

# Chapter 6: Lecture 25

## Linear Algebra, Course 124C, Spring, 2009

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## All the way with $A\vec{x} = \vec{b}$ :

- ▶ Applies to any  $m \times n$  matrix  $A$ .
- ▶ Symmetry of  $A$  and  $A^T$ .

### Where $\vec{x}$ lives:

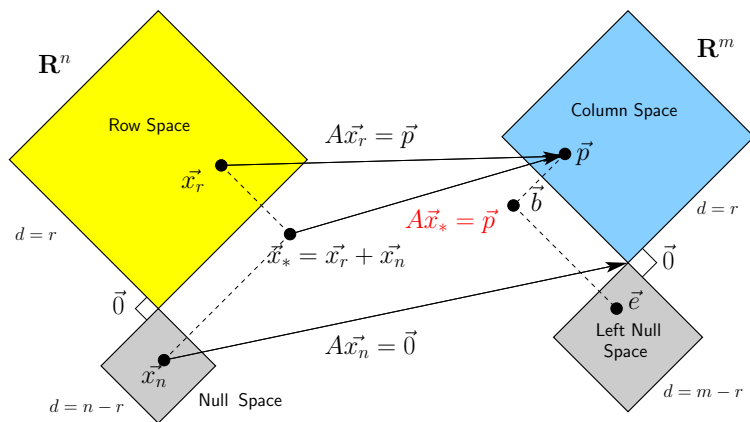
- ▶ Row space  $C(A^T) \subset R^n$ .
- ▶ (Right) Nullspace  $N(A) \subset R^n$ .
- ▶  $\dim C(A^T) + \dim N(A) = r + (n - r) = n$
- ▶ Orthogonality:  $C(A^T) \otimes N(A) = R^n$

### Where $\vec{b}$ lives:

- ▶ Column space  $C(A) \subset R^m$ .
- ▶ Left Nullspace  $N(A^T) \subset R^m$ .
- ▶  $\dim C(A) + \dim N(A^T) = r + (m - r) = m$
- ▶ Orthogonality:  $C(A) \otimes N(A^T) = R^m$



## Best solution $\vec{x}_*$ when $\vec{b} = \vec{p} + \vec{e}$ :



## Fundamental Theorem of Linear Algebra

### Now we see:

- ▶ Each of the four fundamental subspaces has a 'best' orthonormal basis
- ▶ The  $\hat{v}_i$  span  $R^n$
- ▶ We find the  $\hat{v}_i$  as eigenvectors of  $A^T A$ .
- ▶ The  $\hat{u}_i$  span  $R^m$
- ▶ We find the  $\hat{u}_i$  as eigenvectors of  $AA^T$ .

### Happy bases

- ▶  $\{\hat{v}_1, \dots, \hat{v}_r\}$  span Row space
- ▶  $\{\hat{v}_{r+1}, \dots, \hat{v}_n\}$  span Null space
- ▶  $\{\hat{u}_1, \dots, \hat{u}_r\}$  span Column space
- ▶  $\{\hat{u}_{r+1}, \dots, \hat{u}_m\}$  span Left Null space



# Fundamental Theorem of Linear Algebra

## How $A\vec{x}$ works:

- ▶  $A = U\Sigma V^T$
- ▶  $A$  sends each  $\vec{v}_i \in C(A^T)$  to its partner  $\vec{u}_i \in C(A)$  with a stretch/shrink factor  $\sigma_i > 0$ .
- ▶  $A$  is diagonal with respect to these bases and has positive entries (all  $\sigma_i > 0$ ).
- ▶ When viewed the right way, any  $A$  is a diagonal matrix  $\Sigma$ .

Ch. 6: Lec. 25

The fundamental theorem of linear algebra

Approximating matrices with SVD  
The basic idea

Frame 5/6



# Image approximation (80x60)

## Idea: use SVD to approximate images

- ▶ Interpret elements of matrix  $A$  as color values of an image.
- ▶ Truncate series SVD representation of  $A$ :

$$A = U\Sigma V^T = \sum_{i=1}^r \sigma_i \hat{u}_i \hat{v}_i^T$$

- ▶ Use fact that  $\sigma_1 > \sigma_2 > \dots > \sigma_r > 0$ .
- ▶ Rank  $r = \min(m, n)$ .
- ▶ Rank  $r = \#$  of pixels on shortest side.
- ▶ For color: approximate 3 matrices (RGB).

Ch. 6: Lec. 25

The fundamental theorem of linear algebra

Approximating matrices with SVD  
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Frame 6/6

