

Lecture 11

* PCA $X \in \mathbb{R}^{d \times n}$ Project so that we get a lesser

dim. data. $p \ll d$

$$\text{Centered } X_c \leftarrow X - \mu$$

let U_1 be vector.

Proj. of X_c on U_1

$$Y = U_1^T X_c$$

$$\mu_Y = 0$$

$$\text{Var}(Y) = U_1^T S_{X_c} U_1$$

for PCA: $\max. U_1^T S_{X_c} U_1$

$$\text{st. } U_1^T U_1 = 1$$

$$\max. \underline{U_1^T S_{X_c} U_1}$$

$$\underline{S_{X_c} U_1} =$$

$$S_{X_c} U_1 = 0$$

$$U_1 = 0$$

$$\max. f - \lambda g$$

$$\max. U_1^T S_{X_c} U_1 - \lambda (U_1^T U_1 - 1)$$

$\lambda \rightarrow$ Lagrange mult.

$$\nabla_{U_1} \rightarrow 2S$$

$$\nabla_{U_1} \rightarrow 2S_{X_c} U_1 - 2\lambda U_1 = 0$$

$$S_{X_c} U_1 = \lambda U_1$$

$U_1 \rightarrow$ Eigenvector of S_{X_c}

$\lambda \rightarrow$ Eigenvalue.

$$U_1^T S$$

$$\max. U_1^T \underbrace{S_{X_c} U_1}_{\lambda U_1} = \lambda U_1^T U_1 = \lambda$$

$U_1 \rightarrow$ Eigenvector of S_{X_c}

Corresponding to max. eigenvalue.

PCA matrix

$$U = [U_1 \ U_2 \ \dots \ U_d]$$

$$U_i \in \mathbb{R}^{d \times 1}$$

$$U \in \mathbb{R}^{d \times d}$$

Encoding X_c

$$Y = U^T X_c \quad X_c \in \mathbb{R}^{d \times n}$$

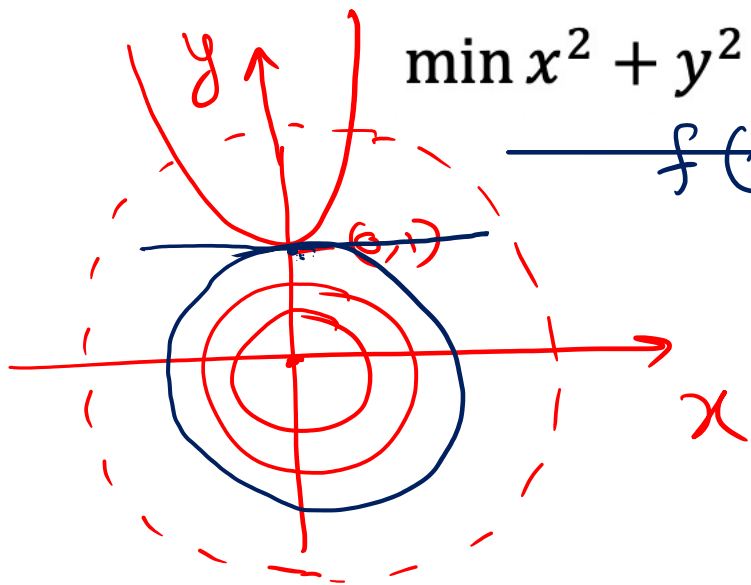
$$Y \in \mathbb{R}^{d \times n}$$

$$U U^T X_c = X_c$$

Take 1st

Take 1st P columns of U

$$U_P = [U_1, U_2 \dots U_P]$$



$$\min x^2 + y^2 \text{ s.t. } y = x^2 + 1$$

$$f(x, y) = x^2 + y^2$$

$$g(x, y) = y - x^2 - 1$$

$$\text{at } (0, 1)$$

$$\nabla f = \begin{bmatrix} 0 \\ 2 \end{bmatrix}$$

$$\nabla g = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\nabla f = 2 \nabla g$$

$$\nabla f = \lambda \nabla g$$

$$\nabla (f - \lambda g) = 0$$

$$\nabla f(x, y) = \begin{bmatrix} 2x \\ 2y \end{bmatrix}$$

$$\nabla g(x, y) = \begin{bmatrix} -2x \\ 1 \end{bmatrix}$$

$$U_p \in \mathbb{R}^{d \times p}$$

$$Y = U_p^T X_c \in \mathbb{R}^{p \times n}$$

$$\text{var. across } U_1 \rightarrow \lambda_1 (\lambda_{\max})$$

$$U_2 \rightarrow \lambda_2 (\text{2nd max.})$$

$$U_d \rightarrow \lambda_d (\text{least})$$

$$\text{Total var} \rightarrow \sum_{i=1}^d \lambda_i = \lambda_T$$

$$\frac{\sum_{j=1}^p \lambda_j}{\lambda_T} = 90\%$$

$$= 95\%$$

If Sx is full rank, how many eigenvectors?
Which eigenvector will be u_1 ?

- What if we minimize? What will be dir of u_1 ?
- What if don't have constraint?
- Are labels included in the formulation? Will it Impact classification?

$$X = \begin{bmatrix} 1 & 3 \\ 4 & 2 \end{bmatrix} \quad \mu = \begin{bmatrix} 2 \\ 3 \end{bmatrix} \quad X - \mu = \begin{bmatrix} -1 & 1 \\ 1 & -1 \end{bmatrix} = X_c$$

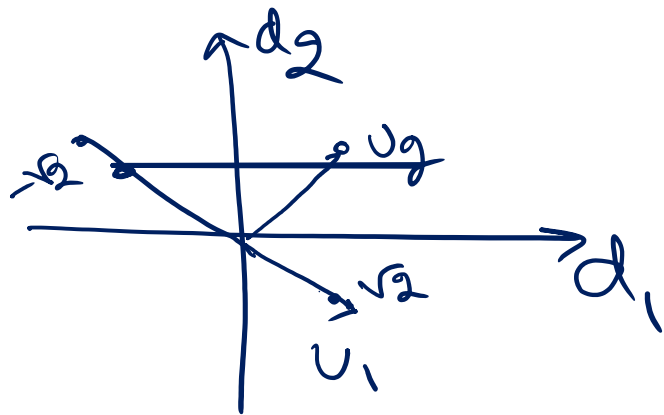
$$S = \frac{1}{2} \sum_{i=1}^2 x_i x_i^T = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$$

Eigenvalues $\rightarrow 4, 0$

Eigenvectors $\rightarrow \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix}' \quad \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}'$

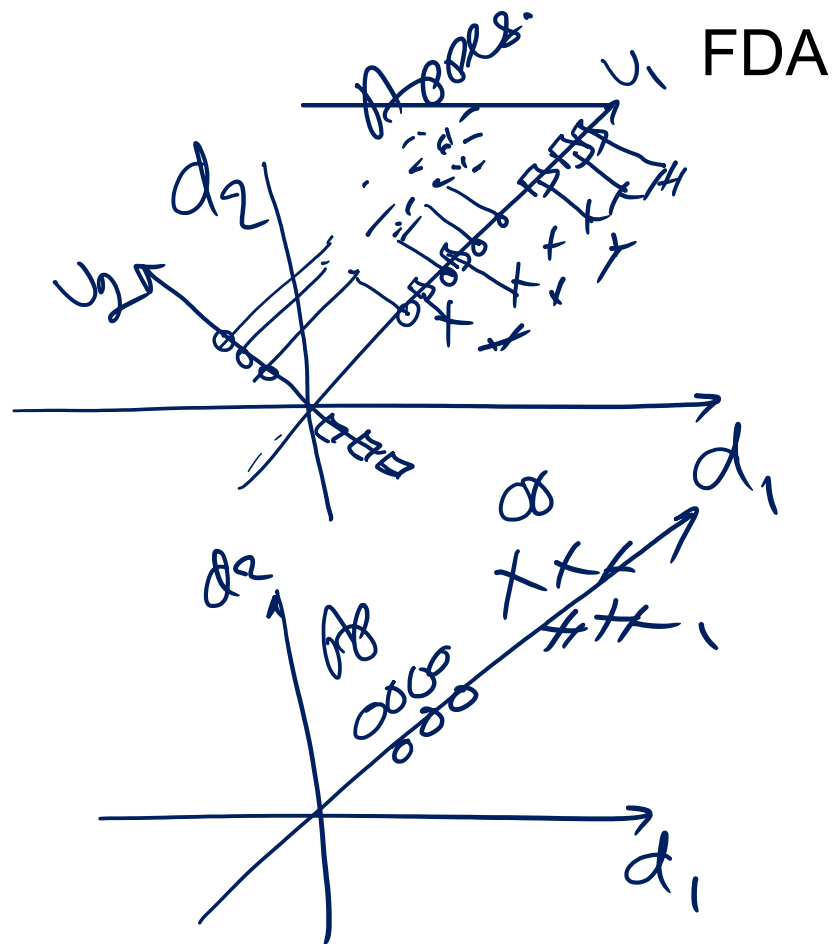
$$U = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$Y = U^T X_c = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}^T \begin{bmatrix} -1 & 1 \\ 1 & -1 \end{bmatrix} = \begin{bmatrix} -\sqrt{2} & \sqrt{2} \\ 0 & 0 \end{bmatrix}$$



$$X_c \leftarrow \cancel{U} \cancel{S} U \Sigma V^T \quad \text{Eigen decomposition.}$$

$$\bullet \text{ SVD}(X_c) = U$$



$X^1 \in$ ~~good of Dept~~
Applied.

$X^2 \in$ Changed.

~~left part~~ x_0

left part $x_0 \rightarrow$ App
change.

$$X = [X^1 \ X^2] \in \mathbb{R}^{d \times 2n}$$