

We know that the way to obtain the components is eigendecomposition of the covariance matrix.

Details are given below -  
~~But there is a trick to do it.~~

$$Z = P D P^{-1}$$

$P$  is the eigenvector of  $Z$

where  $Z$  is the covariance matrix

Use the first  $r$  components of  $D$

But, there is a trick -  
we can just use SVD

① First, mean center  
the data  $x$  and get  $x'$

$$x' = x - \bar{M}$$

② Apply SVD on  $x'$

$$\cancel{x'} = P D$$

$$x' = U \Sigma V^T$$

$U \rightarrow$  eigenvector of  $x' x'^T$

$V \rightarrow$  eigenvector of  $x'^T x'$

$\Sigma \rightarrow$  diagonal matrix  
and diagonal values  
are eigenvalues of  $x'^T x'$

As we already did step (i),  
we get eigenvector of the  
covariance matrix  $x'x^{T}$ .  
This eigenvector matrix is

$U = \begin{pmatrix} 1 & 0 \\ 0 & \sqrt{2} \end{pmatrix}$

So, this is a trick to do PCA.

① centralize data

② Apply SVD on the centralized data.

$U$  matrix is the eigenvector matrix

You can use first  $n$  eigenvectors based on highest  $n$  eigenvalues.

This results into a form i.e.,

Truncated-SVD (+SVD)

step 3: singular values

singular values

. step 3: singular values

singular values

singular values