C. SVD and PCA

With similar computations it is evident that the two methods are intimately related. Let us return to the original $m \times n$ data matrix **X**. We can define a new matrix Y as an $n \times m$ matrix⁹.

$$\mathbf{Y} \equiv \frac{1}{\sqrt{n-1}} \mathbf{X}^T$$

where each column of **Y** has zero mean. The definition of Y becomes clear by analyzing $\mathbf{Y}^T\mathbf{Y}$.

of **Y** becomes clear by analyzing
$$\mathbf{Y}^T \mathbf{Y}$$
.
$$\mathbf{Y}^T \mathbf{Y} = \left(\frac{1}{\sqrt{n-1}} \mathbf{X}^T\right)^T \left(\frac{1}{\sqrt{n-1}} \mathbf{X}^T\right)$$

$$\mathbf{Y}^{T}\mathbf{Y} = \left(\frac{1}{\sqrt{n-1}}\mathbf{X}^{T}\right)^{T} \left(\frac{1}{\sqrt{n-1}}\mathbf{X}^{T}\right)$$
$$= \frac{1}{\sqrt{n-1}}\mathbf{X}^{TT}\mathbf{X}^{T}$$

$$\mathbf{I} \quad \mathbf{I} = \left(\frac{1}{\sqrt{n-1}}\mathbf{A}\right) \left(\frac{1}{\sqrt{n-1}}\mathbf{A}\right)$$
$$= \frac{1}{m-1}\mathbf{X}^{TT}\mathbf{X}^{T}$$

 $=\frac{1}{n-1}\mathbf{X}^{TT}\mathbf{X}^{T}$

 $= \frac{1}{n-1} \mathbf{X} \mathbf{X}^T$ $\mathbf{Y}^T \mathbf{Y} = \mathbf{C}_{\mathbf{Y}}$