

CAP5415

Computer Vision

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HEC-241

Linear Algebra Basics

Lecture 2

Outline

- Vectors
 - Operations
- Matrix
 - Operations
- Transformations
 - Scaling
 - Rotation
 - Translation
- Singular value decomposition

Outline

- **Vectors**
 - Operations
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Vector

- Scalar: $x \in \mathbb{R}$
- Vector: $\mathbf{x} \in \mathbb{R}^N$
 - Row Vector $\mathbf{v} \in \mathbb{R}^{1 \times n}$

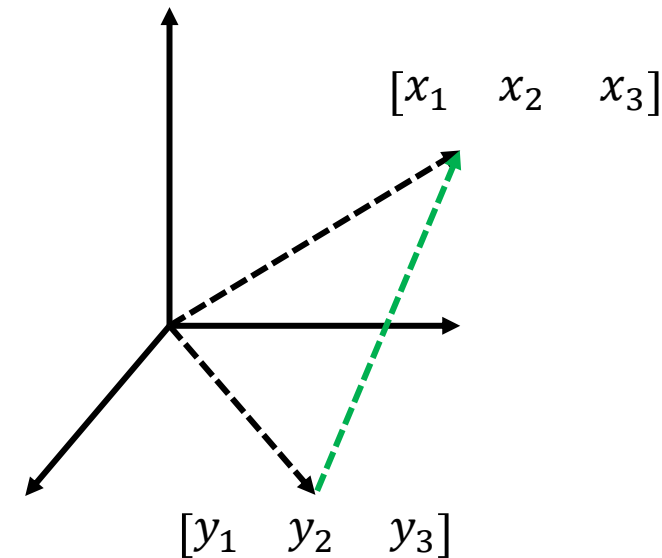
$$\mathbf{x} = [x_1 \quad x_2 \quad \cdots \quad x_n]$$

- Column vector $\mathbf{v} \in \mathbb{R}^{n \times 1}$: $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = [x_1 \quad x_2 \quad \cdots \quad x_n]^T$
- Transpose

Vectors - use

- Store data in memory
 - Feature vectors
 - Pixel values
 - Any other data for processing
- Any point in coordinate system
 - Can be n dimensional
- Difference between two points

$$[x_1 - y_1 \quad x_2 - y_2 \quad x_3 - y_3]$$



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Vector operations

- Norm – size of the vector

- p-norm

$$\|x\|_p = \left(\sum_i |a_i|^p \right)^{\frac{1}{p}} \quad p \geq 1$$

- Euclidean norm

$$\|x\|_2 = \left(\sum_i |a_i|^2 \right)^{1/2}$$

- L1-norm

$$\|x\|_1 = \left(\sum_i |a_i| \right)$$

Vector operations

- Inner product (dot product)
 - Scalar number
 - Multiply corresponding entries and add

$$\mathbf{x}^T \mathbf{y} = [x_1 \quad x_2 \quad \cdots \quad x_n] \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \sum_k^n x_k y_k$$

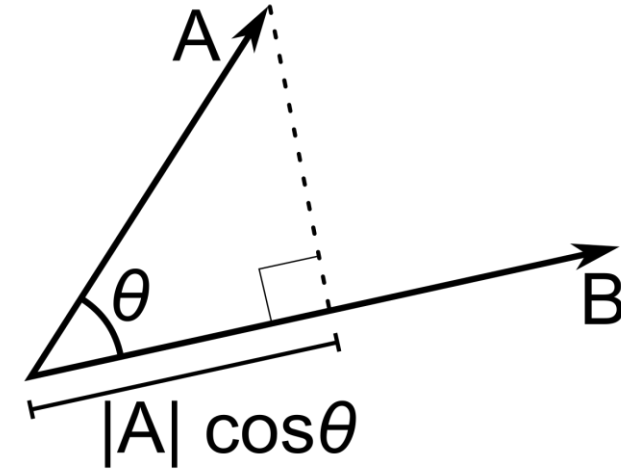
Vector operations

- Inner product (dot product)

$$\mathbf{x}_i^T \mathbf{x}_i = \sum_k^n (x_k^i)^2 = \text{squared norm of } \mathbf{x}_i$$

- $\mathbf{x} \cdot \mathbf{y}$ is also $|\mathbf{x}| |\mathbf{y}| \cos(\text{angle between } \mathbf{x} \text{ and } \mathbf{y})$

- If \mathbf{B} is a unit vector, $\mathbf{A} \cdot \mathbf{B}$ gives projection of \mathbf{A} on \mathbf{B}



Vector operations

- Outer product

$$\mathbf{x}_i \mathbf{x}_j^T = \begin{bmatrix} x_1^i x_1^j & x_1^i x_2^j & \cdots & x_1^i x_n^j \\ x_2^i x_1^j & x_2^i x_2^j & \cdots & x_2^i x_n^j \\ \vdots & \vdots & \ddots & \vdots \\ x_n^i x_1^j & x_n^i x_2^j & \cdots & x_n^i x_n^j \end{bmatrix} \quad (\text{a matrix})$$

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Matrix

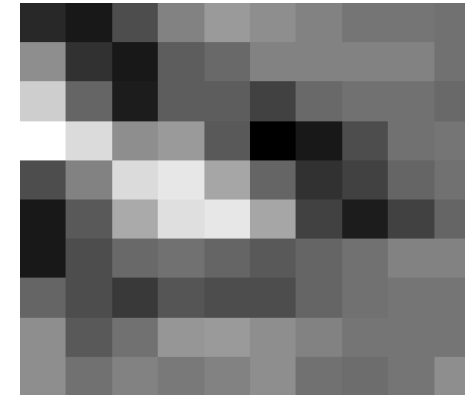
- Array $\mathbf{A} \in \mathbb{R}^{m \times n}$ of numbers with shape m by n,
 - m rows and n columns

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

- A row vector is a matrix with single row
- A column vector is a matrix with single column

Matrix - use

- Image representation – grayscale
 - One number per pixel
 - Stored as $n \times m$ matrix



0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

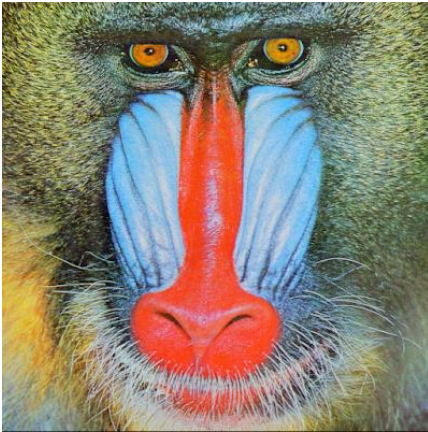
Matrix - use

- Image representation
 - RGB
 - 3 numbers per pixel
 - Stored as $n \times m \times 3$ matrix

0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0



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Matrix operations

- Addition

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} + \begin{bmatrix} e & f \\ g & h \end{bmatrix} = \begin{bmatrix} a + e & b + f \\ c + g & d + h \end{bmatrix}$$

- Both matrices should have same shape
 - except with a scalar

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} + 2 = \begin{bmatrix} a + 2 & b + 2 \\ c + 2 & d + 2 \end{bmatrix}$$

- Same with subtraction

Matrix operations

- Scaling

$$s \times \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} sxa & sxb \\ sxc & sxd \end{bmatrix}$$

- Hadamard product

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \odot \begin{bmatrix} e & f \\ g & h \end{bmatrix} = \begin{bmatrix} axe & bxf \\ cxg & dxh \end{bmatrix}$$

Matrix operation

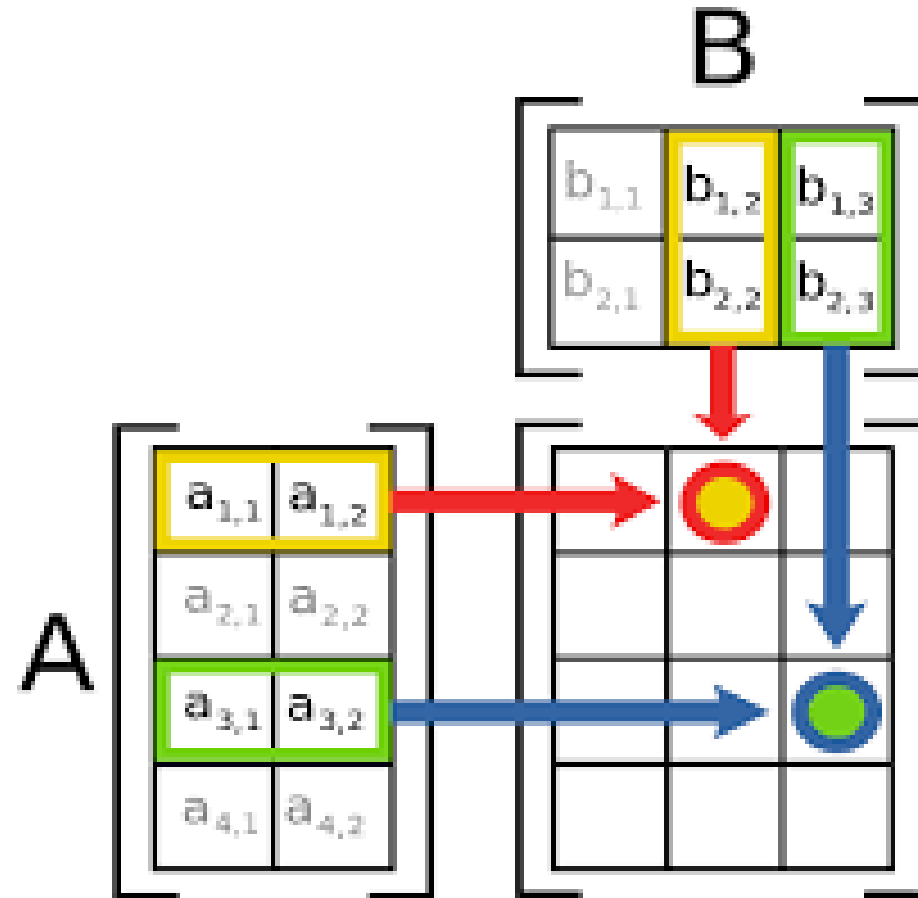
- Transpose

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

$$\mathbf{A}^T = \begin{bmatrix} a_{11} & a_{21} & \cdots & a_{m1} \\ a_{12} & a_{22} & \cdots & a_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \cdots & a_{mn} \end{bmatrix}$$

Matrix operation

- Matrix Multiplication
 - Compatibility?
 - $m \times n$ and $n \times p$
 - Results in $m \times p$ matrix

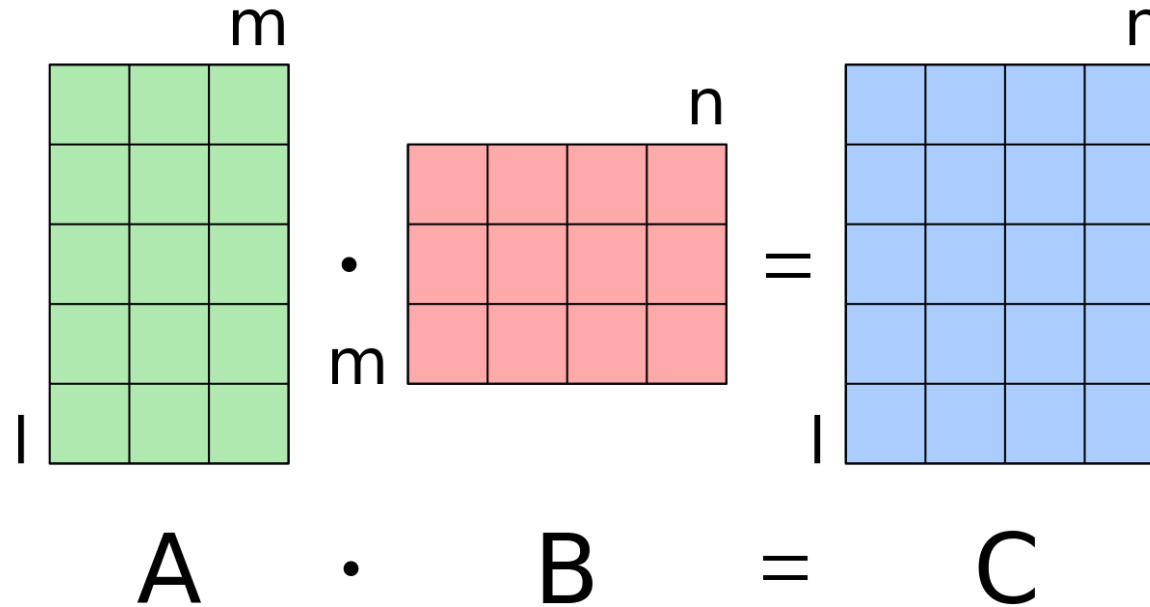


Matrix operation

- Matrix Multiplication – another interpretation (my favorite)
 - Let \mathbf{a}_i denote the i -th column of the matrix \mathbf{A} , and
 - \mathbf{b}_j denote the j -th column of the matrix \mathbf{B} .
 $\mathbf{A} = [\mathbf{a}_1 \quad \mathbf{a}_2 \quad \cdots \quad \mathbf{a}_n]$, and $\mathbf{B} = [\mathbf{b}_1 \quad \mathbf{b}_2 \quad \cdots \quad \mathbf{b}_m]$
 - The first column of \mathbf{AB}
 - Linear combination of all the columns in \mathbf{A}

$$[\mathbf{a}_1 b_{11} + \mathbf{a}_2 b_{12} + \cdots + \mathbf{a}_n b_{1n}]$$

Matrix operation

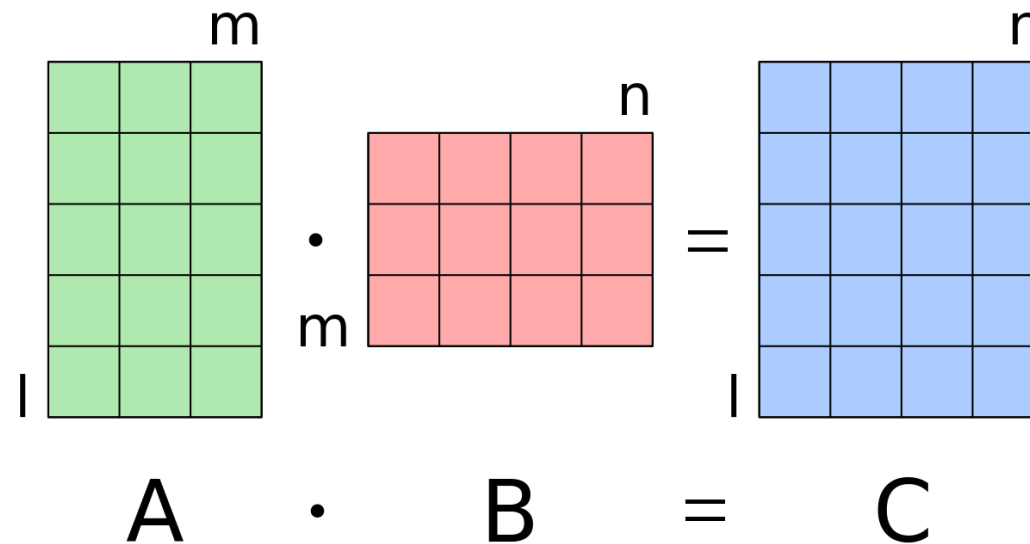


$$[a_1b_{11} + a_2b_{12} + \dots + a_nb_{1n}]$$

- Similarly, we can get other columns...

Matrix operation

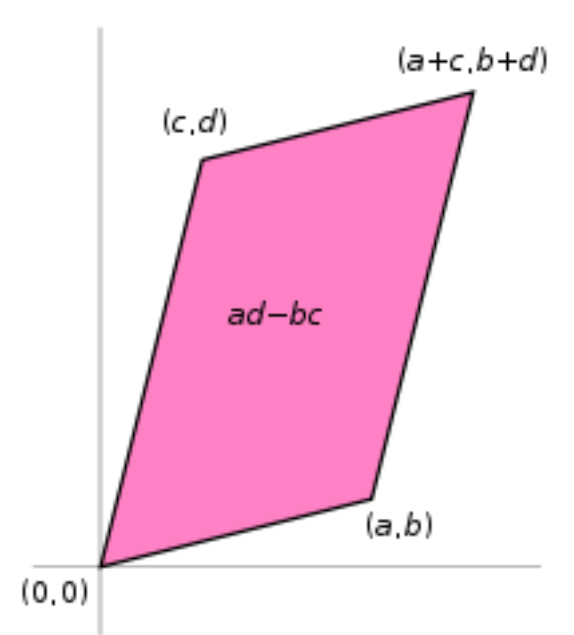
- How about linear combination of all rows of **B**?
 - Each row of **C = AB** is a linear combination of rows of **B**



$$[b_1 a_{11} + b_2 a_{21} + \dots + b_n a_{n1}]$$

Matrix operation

- Determinant
 - A scalar
- For $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$, $\det(A) = ad - bc$



- Represents area of the parallelogram described by the vectors in the rows of the matrix

Matrix operation

- Determinant

- The determinant of a matrix A is denoted by

$$|A| = \sum_{i=1}^K a_{ij} C_{ij}$$

where C_{ij} is the cofactor of a_{ij} defined by

$$C_{ij} = (-1)^{i+j} |M_{ij}|, \text{ and}$$

M_{ij} is the minor of matrix A formed by eliminating row i and column j of A

- Some properties

- $|AB| = |A||B|$

- $|AB| = |BA|$

- $|A^T| = |A|$

$$|A| = \begin{vmatrix} a & b & c \\ d & e & f \\ g & h & i \end{vmatrix} = a \begin{vmatrix} e & f \\ h & i \end{vmatrix} - b \begin{vmatrix} d & f \\ g & i \end{vmatrix} + c \begin{vmatrix} d & e \\ g & h \end{vmatrix}$$

Matrix operation

- Trace
 - $\text{Tr}(A)$ = sum of diagonal elements

$$\text{Tr} \begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \\ a_{20} & a_{21} & a_{22} \end{bmatrix} = a_{00} + a_{11} + a_{22}$$

- Properties
 - $\text{tr}(AB) = \text{tr}(BA)$
 - $\text{tr}(A + B) = \text{tr}(A) + \text{tr}(B)$

Matrix operation

- Inverse
 - Given a matrix A , its inverse A^{-1} is a matrix such that
$$\mathbf{AA^{-1} = A^{-1}A = I}$$
- Inverse does not always exist
 - Singular vs non-singular
- Properties
 - $(A^{-1})^{-1} = A$
 - $(AB)^{-1} = B^{-1}A^{-1}$

Special matrices

- Symmetric matrix

$$\mathbf{A}^T = \mathbf{A}$$

$$\begin{bmatrix} 1 & 1 & -1 \\ 1 & 2 & 0 \\ -1 & 0 & 5 \end{bmatrix}$$

- Skew-symmetric matrix

$$\mathbf{A}^T = -\mathbf{A}$$

$$\begin{bmatrix} 0 & 1 & -2 \\ -1 & 0 & 3 \\ 2 & -3 & 0 \end{bmatrix}$$

Special matrices

- Diagonal matrix
 - Used for row scaling

$$A = \begin{bmatrix} A_1 & 0 & \cdots & 0 \\ 0 & A_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & A_n \end{bmatrix}$$

- Identity matrix
 - Special diagonal matrix
 - 1 along diagonals

$$\mathbf{I} \cdot \mathbf{A} = \mathbf{A}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

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Questions?

Linear Algebra Basics

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Transformations

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Transformation - scaling

- Matrices are useful for vector transformations
- Matrix multiplication

$$x' = Ax$$

$$\begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix} \times \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} s_x x \\ s_y y \end{bmatrix}$$

- Linear combination of columns

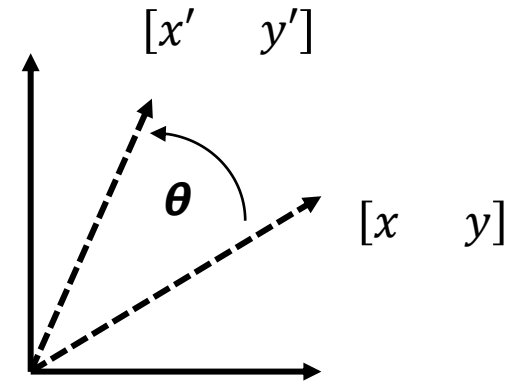
Transformation

- Rotation
 - Matrix multiplication to rotate a vector
- Rotation matrix

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

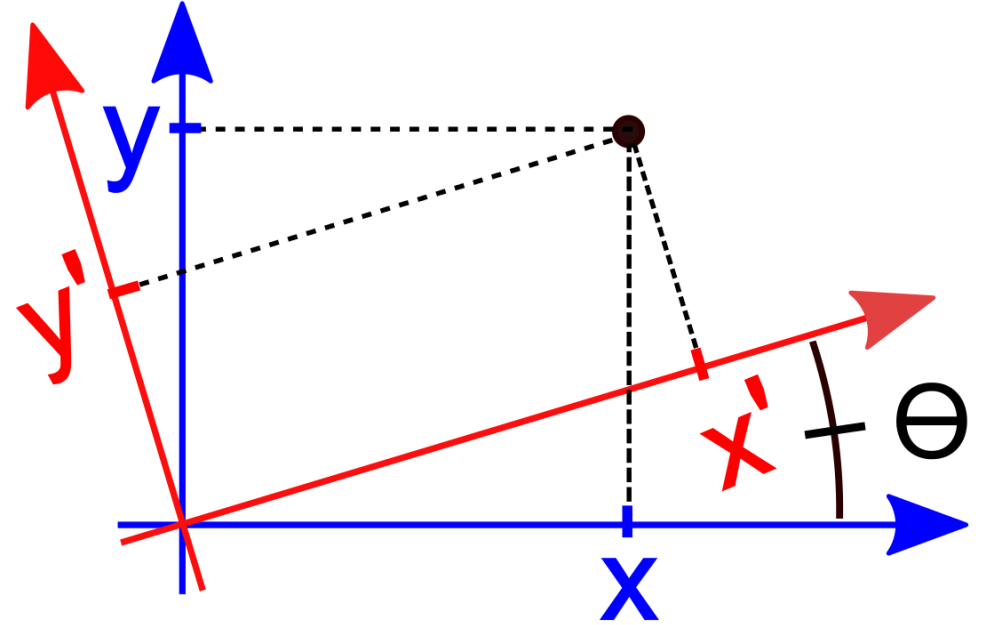
$$x' = \cos\theta x - \sin\theta y$$

$$y' = \sin\theta x + \cos\theta y$$



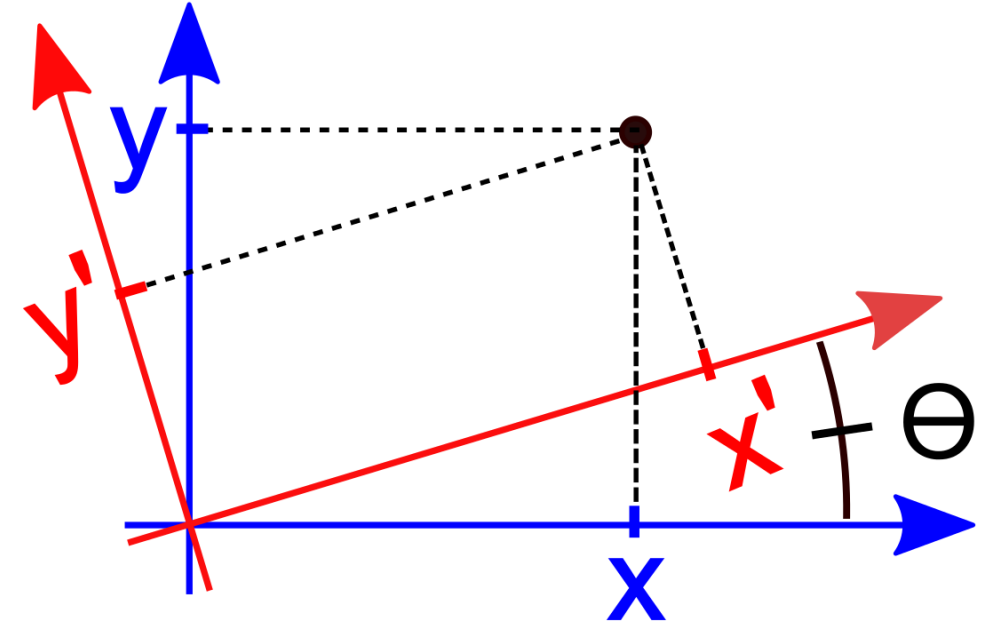
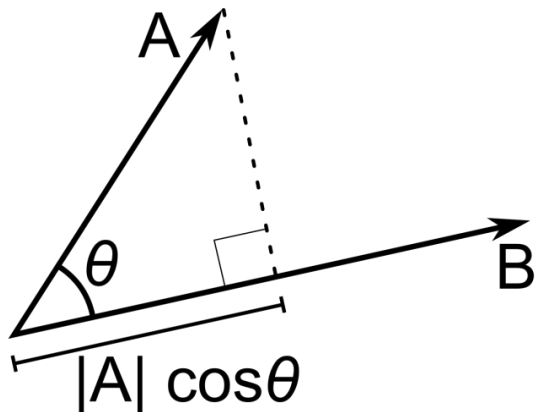
Transformation - rotation

- Rotating axis first
- Vector $v = [x \ y]$
 - x – projection of v on x axis
 - y – projection of v on y axis



Transformation - rotation

- To rotate the axis, we need to find
 - x component in new x-axis
 - y component in new y-axis
- Remember vector dot product?



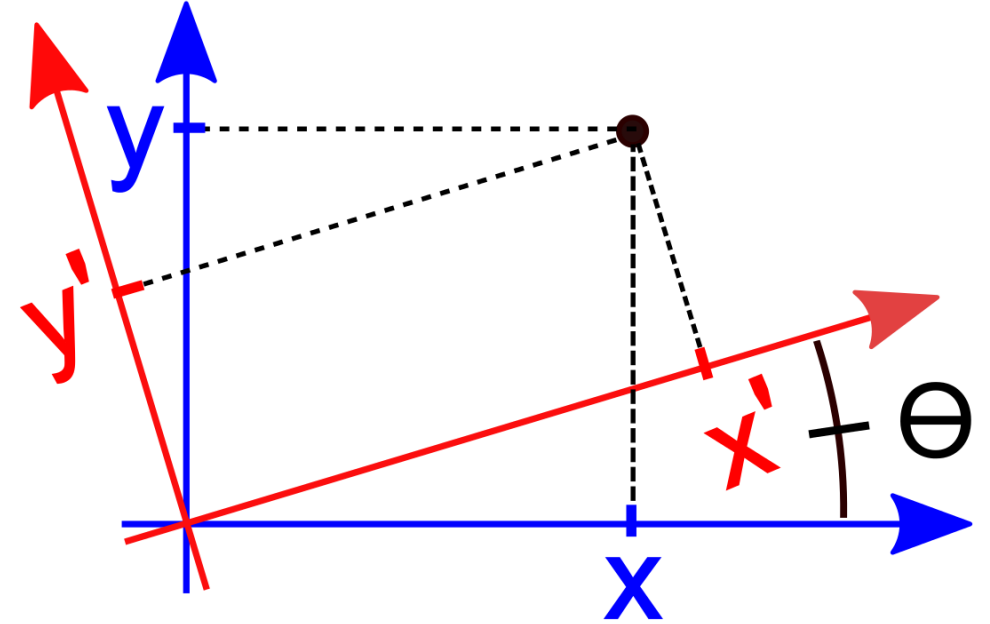
Transformation - rotation

- Now we need new x and y axis

$$x' = v \text{ dot new x-axis}$$

$$y' = v \text{ dot new y-axis}$$

- For rotation of θ
 - New x-axis = $[\cos\theta, \sin\theta]$
 - New y-axis = $[-\sin\theta, \cos\theta]$



Transformation - rotation

$$x' = v \text{ \textbf{dot} } \text{new x-axis}$$

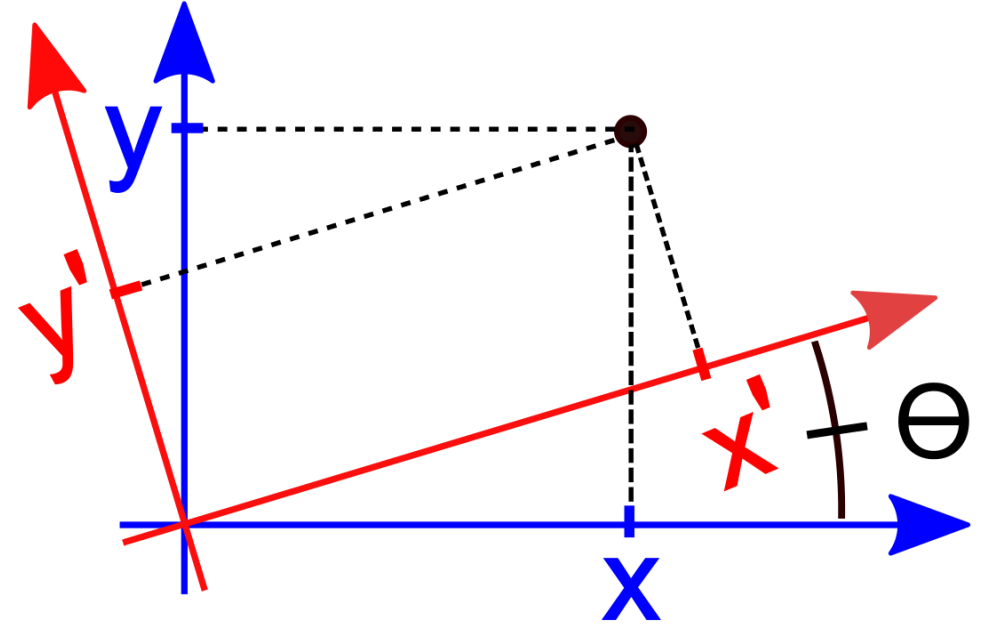
$$y' = v \text{ \textbf{dot} } \text{new y-axis}$$

$$\text{New x-axis} = [\cos\theta, \sin\theta]$$

$$\text{New y-axis} = [-\sin\theta, \cos\theta]$$

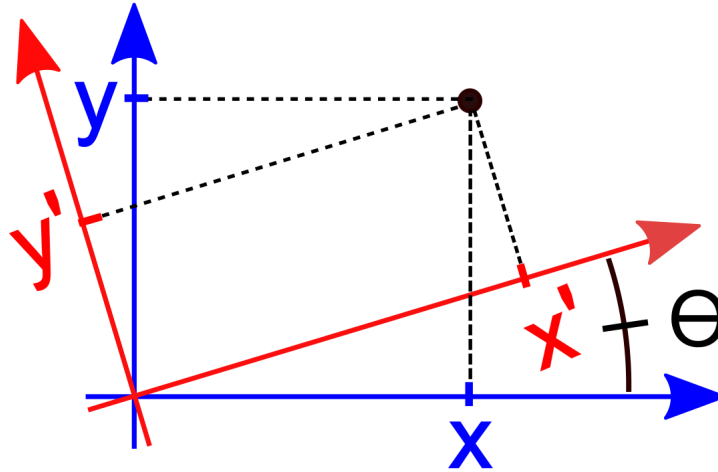
We can form a matrix using new axis

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$



Transformation - rotation

- When we rotate the axis to left
- We are rotating the vector to right

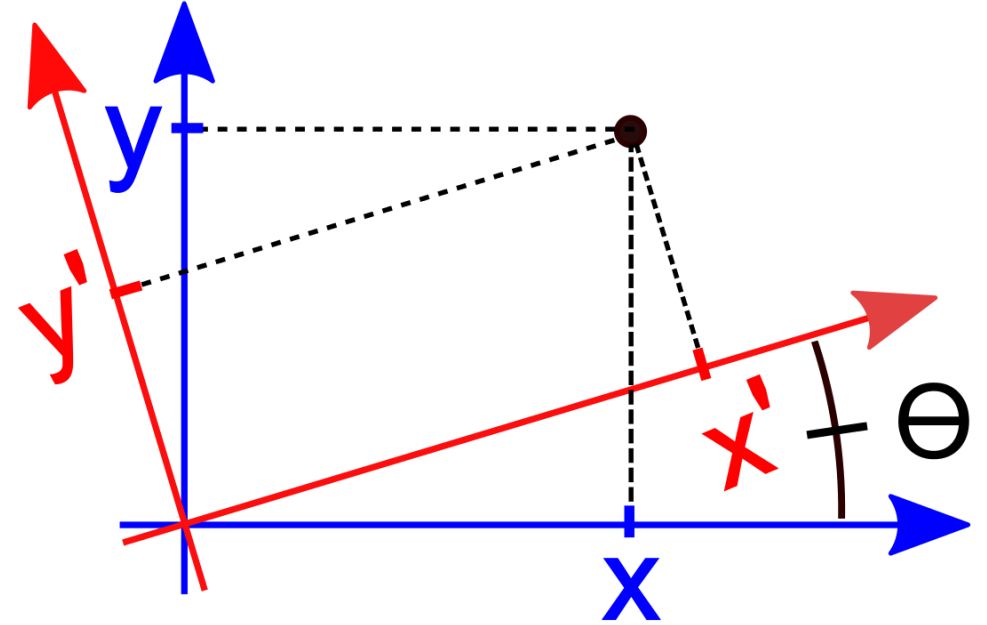


- We can use rotation matrix to rotate the vector

Transformation - rotation

- We need new x y axis coordinates
 - When we rotate the axis right
- Updated rotation matrix

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$



Transformation

- Linear combination

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \times \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} ax + by \\ cx + dy \end{bmatrix}$$

- Sufficient for
 - scaling
 - rotating and
 - skew transformations
- But no shifting

Transformation

- Linear combination

$$\begin{bmatrix} a & b & 0 \\ c & d & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} ax + by \\ cx + dy \\ 1 \end{bmatrix}$$

- Still be able to
 - scaling
 - rotation and
 - skew transformations

Transformation

- Homogenous system

$$\begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} ax + by + c \\ dx + ey + f \\ 1 \end{bmatrix}$$

- We can also perform shifting now
- This is called homogenous coordinates

Scaling + rotation + translation

- Careful about the order

$$V' = (TRS)V$$

$$\begin{bmatrix} 1 & 0 & t_y \\ 0 & 1 & t_x \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

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Linear independence

- Linear independence

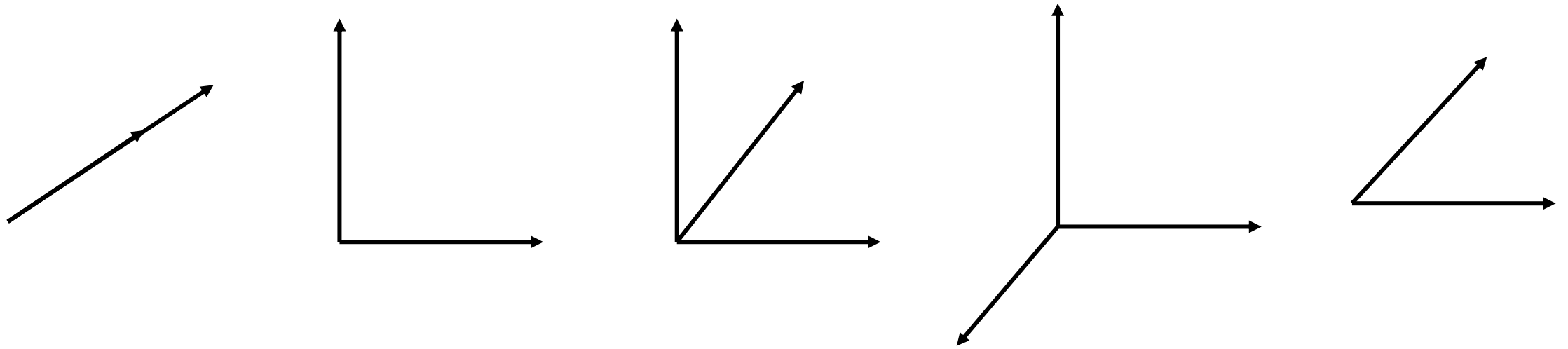
$\{\mathbf{x}_1, \mathbf{x}_2 \cdots, \mathbf{x}_M\}$ is a set of linearly independent vectors provided

$$a_1\mathbf{x}_1 + a_2\mathbf{x}_2 + \cdots + a_M\mathbf{x}_M = \mathbf{0} \Rightarrow a_1 = 0 = a_2 = \cdots = a_M$$

- In other words, none of the vectors can be expressed as a linear combination of the other vectors

- Each vector is perpendicular to every other vector
- For example, axis in cartesian coordinate system

Intuition



- In terms of features
 - Person recognition – [height, hair color, weight, specs, eye color, etc.]

Matrix factorization

- Singular value decomposition (SVD)

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

- If A is $m \times n$ matrix, then
 - U will be $m \times m$,
 - Σ will be $m \times n$, and
 - V^T will be $n \times n$
- U and V are unitary matrices
 - Each column is a unit vector
- Σ is a diagonal matrix

Singular value decomposition

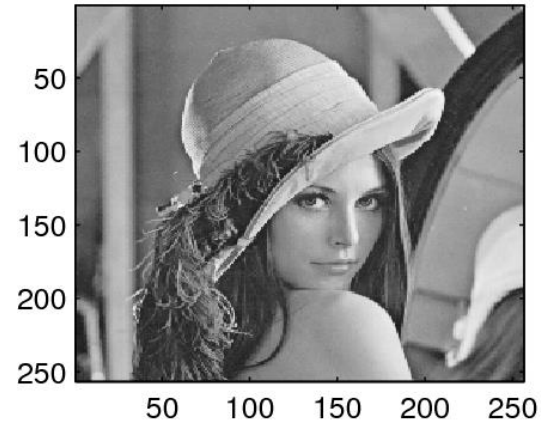
- Interpretation

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$$

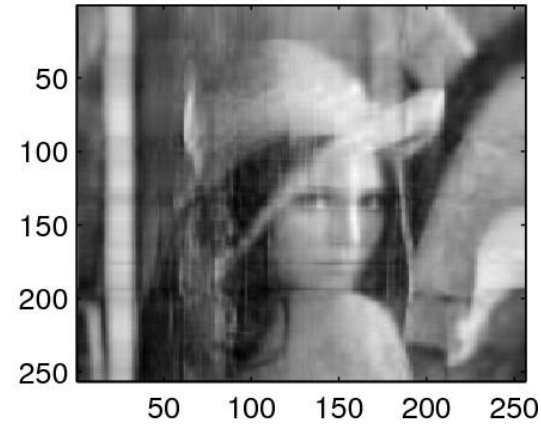
- Columns of \mathbf{U} are scaled by values in $\mathbf{\Sigma}$
- The resultant columns are linearly combined by \mathbf{V}
- \mathbf{A} is formed as a linear combination of columns of \mathbf{U}
- If we use all column, we will get original \mathbf{A}
- We can just use few columns of \mathbf{U} and we get an approximation
 - We call these columns principal components

SVD application

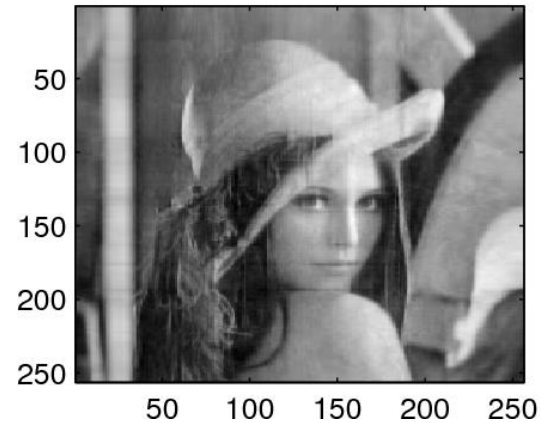
Original image 256 singular values



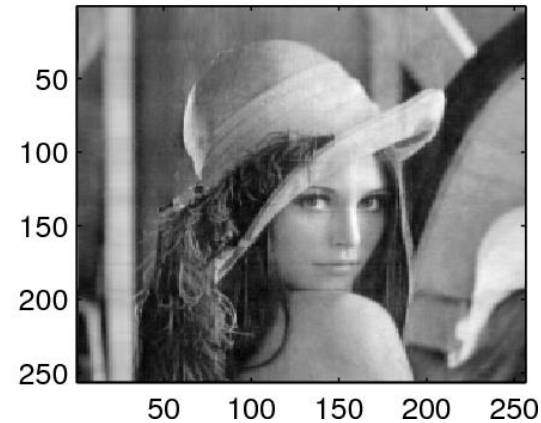
retaining 20 singular values



retaining 50 singular values



retaining 85 singular values



Questions?

Sources for this lecture include materials from works by Abhijit Mahalanobis and Fei Fei Li