca$x[,p]))%*%t(as.matrix(new_pca$x[p,])))
    mean_face_t=t(means_mat)
    p=p+1
    face_vec=as.vector(mean_face_t)
    z=cbind(z, face_vec)
}
}
final_matrix2=rbind(final,z)
}

```