Q2.2 Dual PCA of Yale Face Database **Importing Libraries** In [1]: import numpy as np import matplotlib.pyplot as plt import scipy.io plt.rcParams['figure.figsize'] = [10,5] Importing Yale Face Dababase In [2]: data = scipy.io.loadmat('./YaleFaceDataBase/Yale_64x64.mat') In Dual PCA if A has dimensions n by t then $n \gg t$ Taking first t-number of images for training In [3]: t = 150X = np.array(data['fea'])[:t,:].T In [4]: Xmean = X.mean(axis=1, keepdims=True) Xm = X - XmeanIn [5]: print(Xm.shape) (4096, 150)Visualizing one of the sample image In [6]: img = plt.imshow(X[:,1].reshape(64,64).transpose()) img.set_cmap('gray') plt.axis('off') plt.show() Calculating At*A In [7]: XtX = np.matmul(Xm.T, Xm)In [8]: print(XtX.shape) (150, 150)Calculating Eigen values of At*A In [9]: eigValues, eigVectors = np.linalg.eigh(XtX) In [10]: print(eigValues) [-9.31601916e-09 -1.81932104e-09 2.50805120e-11 6.21710919e+04 8.59125556e+04 2.04228862e+05 2.11942004e+05 2.27778287e+05 2.45877139e+05 2.48935034e+05 2.61768761e+05 2.81587371e+05 2.87727134e+05 2.94493510e+05 2.99302549e+05 3.04625394e+05 3.09637639e+05 3.23721047e+05 3.32884885e+05 3.38567033e+05 3.57493821e+053.61945240e+053.66792327e+053.76439271e+053.86853324e+053.99484472e+054.05011945e+054.18832856e+054.28724230e+054.30747311e+054.43266343e+054.55533425e+054.59853149e+054.70594424e+054.74707029e+054.89340006e+05 5.16791173e+05 5.26939777e+05 5.30587323e+05 5.43556548e+05 5.71222769e+05 5.77657089e+05 5.81025461e+05 5.94021592e+05 6.01079311e+05 6.08513227e+05 6.16588876e+05 6.55173458e+05 6.75456752e + 05 6.87058278e + 05 6.95057133e + 05 7.09786552e + 057.23948716e+05 7.37620959e+05 7.63339470e+05 7.72923728e+05 7.95124296e+05 8.00871360e+05 8.38725093e+05 8.66622898e+05 8.83355570e+05 8.98292380e+05 9.06103949e+05 9.25543606e+05 9.27096698e+05 9.54275562e+05 9.82856634e+05 1.00377235e+06 1.01068913e+06 1.03363897e+06 1.05471367e+06 1.06496997e+06 1.09152230e+06 1.13485347e+06 1.15647391e+06 1.17119843e+06 1.21833494e+06 1.24221582e+06 1.27482419e+06 1.29179711e+06 1.34801534e+06 1.39016603e+06 1.43486715e+06 1.46625796e+061.49384225e+06 1.51837450e+06 1.56878060e+06 1.60236414e+06 1.63786650e+06 1.70253015e+06 1.74280119e+06 1.77591272e+06 1.85114296e+06 1.89244886e+06 1.93664368e+06 2.03311434e+06 2.04949479e+06 2.17793057e+06 2.22494229e+06 2.27632881e+06 2.36096126e+06 2.39260104e+06 2.47879183e+06 2.58928405e+06 2.63171136e+06 2.81075972e+06 2.94613938e+06 2.97347169e+06 3.05251301e+06 3.17320774e+06 3.50437004e+06 3.52343595e+063.56516647e+06 3.84817695e+06 3.93203933e+06 4.16951502e+064.48642508e+06 4.71018644e+06 5.02710731e+06 5.36278682e+06 5.58171194e+06 5.67220922e+06 5.92610205e+06 6.34470343e+06 6.68814138e+06 6.84549167e+06 7.37659104e+06 7.79122096e+06 7.99443808e+06 9.27090838e+06 1.03605883e+07 1.06054777e+07 1.16768149e+07 1.19870162e+07 1.30195907e+07 1.42187369e+07 1.71881454e+07 1.86918862e+07 2.00183011e+07 2.46460019e+07 2.56679223e+07 2.91281971e+07 3.51661170e+07 4.08503725e+07 5.72544262e+07 7.47329422e+07 8.18420061e+07 1.70424206e+08 1.94280675e+08 3.28072532e+08] Sorting eigen values in descending values and changing order of eigen vectors correspondingly In [11]: idx = eigValues.argsort()[::-1] eigValues = eigValues[idx] eigVectors = eigVectors[:,idx] In [12]: print(eigValues) 7.47329422e+07 5.72544262e+07 4.08503725e+07 3.51661170e+07 2.91281971e+07 2.56679223e+07 2.46460019e+07 2.00183011e+07 1.86918862e+07 1.71881454e+07 1.42187369e+07 1.30195907e+07 1.19870162e+07 1.16768149e+07 1.06054777e+07 1.03605883e+07 9.27090838e+06 7.99443808e+06 7.79122096e+06 7.37659104e+06 6.84549167e+06 6.68814138e+06 6.34470343e+06 5.92610205e+06 5.67220922e+06 5.58171194e+06 5.36278682e+06 5.02710731e+06 4.71018644e+06 4.48642508e+06 4.16951502e+06 3.93203933e+06 3.84817695e+06 3.56516647e+06 3.52343595e+06 3.50437004e+06 3.17320774e+06 3.05251301e+06 2.97347169e+06 2.94613938e+06 2.81075972e+06 2.63171136e+06 2.58928405e+06 2.47879183e+06 2.39260104e+06 2.36096126e+06 2.27632881e+06 2.22494229e+06 2.17793057e+06 2.04949479e+06 2.03311434e+06 1.93664368e+06 1.89244886e+06 1.85114296e+06 1.77591272e+06 1.74280119e+06 1.70253015e+06 1.63786650e+06 1.60236414e+06 1.56878060e+06 1.51837450e+06 1.49384225e+06 1.46625796e+06 1.43486715e+06 1.39016603e+06 1.34801534e+06 1.29179711e+06 1.27482419e+06 1.24221582e+06 1.21833494e+06 1.17119843e+06 1.15647391e+06 1.13485347e+06 1.09152230e+06 1.06496997e+06 1.05471367e+06 1.03363897e+06 1.01068913e+06 1.00377235e+06 9.82856634e+059.54275562e+05 9.27096698e+05 9.25543606e+05 9.06103949e+05 8.98292380e+05 8.83355570e+05 8.66622898e+05 8.38725093e+05 8.00871360e+05 7.95124296e+05 7.72923728e+05 7.63339470e+05 7.37620959e+05 7.23948716e+05 7.09786552e+05 6.95057133e+05 6.87058278e+05 6.75456752e+05 6.55173458e+05 6.16588876e+05 6.08513227e+05 6.01079311e+05 5.94021592e+05 5.81025461e+05 5.77657089e+05 5.71222769e+05 5.43556548e+05 5.30587323e+05 5.26939777e+05 5.16791173e+05 4.89340006e+05 4.74707029e+054.70594424e+05 4.59853149e+05 4.55533425e+05 4.43266343e+05 4.30747311e+054.28724230e+054.18832856e+054.05011945e+053.99484472e+053.86853324e+053.76439271e+053.66792327e+053.61945240e+053.57493821e+053.38567033e+053.32884885e+05 3.23721047e+05 3.09637639e+05 3.04625394e+05 2.99302549e+05 2.94493510e+05 2.87727134e+05 2.81587371e+05 2.61768761e+05 2.48935034e+05 2.45877139e+05 2.27778287e+05 2.11942004e+05 2.04228862e+05 8.59125556e+04 6.21710919e+04 2.50805120e-11 -1.81932104e-09 -9.31601916e-09] In [13]: eigVals = eigValues.copy() Creating Singular value matrix In [14]: D = abs(eigVals)**0.5D = np.diag(D)In [15]: print(D) $[[1.81127726e+04 \ 0.00000000e+00 \ 0.00000000e+00 \ \dots \ 0.00000000e+00 \]$ 0.00000000e+00 0.00000000e+00] [0.00000000e+00 1.39384603e+04 0.00000000e+00 ... 0.00000000e+00 0.00000000e+00 0.00000000e+00] $[0.000000000e+00\ 0.00000000e+00\ 1.30546622e+04\ \dots\ 0.000000000e+00$ 0.00000000e+00 0.00000000e+00] $[0.000000000e+00\ 0.00000000e+00\ 0.00000000e+00\ \dots\ 5.00804473e-06]$ 0.00000000e+00 0.00000000e+00] [0.00000000e+00 0.00000000e+00 0.0000000e+00 ... 0.00000000e+00 4.26534998e-05 0.00000000e+00] $[0.000000000e+00\ 0.00000000e+00\ 0.00000000e+00\ \dots\ 0.00000000e+00$ 0.00000000e+00 9.65195274e-05]] Visualizing Singular values matrix pattern In [16]: plt.figure(1) plt.semilogy(D) plt.title('Singular Values') plt.show() plt.figure(2) plt.plot(np.cumsum(D)/np.sum(D)) plt.title('Singular Values: Cumulative Sum') plt.show() Singular Values 10^{4} 10^{2} 10⁰ 10^{-2} 10^{-4} Singular Values: Cumulative Sum 1.0 0.8 0.6 0.4 0.2 5000 10000 15000 20000 Formint V.transpose() Matrix In [17]: Vt = eigVectors.copy().T Reconstruction of Training data xcap = XVVtIn [18]: Y = D @ VtIn [19]: Xcap = X @ Vt.T @ np.linalg.inv(D) @ Y In [20]: print(Xcap.shape) (4096, 150) Visualizing Reconstructed Data In [21]: img = plt.imshow(Xcap[:,5].reshape(64,64).T) img.set_cmap('gray') plt.axis('off') plt.show() In [22]: plt.figure(figsize=(16,20)) **for** i **in** range(1,81): plt.subplot(10,8,i,xticks=[],yticks=[]) img = plt.imshow(Xcap[:,i-1].reshape(64,64).T,cmap='gray') plt.title(f'{i}') plt.plot() Reconstruction of Test Data $ycap = XV(\Sigma^{-2})VtXtx$ Calculating D inverse In [23]: invD_sq = np.linalg.inv(np.matmul(D,D)) Getting test data here t is sample size intially defined so we're taking 165-t images as test data In [24]: X_test = np.array(data['fea'])[t:,:].T Projecting test data In [25]: y = np.linalg.inv(D) @ Vt.T @ X.T @ X_test Reconstructing test data In [26]: x_reconstruct = X @ Vt.T @ np.linalg.inv(D) @ y Visualizing test data In [27]: $img = plt.imshow(x_reconstruct[:, 6].reshape(64, 64).T)$ img.set_cmap('gray') plt.axis('off') plt.show() In Dual PCA, in most cases reconstruction of test data i.e. out of sample reconstruction is not possible