2 Σ - square matrix

eigenvalue decomposition

$$\Sigma = U \Lambda U^T$$

$$\Sigma^{-1} = (U \Lambda U^T)^{-1} = U^{-T} \Lambda^{-1} U^{-1} = \{U^T U = I\} =$$

$$= U \Lambda^{-1} U^T$$

$$(x-\mu)^T \Sigma^{-1} (x-\mu) = (x-\mu)^T U \Lambda^{-1} U^T (x-\mu) =$$

$$= (x-\mu)^T U \Lambda^{-\frac{1}{2}} \Lambda^{-\frac{1}{2}} U^T (x-\mu) =$$

$$= \{(AB)^T = B^T A^T\} = \underbrace{(U^T \Lambda^{-\frac{1}{2}} (x-\mu))^T}_{A} (U^T \Lambda^{-\frac{1}{2}} (x-\mu))$$

$$A = \underbrace{U^T \Lambda^{-\frac{1}{2}}}(x-\mu)$$

↳ This is just a linear mapping of the deviation from the mean.

view 1

$$(U^T \Lambda^{-\frac{1}{2}} (x-\mu))^T I (U^T \Lambda^{-\frac{1}{2}} (x-\mu))$$

- The mapping $U^T \Lambda^{-\frac{1}{2}}$ maps the data to a representation to a space where the covariance is spherical

view 2

$$(U^T (x-\mu))^T \Lambda^{-1} (U^T (x-\mu))$$

- The mapping U^T maps the data to a representation to a space where the covariance is diagonal.

IMPORTANT: The transformation makes the dimensions independent.