Consider we are using PCA to compress face images using top K eigenvectors and then we do the reconstruction. Then

(A) **[Ans]** Compression (for face images) is lossy

(B) Compression (for face images) is lossless

(C) **[Ans]** Reconstruction will be bad for non-face images (say buildings)

(D) Reconstruction will be good for non-face images (say buildings)

(E) None of these

Consider we are dong PCA to go from R^2 data to R^1. Consider each point is denoted by (X_i, Y_i). Then in which of these situations will PCA work reasonably well:

(A) **[Ans]** $Y_i = X_i + 10$

(B) **[Ans]** $Y_i = X_i + 10 + \epsilon_i$ where $\epsilon_i \sim N(0, 1)$

(C) $X_i^2 + Y_i^2 = 10$

(D) $X_i^2 + Y_i^2 <= 10$

(E) None of these

Consider we have data in R^2. Then the linear regression line and the PCA line

(A) will always be the same

(B) will never be the same

(C) **[Ans]** can sometimes be the same

(D) None of these

We want to do PCA using gradient descent. Assume that Σ is the covariance matrix, η is the learning rate. Then the update rule is

(A) $u_{k+1} = \eta \Sigma u_k$

(B) **[Ans]** $u_{k+1} = (I + \eta \Sigma) u_k$

(C) $u_{k+1} = (I - \eta \Sigma) u_k$

(D) None of these

PCA solves this problem:

$$\max_{u} u^T \Sigma u - \lambda(u^T u - 1)$$

where Σ is the covariance matrix. Which of the following are true regarding PCA

(A) **[Ans]** λ is the variance captured by the eigen vector u

(B) **[Ans]** Sum of variances captured by all eigenvectors is tr(Σ)

(C) If all data points are on a line then at least one of the eigenvalues is 1

(D) **[Ans]** If all data points are on a line then at least one of the eigenvalues is 0