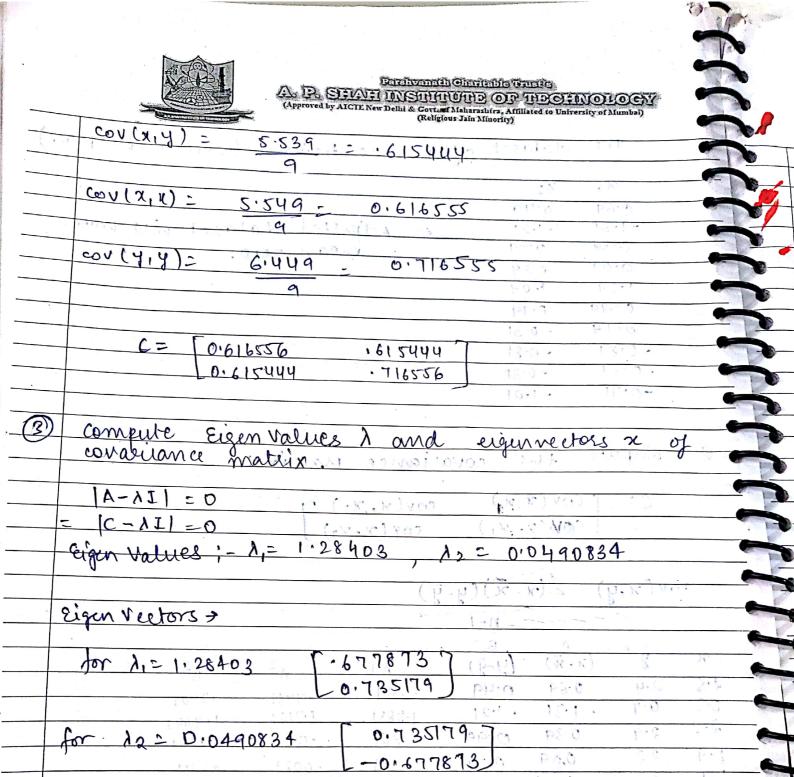
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	Prof. Jaya Gupta				1 500	Department of Computer Engineering
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## P. STANTI INSTITUTIVE OF TIPES TO A STANTA OF A STANTA

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	1.29	1.09			100		
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Total sample variance : (sum of eigen Values)

1711 10-1 -

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Department of Computer Engineering

DH. C.



## Paranyamith Chartable Trusts

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Var.	Eigenvector 1 Eigenvector 2
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N <sub>2</sub>	.735678
<i>C'</i>	
EigenValue	1.2840
% of total	1.004 5/1 500
Variance	1.2840/1.333
Vasiance	- 1 96.34.
At cons	1 be seen that approximately 96% of the
total mo	siance is concentrated in eigenvector I
and lu	divine di comprissa ca an eigenveror I
	in eigenvector 2
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The eigen	westor with the highest reigenvalue is
The eigen	westor with the highest reigenvalue is
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The eigen the prix compone Some infor	meetor with the highest reigenvalue is reipal component of the dataset.  ents of lesser significance can be igneration is lost, but if eigenvalues are not not much is lost. If some
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The eigente the prix componers small, to componers	nucetor with the highest reigenvalue is reipal component of the dataset.  ents of lesser significance can be igneration is lost, but if eigenvalues are hen not much is lost. If some less are left out, then the final data have loss dimensions them

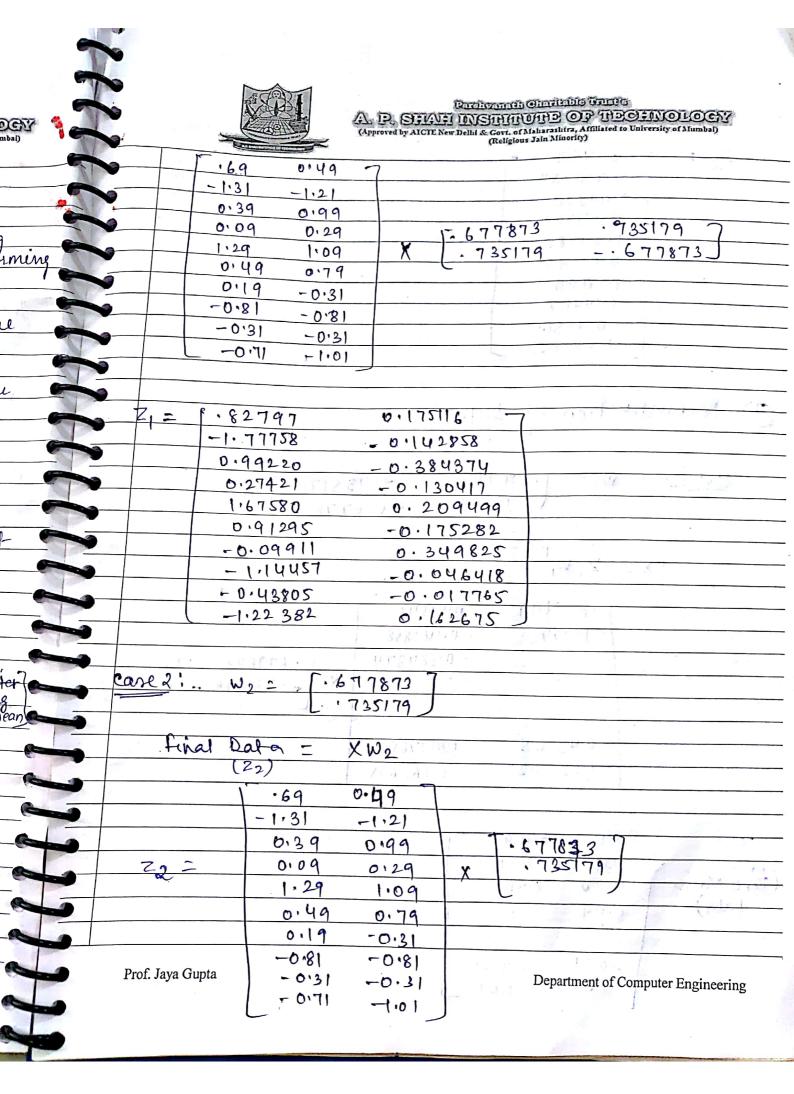
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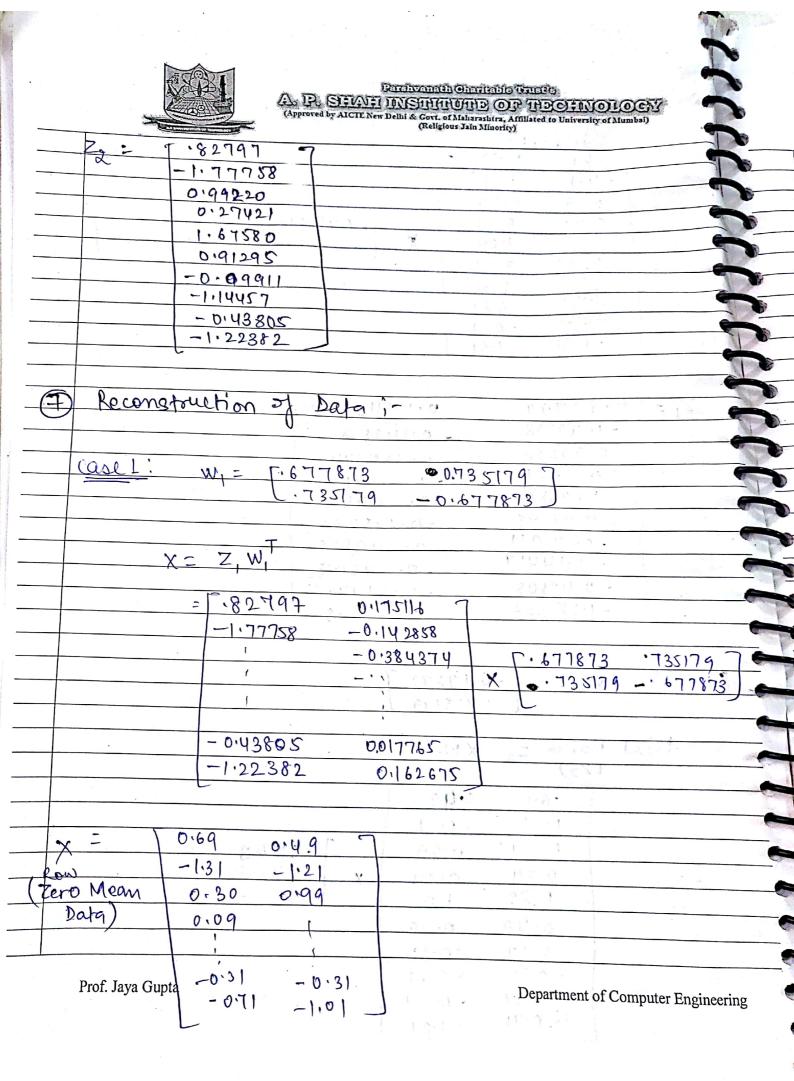


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_ 75	5) form a teature white	
-	form a feature vector and construct the projection matrix W>	C. C.
	projection matrix W>	1
_	frojection matrix w is calculated by taking the eigenvectors that are choosen and forming a matrix with them in columns.	
	the eigenvectors that are all appears and torming	
	a mateir with teams in	1
	columns.	11
	Here, there are two eigenvectors, so there are 2 choices of matrices.	
	maurice of maurice.	
	* A feature vector can be formed with both the	
	eigenvalues vectors:	
	and the state of t	1
	W, = [.677873 .735149 7	
	[.735779677873]	130
	- The Bully of the Control of the Co	
7	If the smaller, less significant component is left	
V 5 4 7	out, then there will be a grigle column:	
	A STATE OF THE STA	
	W2 = \.677873 7	
	W) - 0 ((0 1)	
	· 7351791)	
-	Imp.	
	Datasit af	chla
6)	Transform the original dataset: Subtraction	Q
	Transform the original dataset: (Subtraction	nean
->-	\ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \	
	The new dataset is derived by taking Z = XW.	-
		X I I
	20061 W [677873 .735179]	
(	20sel: W1= 1677873 .735179	
=	20sel: W1= 1677873 .735179 - 677873)	6
	The second secon	
	Final Data = XW,	
	$(Z_1)$	
	· doloret alter lubbrachus	100 100 100 100 100 100 100 100 100 100
	dataset after subtracting	
	the mean.	9
	- CO - L. Proince	

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	(Approved by AICTE New Delhi & Govt. of Maharashira, Affiliated to University of Mumbal) (Religious Jain Minority)
Rowon	iginal Data - RowZero Mean Data + Original Mean
	- X + [(.81   1.91)
	= 2.5 2.47
	0.5 0.7
	2.2 2.9
	3.1
_	, , , , , , , , , , , , , , , , , , , ,
	in commence of many our interests to the same as as
	1.6
	1.1 .09.5 1.16. 2.10
0 0 .	——————————————————————————————————————
Case 2:	$X_1 = Z_2 \cdot W_2$ $= \begin{bmatrix} \cdot & 2797 \end{bmatrix}$
ase 2.	-1.77758
ase 2.	= [82797]
ase 2.	1= \( \cdot
ase 2.	-1.77758 -1.77758 -0.43805
ase 2.	1= \( \cdot
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ase 2.	-1.77758  -0.43805  -1.22382  -0.56126  0.60870
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ase 2.	-1.77758  -0.43805  -1.22382  -0.56126  0.60870
ase 2.	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$
ase 2.	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$

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Row original Rata = Row zero Mean Rata + original mean = X, + [1.8] 1.91]

It is seen that if only the first eigenvector is considered, then the data can be reconstructed similar to the original dataset.

Assignment! Use PCA to arrive at the transformed matrix for given matrix A.

(1) - 1 11 1

$$A^{T} = \begin{bmatrix} 2 & 1 & 0 & -1 \\ 4 & 3 & 1 & 0.5 \end{bmatrix}$$