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# Linear Systems

Math 214 Spring 2006  
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Fowler 307 MWF 2:30pm - 3:25pm  
<http://faculty.oxy.edu/ron/math/214/06/>

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*Class 32: Wednesday April 26*

**TITLE** Singular Value Decomposition

**CURRENT READING** Poole 7.4

## Summary

Our final new topic will be the singular value decomposition of a matrix.

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*Homework Assignment*

*Poole, Section 7.4 : 2,5,6,7,13,45,46,47.*

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### DEFINITION

The **singular values** of a  $m \times n$  matrix  $A$  are the square roots of the eigenvalues of  $A^T A$  and are usually denoted by  $\sigma_1, \sigma_2, \sigma_3 \dots \sigma_n$ . Often the singular values are arranged so that  $\sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \dots \geq \sigma_n$ .

### Theorem 7.13

Let  $A$  be an  $m \times n$  matrix with singular values  $\sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \dots \geq \sigma_r > 0$  and  $\sigma_{r+1} = \sigma_{r+2} = \dots = \sigma_n = 0$ . THEN there exists an  $m \times m$  orthogonal matrix  $U$ , an  $n \times n$  orthogonal matrix  $V$ , and a block-diagonal  $m \times n$  matrix  $\Sigma$  such that  $A = U\Sigma V^T$ .

The columns of  $U$  are called the left singular vectors of  $A$  and the columns of  $V$  are called the right singular vectors of  $A$ .  $U$  and  $V$  are NOT uniquely determined by  $A$  but  $\Sigma$  must contain the singular values of  $A$ .

### EXAMPLE

Find the singular value decomposition for the matrix  $A = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ .

**Theorem 7.15**

Let  $A = U\Sigma V^T$  be a singular value decomposition of an  $m \times n$  matrix  $A$ . Let  $\sigma_1, \sigma_2, \sigma_3, \dots, \sigma_r$  be all the nonzero singular values of  $A$ . THEN

- (a) The rank of  $A$  is  $r$ .
- (b) The first  $r$  columns of  $U$ ,  $[\vec{u}_1, \vec{u}_2, \dots, \vec{u}_r]$  form an orthonormal basis for  $\text{col}(A)$ .
- (c) The last  $m - r$  columns of  $U$ ,  $[\vec{u}_{r+1}, \vec{u}_{r+2}, \dots, \vec{u}_m]$  form an orthonormal basis for  $\text{null}(A^T)$ .
- (d) The first  $r$  columns of  $V$ ,  $[\vec{v}_1, \vec{v}_2, \dots, \vec{v}_r]$  form an orthonormal basis for  $\text{row}(A)$ .
- (e) The last  $n - r$  columns of  $V$ ,  $[\vec{v}_{r+1}, \vec{v}_{r+2}, \dots, \vec{v}_n]$  form an orthonormal basis for  $\text{null}(A)$ .

Pretty cool, eh?

Notice also, that by definition  $A\vec{v}_i = \sigma_i\vec{u}_i$  for  $i = 1$  to  $r$ . So, singular values are “eigenvalue-like.” There are similarities and differences between eigenvalues and singular values, however.

**GROUPWORK**

Consider  $A = \begin{bmatrix} 2 & 0 & 1 \\ 0 & 3 & 0 \\ 1 & 0 & 4 \end{bmatrix}$ . What important property do you notice about  $A$ ?

Find the eigenvalues of  $A$ .

Find the singular values of  $A$  (i.e. the positive square roots of the eigenvalues of  $A^T A$ ).

What do you notice about the answers to the two previous questions? Explain your observation.

Recall that if  $A \sim B$  then the eigenvalues of  $A$  and  $B$  are equal. This is NOT true for singular values.

Recall that the determinant of a matrix  $A$  is equal to the product of the eigenvalues; it is also equal to **the product of the singular values of  $A$** .