

Suppose A is invertible, why is $B = A^T A$ also?

- Since A is invertible so is A^T .
- The product of invertible matrices is also invertible, so B is invertible...

What's the inverse?

$$B^{-1} = (A^T A)^{-1} = A^{-1} (A^T)^{-1} = A^{-1} (A^{-1})^T$$

Check it

$$\begin{aligned} B B^{-1} &= A^T A A^{-1} (A^{-1})^T = A^T (A^{-1})^T = (A^{-1} A)^T \\ &= (I)^T = I \end{aligned}$$

Simplifying assumption: A is invertible. That means B invertible which further means all the eigenvalues λ_i of B are non-zero.

x_i is an orthonormal eigenbasis by the spectral theorem.

$B = A^T A$, $Bx_i = \lambda_i x_i$ Let $y_i = Ax_i$ Claim y_i are orthogonal ✓

$\|y\| = \sqrt{\lambda_i}$ $z_i = \frac{y_i}{\sqrt{\lambda_i}}$ ← orthonormal? what if $\lambda_i = 0$

$AS = A \begin{bmatrix} | & | & \dots & | \\ x_1 & x_2 & \dots & x_n \\ | & | & \dots & | \end{bmatrix} = \begin{bmatrix} | & | & \dots & | \\ y_1 & y_2 & \dots & y_n \\ | & | & \dots & | \end{bmatrix}$

The difficulty here is that x_i might be in the nullspace of A ... Then $y_i = 0$ and it's not possible to turn

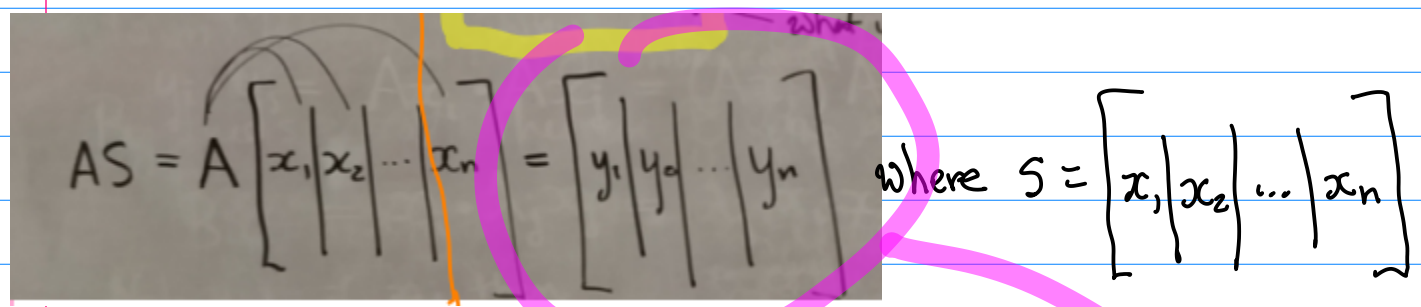
B

$$y_i \cdot y_j = A x_i \cdot A x_j \approx (A x_i)^T A x_j = x_i^T A^T A x_j$$

$$\approx x_i^T B x_j = x_i^T \lambda_j x_j = \lambda_j x_i \cdot x_j = \begin{cases} \lambda_j & \text{if } i=j \\ 0 & \text{if } i \neq j \end{cases}$$

Thus $\|y_i\| = \sqrt{\lambda_i}$ and by assumption $\lambda_i \neq 0$ since A was invertible...

Define $z_i = \frac{y_i}{\sqrt{\lambda_i}}$ and these are orthonormal..



Handwritten equation: $AS = A \begin{bmatrix} | & | & \dots & | \\ x_1 & x_2 & \dots & x_n \\ | & | & \dots & | \end{bmatrix} = \begin{bmatrix} | & | & \dots & | \\ y_1 & y_2 & \dots & y_n \\ | & | & \dots & | \end{bmatrix}$ where $S = \begin{bmatrix} | & | & \dots & | \\ x_1 & x_2 & \dots & x_n \\ | & | & \dots & | \end{bmatrix}$

Define $V = \begin{bmatrix} | & | & \dots & | \\ z_1 & z_2 & \dots & z_n \\ | & | & \dots & | \end{bmatrix}$

- V is square
- V has orthonormal cols...

Thus $V^T = V^{-1}$

Recall also that $S^T = S^{-1}$.

$$V \begin{bmatrix} \sqrt{\lambda_1} & & & 0 \\ & \sqrt{\lambda_2} & & \\ & & \dots & \\ 0 & & & \sqrt{\lambda_n} \end{bmatrix} = \begin{bmatrix} | & | & \dots & | \\ z_1 & z_2 & \dots & z_n \\ | & | & \dots & | \end{bmatrix} \begin{bmatrix} \sqrt{\lambda_1} & & & \\ & \sqrt{\lambda_2} & & \\ & & \dots & \\ 0 & & & \sqrt{\lambda_n} \end{bmatrix}$$

The same so...

$$= \begin{bmatrix} | & | & \dots & | \\ \frac{y_1}{\sqrt{\lambda_1}} & \frac{y_2}{\sqrt{\lambda_2}} & \dots & \frac{y_n}{\sqrt{\lambda_n}} \\ | & | & \dots & | \end{bmatrix} \begin{bmatrix} \sqrt{\lambda_1} & & & \\ & \sqrt{\lambda_2} & & \\ & & \dots & \\ 0 & & & \sqrt{\lambda_n} \end{bmatrix} = \begin{bmatrix} | & | & \dots & | \\ y_1 & y_2 & \dots & y_n \\ | & | & \dots & | \end{bmatrix}$$

Therefore,

$$AS = V\Sigma \quad \text{where } \Sigma = \begin{bmatrix} \sqrt{\lambda_1} & & & & \\ & \sqrt{\lambda_2} & & & \\ & & \dots & & \\ 0 & & & & \sqrt{\lambda_n} \\ & & & & & & & 0 \end{bmatrix}$$

Or

$$A = V\Sigma S^T$$

← singular value decomposition of the matrix A.

usually the matrix S is called U = $\begin{bmatrix} | & | & \dots & | \\ x_1 & x_2 & \dots & x_n \\ | & | & \dots & | \end{bmatrix}$

usually $\sigma_i = \sqrt{\lambda_i}$ so $\Sigma = \begin{bmatrix} \sigma_1 & & & & \\ & \sigma_2 & & & \\ & & \dots & & \\ 0 & & & & \sigma_n \\ & & & & & & & 0 \end{bmatrix}$

↑ singular values

$$A = V\Sigma U^T$$

↑ orthogonal matrix

↑ orthogonal matrix

↑ diagonal.

Treat the case where A is not invertible now and work a numerical example on Friday...

So if A is not invertible then some of the z's don't exist... so instead of n vectors, there are only m of them where $m < n$.

$$z_i = \frac{y_i}{\sqrt{\lambda_i}}$$

If $\lambda_i = 0$ can't divide here and anyway that would mean $y_i = 0$ in the first place

Assume $\lambda_i \neq 0$ for $i = 1, \dots, m$
and $\lambda_i = 0$ for $i = m+1, \dots, n$.

Thus

$$V = \left[\begin{array}{c|c|c|c} z_1 & z_2 & \dots & z_m \\ \hline \hline \hline \hline \end{array} \right] \text{ missing vectors}$$

↑ Idea, make up some vectors and plop them in here.

$$V = \left[\begin{array}{c|c|c|c|c|c} z_1 & z_2 & \dots & z_m & v_{m+1} & \dots & v_n \\ \hline \hline \hline \hline \hline \hline \end{array} \right]$$

add vectors that are orthonormal to the ones we already have...

- Square
 - orthonormal columns
- So $V^T = V^{-1}$

$$\Sigma = \left[\begin{array}{cccc} \sigma_1 & & & \\ & \sigma_2 & & \\ & & \dots & \\ & & & \sigma_m & & \\ & & & & 0 & \dots & 0 \end{array} \right]$$

• It doesn't matter what the new vectors are because they are multiplied by the zeros in Σ anyway and disappear.

$$A = V \Sigma U^{-1}$$