



# Other Applications in CS

CS 355: Introduction to Graphics and Image Processing

# Math Applications in CS

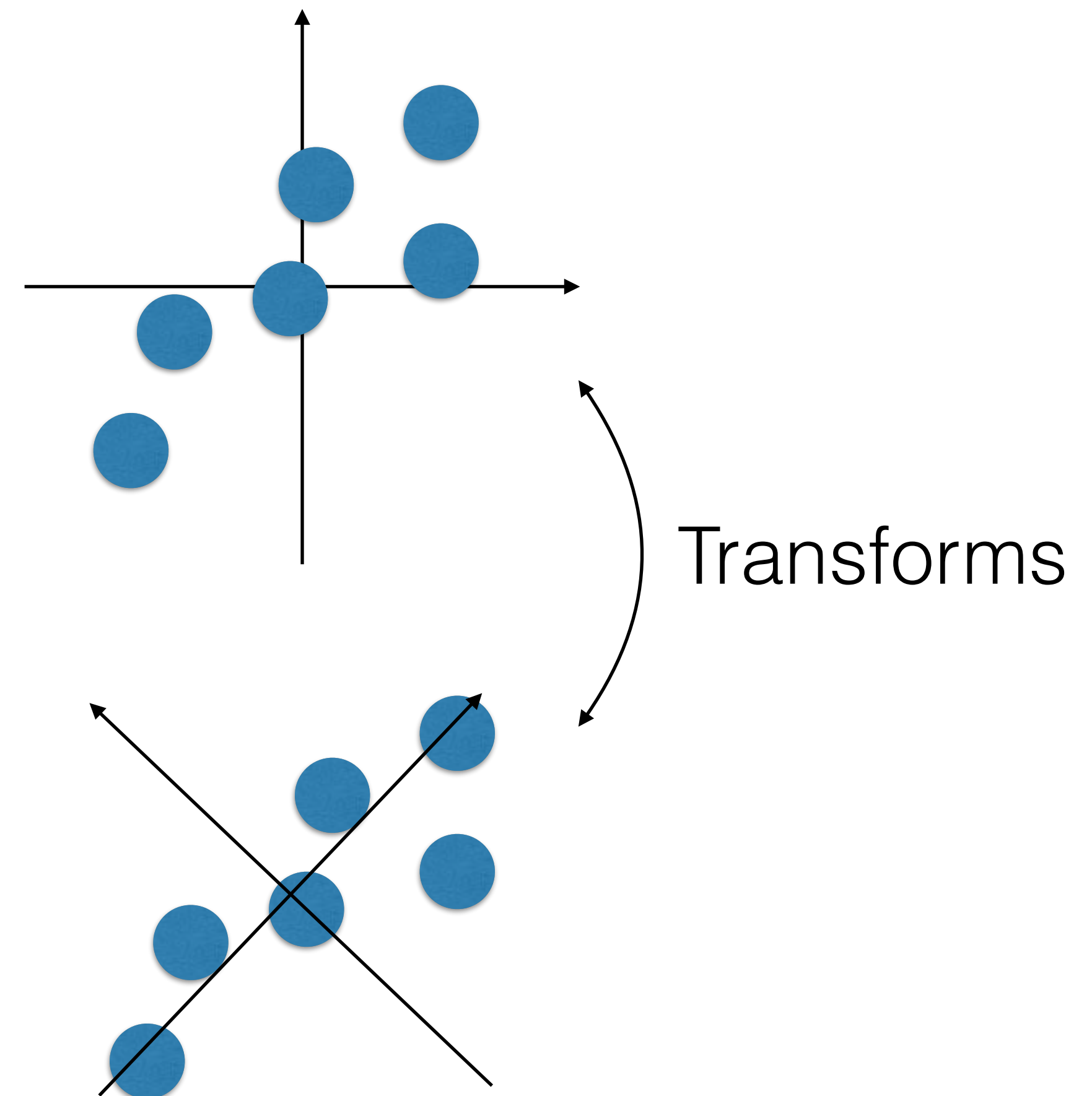
- All the “discrete math” from CS 235, 252, etc.
  - Sets, relations, functions, ...
- Linear algebra
  - Geometric transformations
  - Data transforms
  - Systems of equations
  - Eigensystems

# Data as Vectors

*Lots of things can be thought of as  
points/vectors in some space*

# Data Transforms

- Common pattern in data analysis:
  - Represent data as vectors
  - Convert to a different coordinate system
  - Analyze (or change!) while in that coordinate system
  - Convert back (if needed)



# Data Transforms

- Same form as any other change of coordinates
- Transform using dot products
- Convert back using weighted sum

The diagram illustrates the transformation of data. At the top, three labels are positioned: 'transformed data' on the left, 'original data' in the center, and 'basis set' on the right. Arrows point from each of these labels down to the first equation,  $g[i] = \sum_k f[k] e_i[k]$ . In this equation,  $g[i]$  is aligned under 'transformed data',  $f[k]$  is aligned under 'original data', and  $e_i[k]$  is aligned under 'basis set'. Below this equation is the second equation,  $f[k] = \sum_i g[i] e_i[k]$ , which represents the inverse transformation.

$$g[i] = \sum_k f[k] e_i[k]$$
$$f[k] = \sum_i g[i] e_i[k]$$

# Fourier Analysis

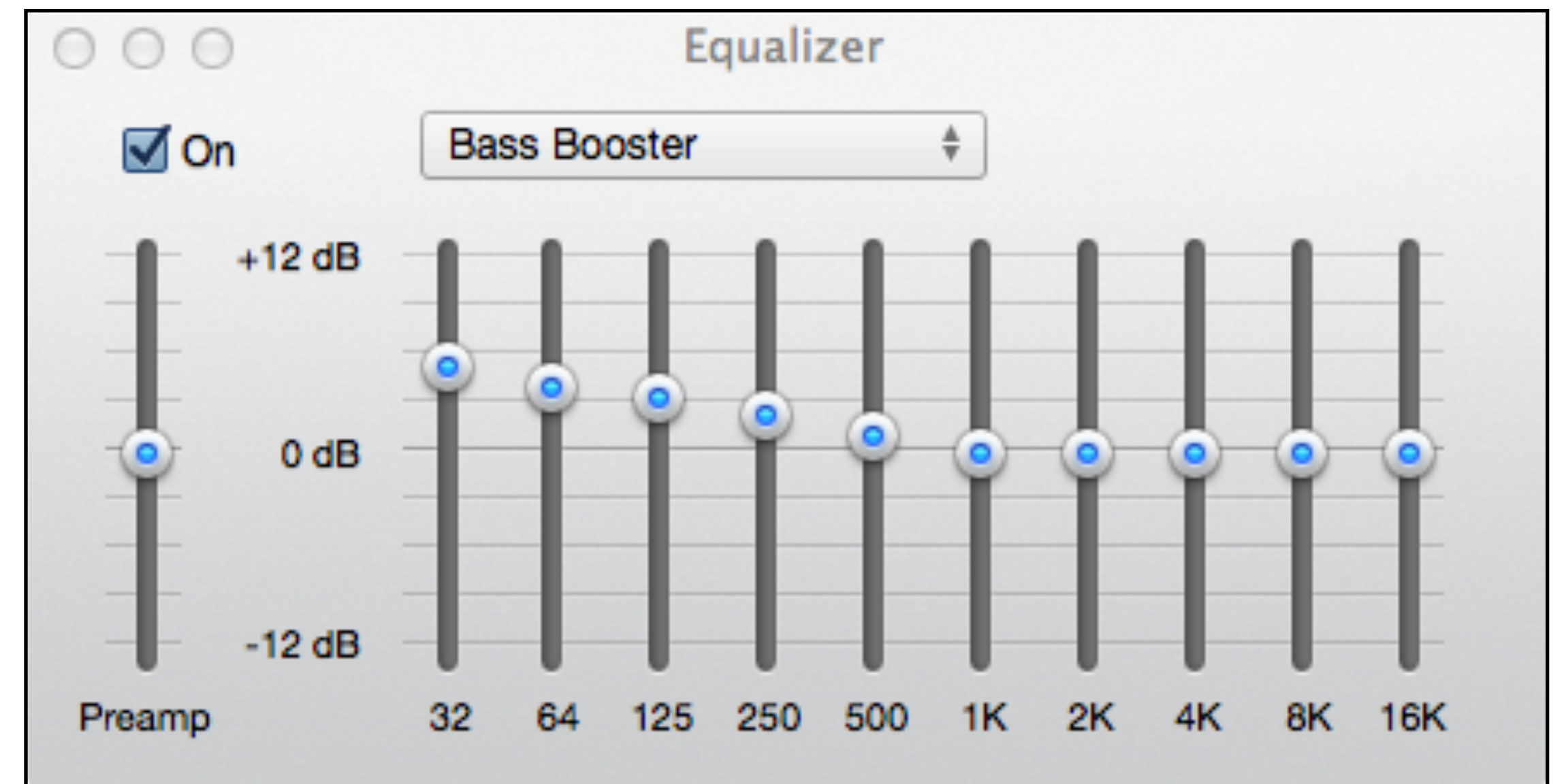
- Sampled sines and cosines of different frequencies form an orthonormal basis set
- Can decompose any waveform into a weighted sum of sines and cosines of different frequencies
- Great for analysis, manipulation, etc.

$$c[u] = \frac{1}{N} \sum_{t=0}^{N-1} f[t] \cos(2\pi ut/N)$$

$$s[u] = \frac{1}{N} \sum_{t=0}^{N-1} f[t] \sin(2\pi ut/N)$$

# Frequency Manipulation

- Can use frequency-based representation to do manipulation
  - Boost bass/treble
  - Boost typical range of human speaking (hearing aides do this)
  - Suppress unwanted sounds
  - Smoothing / sharpening
  - And lots more...



# Audio Compression

- Fact: your ear doesn't hear all frequencies equally well (and it's different for everybody)
- Idea: don't not spend as many bits of precision on the ones we don't as hear well anyway



# Audio Compression

- Compression:
  - Convert to a frequency-based representation
  - Use more bits to store the coefficients for the frequencies we hear better; fewer for the ones we don't hear well
  - Store in this form
- Decompression:
  - Use lossy coefficients and convert back to a PCM representation
  - Play!

This is how MP3 compression works!

# Image Compression

- Can we do something similar with images?
- Fact: your eye is less accurate in sensing very rapid changes in brightness across an image (fine texture)
- Idea: use the same approach in the 2D frequency domain for images
- This is the basis of JPEG  
(uses Discrete Cosine Transform instead of Fourier)

# Classification

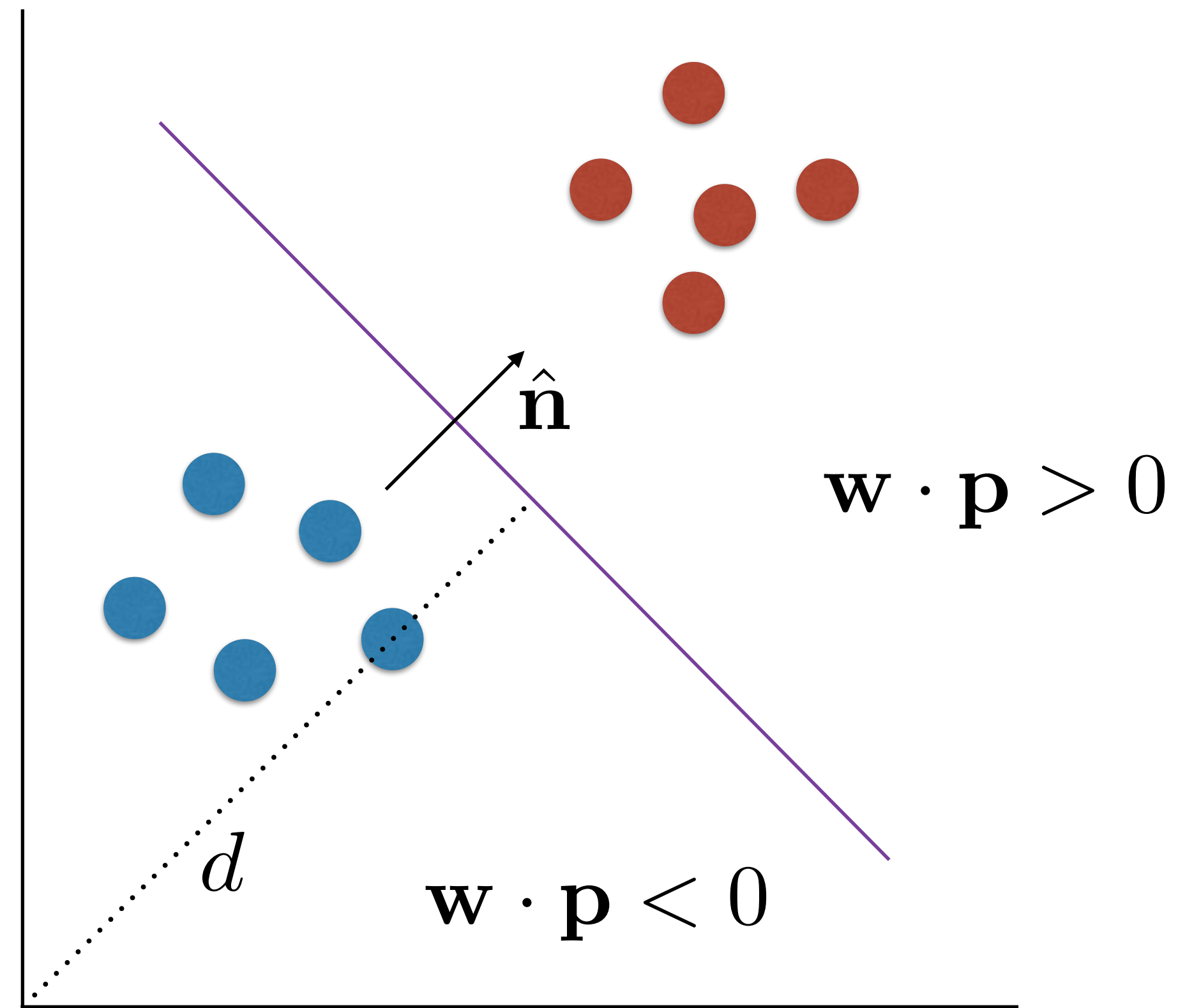
- Simple problem:
  - Two classes of things, with lots of examples of each
  - New thing — what kind is it?
- Approach:
  - Measure “features” of the things
  - Put features together in a vector
  - Look at the problem geometrically
  - Changing the coordinate system can make a huge difference!

(basis for pattern recognition, machine learning, other AI, ...)

# Classification

$$\mathbf{p} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \\ 1 \end{bmatrix}$$

$$\mathbf{w} = \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_k \\ -d \end{bmatrix}$$



# Classification

- But what if it's complicated, and you can't easily solve for **w**?
- Can you iteratively tweak the values in **w** until you “get it right”?
- The entries of **w** act as “weights” in a weighted combination of features, so it's called a *weight vector*

$$\mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_k \\ w_{k+1} \end{bmatrix} \quad \mathbf{p} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \\ 1 \end{bmatrix}$$

$$\mathbf{w} \cdot \mathbf{p} = \sum_{i=1}^k w_i x_i + w_{k+1}$$

This is basically the heart of what neural networks do!

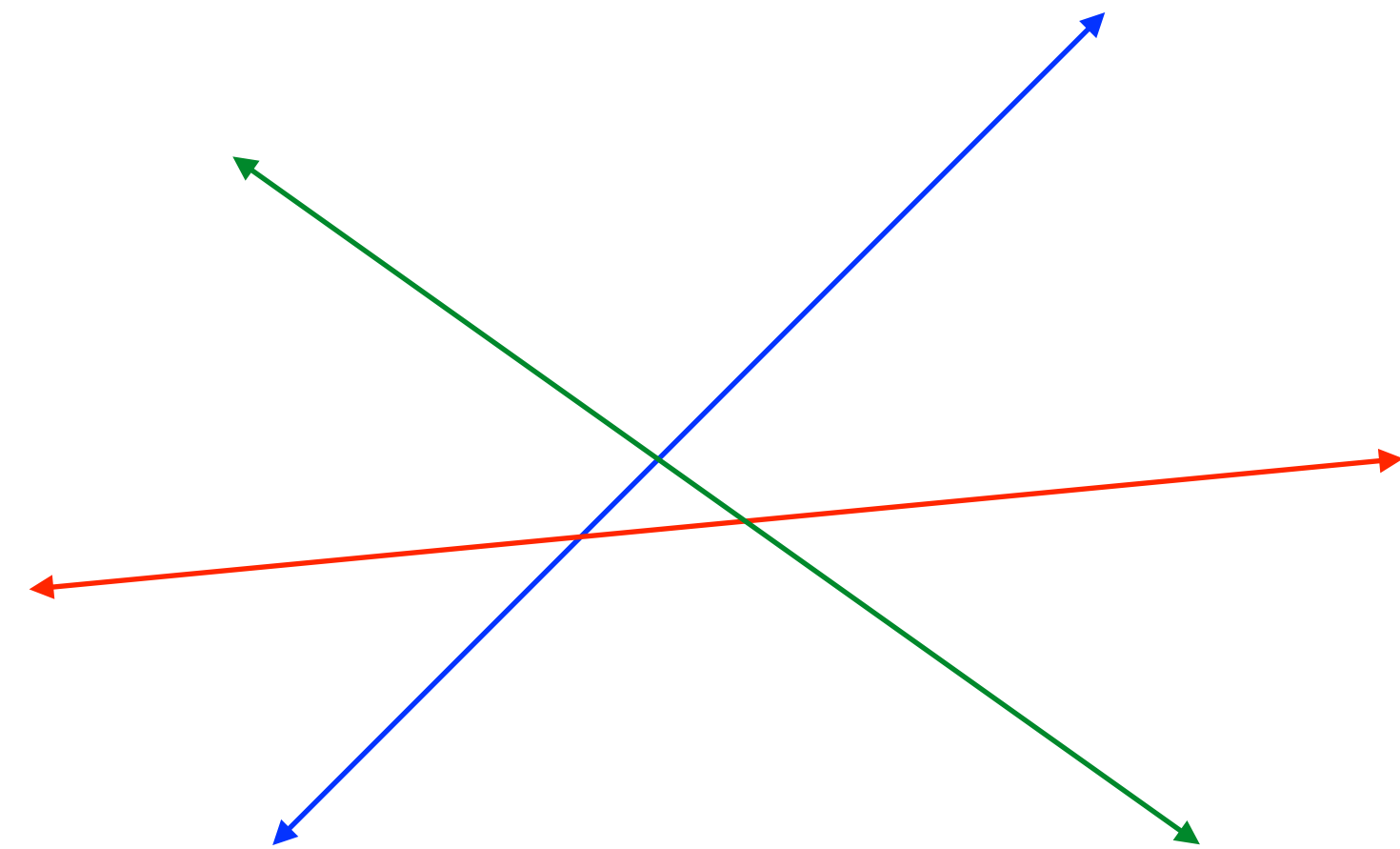
# Systems of Equations

- If you need to solve for  $n$  unknowns, you need  $n$  equations, right?
- What if the data is noisy?
- Idea: get more data and let the noise “average out”
- But now there are too many equations!

$$\mathbf{Ax} = \mathbf{b}$$

# Overconstrained Systems

- When you have too many equations, there may not be a solution
- Idea: get as close as possible to fitting all of the equations
- If you use a squared-error metric, this leads to a *least-squares solution*



$$\text{minimize } \|\mathbf{Ax} - \mathbf{b}\|^2$$

# Eigensystems

- The actions of some matrices are sometimes described more easily when converted to another coordinate system
- Some matrices are *pure scaling* along certain key directions
- A useful tool for analyzing these are *eigensystems*
  - Eigenvectors - directions of scaling
  - Eigenvalues - amount of scaling in each direction

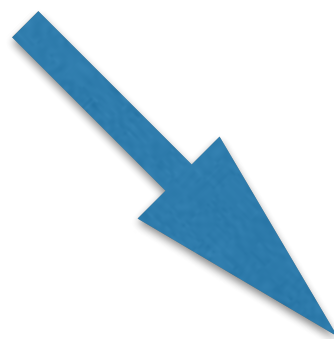


# Eigensystems

What does this matrix do?

$$\begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix}$$

Scales by 4 in the direction  $[1, 1]$   
and by 2 in the direction  $[-1, 1]$



Eigenvectors:

$$\begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$



Eigenvalues:

4, 2

# Coming up...

- Applications in Computer Vision (and CS 450) — Dr. Farrell
- Applications in Computer Graphics (and CS 455) — Dr. Egbert