

# Image Matching

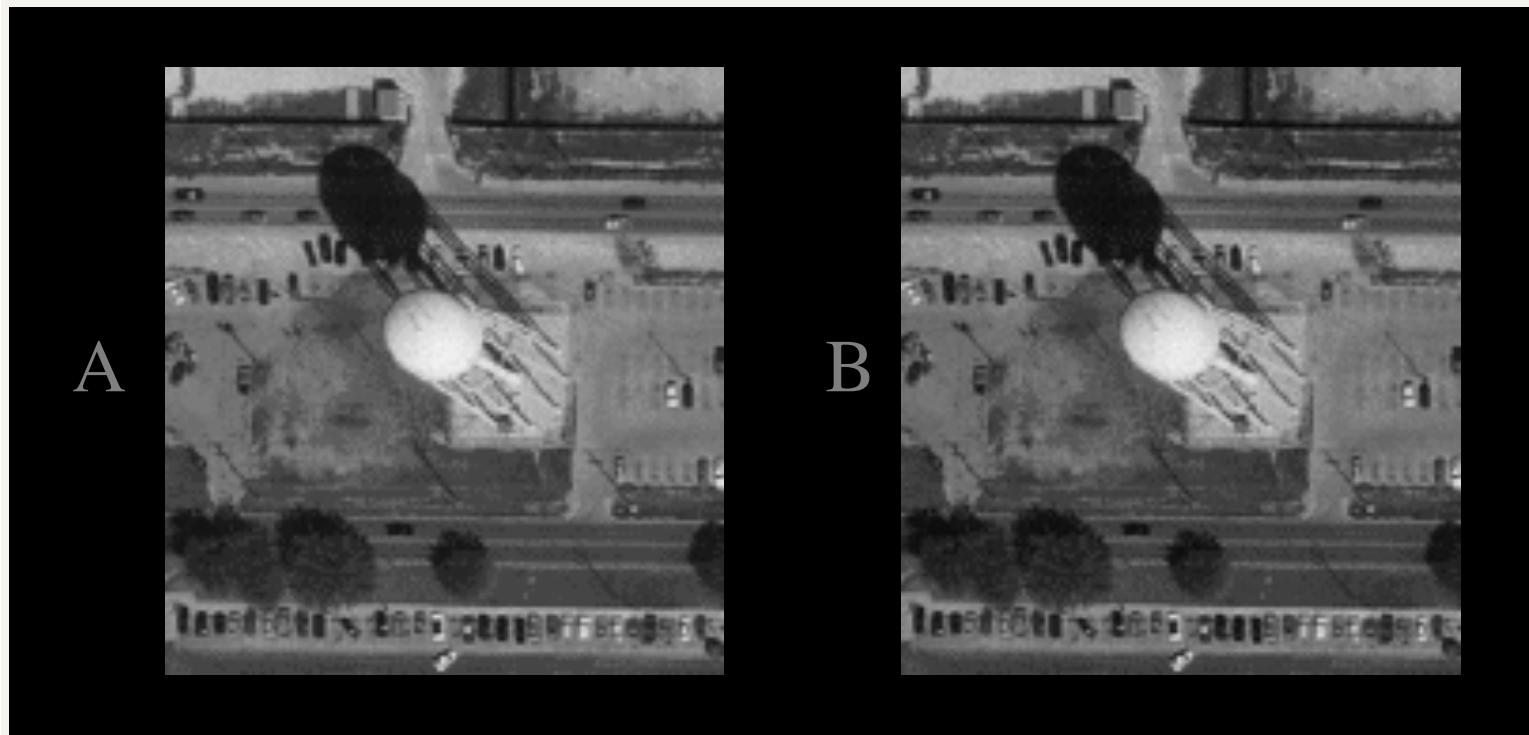
Lecture #04

February 1, 2013

The logo for Colorado State University, featuring a green wavy line with yellow lines underneath, and the text "Colorado State University" in a gold serif font.

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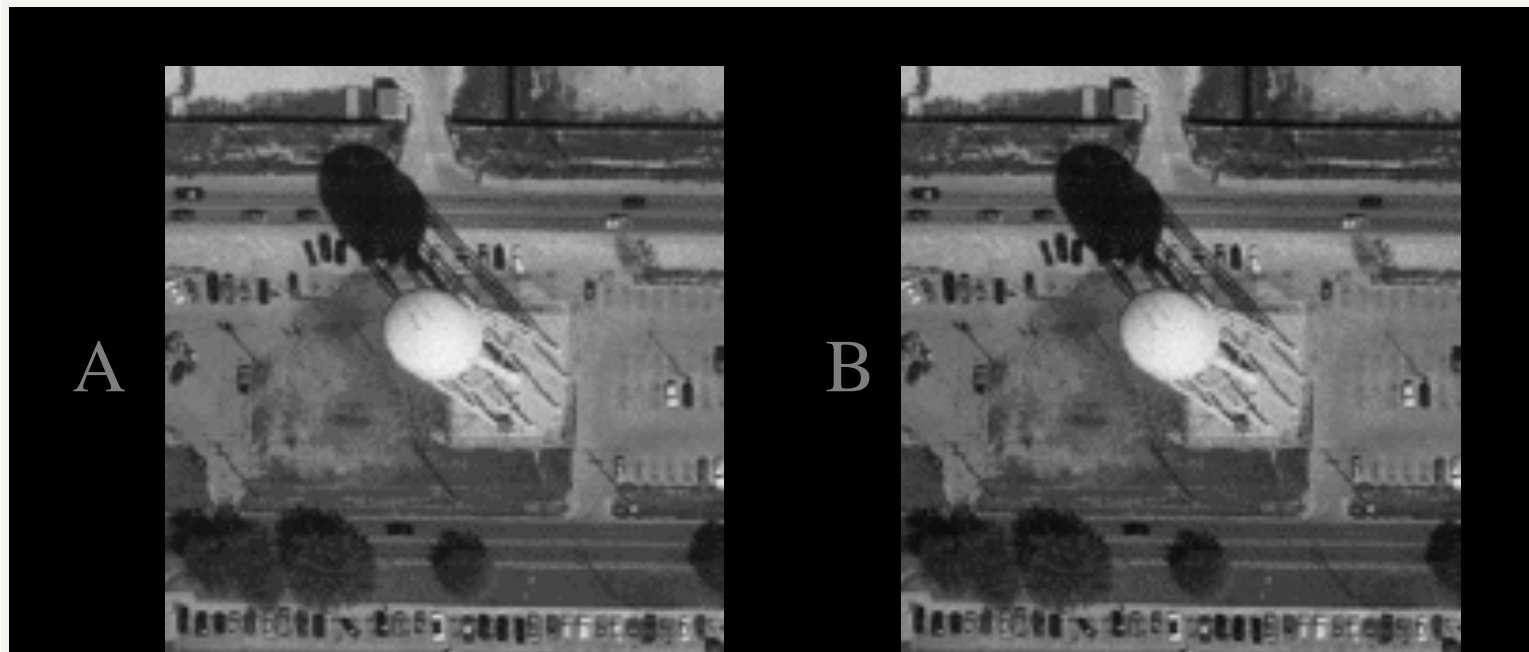
# How do we (directly) compare two images?



Are these images the same? Are they similar?

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# Pixel-wise Comparison



*Or, normalized by image area, about 5 grey values per pixel.*

$$8,140 = \sum_x \sum_{y < 161}^{x < 148} |A(x, y) - B(x, y)|$$

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# Backup - what is “similarity”?

Consider two vectors/points.

$$X = \begin{pmatrix} x_1 \\ x_2 \\ \dots \\ x_n \end{pmatrix} \quad Y = \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{pmatrix}$$

*Distance vs. similarity:*

$$S : R^n \times R^n \rightarrow R$$

$$D : R^n \times R^n \rightarrow R$$

$$S \propto 1/D$$

## Common Approaches

Euclidean (L2) Distance

City Block (L1) Distance

Pearson's Correlation

Linear Correlation

Important, Less Common

Mahalanobis Distance

Mutual Information

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# Simple Distances (norms)

L1 - City Block Distance

$$\sum_{x,y} (|A(x,y) - B(x,y)|)$$

L2 - Euclidean Distance

$$\sqrt{\sum_{x,y} (A[x,y] - B[x,y])^2}$$

Generalized L-norm

$$\sqrt[l]{\sum_{x,y} (|A(x,y) - B(x,y)|)^l}$$

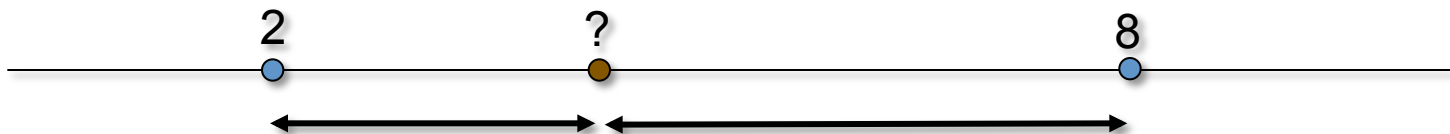
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# Properties of L1 Distance

Consider the following problem:

*Find the unique point “closest” to  $k$  other points.*

For simplicity, do this in  $\mathbb{R}$  (a line) with  $k = 2$ .



See the problem yet?

$$|2 - 3| + |8 - 3| = 6 \quad |2 - 4| + |8 - 4| = 6$$

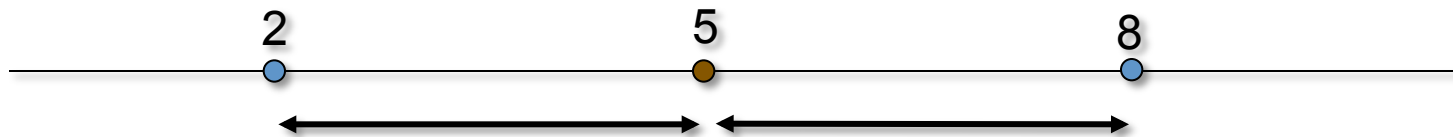
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# In Comparison, Consider L2

*Find the unique point “closest” to  $k$  other points.*



Using L2,



$$\sqrt{(2 - 5)^2 + (8 - 5)^2} = \sqrt{18} \qquad \sqrt{(2 - 4)^2 + (8 - 4)^2} = \sqrt{20}$$

Best

Not as Good

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# Sources of Image Variation

↑  
info

- Change in scene content
  - Out-of-plane rotation, scale change
  - In-plane translation, rotation
- 

- Change in illumination
- 

↓  
noise

- Change in mixed-pixels
- Change in gain, f-stop
- Electronic noise

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# Motivating Pearson's Correlation

Let's play a Game

*Two vectors are similar to the extent that the value at a dimension in one lets you predict the value in the other*

<b>CS 510 Guess The Next Number Game</b>								
<b>Solutions</b>								
	Game 1				Game 2			
	X	Y	Y-True	Check	X	Y	Y-True	Check
1	4	3			4	1		
2	1	4			1	3		
3	3	2			3	3		
4	2	5			2	3		
5	5	5			5	0		
6	1	2			1	3		
7	4	5			4	1		
8	5	4			5	1		
9	5	2			5	0		
10	4	3			4	2		
11	4				4			
12	3				3			
13	5				5			
14	3				3			
15	4				4			
16	2				2			
17	1				1			
18	2				2			
19	1				1			
20	1				1			

# The results of the Game

- First Game - Random
  - Expected ~20% correct
- Second Game
  - Invert 1-5 to 4-0
  - Add some noise
- Game 2 - features
  - Nearly perfect prediction
  - ... to within one value.
- Punch line
  - **Correlation measures predictability!**

**CS 510 Guess The Next Number Game**

**Solutions**

	Game 1				Game 2				
	X	Y	Y-True	Check	X	Y	Y-True	Check	
1	4	3	3		4	1	1		
2	1	4	4		1	3	3		
3	3	2	2		3	3	3		
4	2	5	5		2	3	3		
5	5	5	5		5	0	0		
6	1	2	2		1	3	3		
7	4	5	5		4	1	1		
8	5	4	4		5	1	1		
9	5	2	2		5	0	0		
10	4	3	3		4	2	2		
11	4		5		4		1		
12	3		3		3		2		
13	5		5		5		1		
14	3		3		3		2		
15	4		4		4		1		
16	2		2		2		4		
17	1		4		1		3		
18	2		5		2		4		
19	1		4		1		4		
20	1		2		1		3		
	Tally					Tally			

# Pearson's Correlation

$$\frac{\sum_{x,y} (A(x,y) - \bar{A})(B(x,y) - \bar{B})}{\sqrt{\sum_{x,y} (A(x,y) - \bar{A})^2} \sqrt{\sum_{x,y} (B(x,y) - \bar{B})^2}}$$

*What is the underlying model?*

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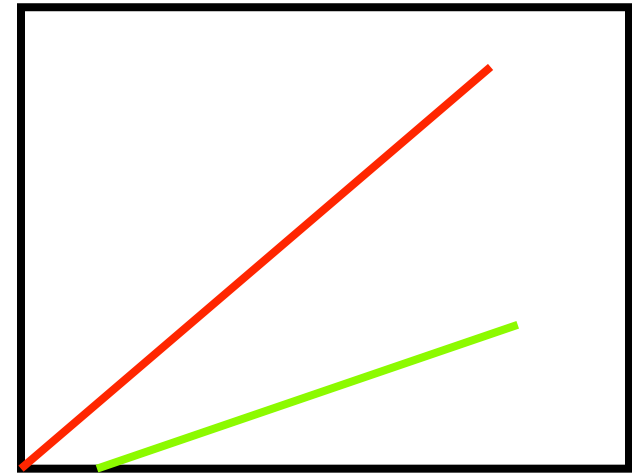
# Assumptions of Correlation

$$\frac{\sum_{x,y} (A(x,y) - \bar{A})(B(x,y) - \bar{B})}{\sqrt{\sum_{x,y} (A(x,y) - \bar{A})^2} \sqrt{\sum_{x,y} (B(x,y) - \bar{B})^2}}$$

- Two signals vary linearly
  - Constant shift to either signal has no effect.
  - Increased amplitude has no effect.
- This minimizes sensitivity to:
  - changes in (overall) illumination
  - offset or gain.

# Special Cases

- Any two linear functions with positive slope have correlation 1.
  - Only the sign of the slope matters.
- Any two linear functions with differently signed slopes have correlation -1.
  - This is called anti-correlation
  - Anti-correlation = correlation for prediction.
  - For matching, it may or may not be as good...
- Correlation undefined for slope = 0 ( $\sigma=0$ )



# Correlation (cont.)

- Correlation is **sensitive** to:
  - Translation
  - Rotation: in-plane and out-of-plane
  - Scale
- Because it ...
  - Assumes pixels align one atop the other.
  - Compares two images pixel by pixel.
- Translation handled by convolution
  - Example, alignment by template matching

# Computing Correlation

- Note that adding a constant to a signal does not change its correlation to any other signal, so
  - Let's subtract average A from A(x,y)
  - Let's subtract average B from B(x,y)
  - The mean of both signals is now zero
  - Then correlation reduces to:

$$\frac{A \cdot B}{\sqrt{\sum_{x,y} (A(x,y) - \bar{A})^2} \sqrt{\sum_{x,y} (B(x,y) - \bar{B})^2}}$$

# Computing Correlation (II)

- For zero-mean signals, we can scale them without changing their correlation scores
  - Multiply A by the inverse of its length
  - Multiply B by the inverse of its length
  - Both signals are now unit length
  - Then correlation reduces to:

$$A \cdot B$$

- Gives rise to ‘Correlation Space’.



# Correlation Space

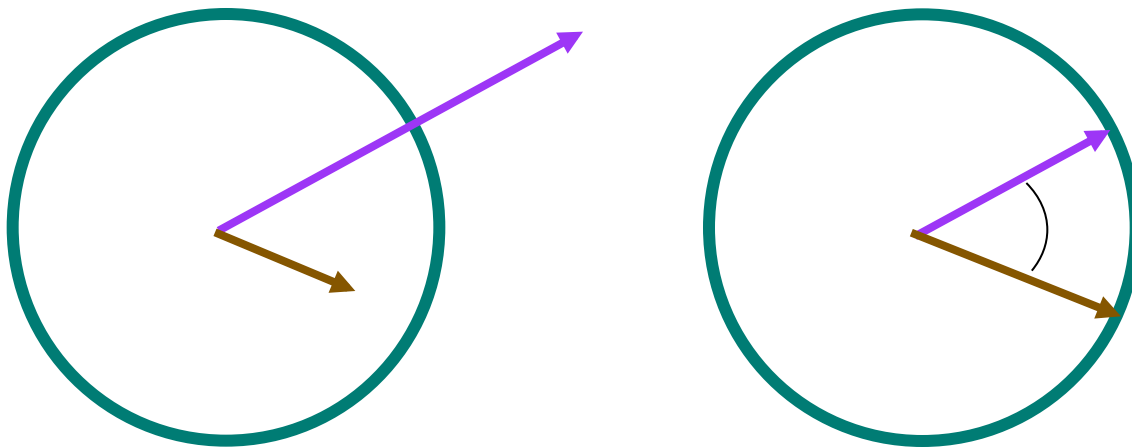
- Why zero-mean & unit-length your images?
- Consider database retrieval
  - Compare new image A ...
  - with many images in database.
  - When database images are stored in their zero-mean & unit-length form, then
  - Preprocess A (zero-mean, unit-length)
  - Compute dot products

# Correlation Space (II)

- New idea: image as a point in an  $N$  dimensional space
  - $N = \text{width} \times \text{height}$
- Zero-mean & unit-length images lie on an  $N-1$  dimensional “correlation space” where the dot product equals correlation.
  - This is a highly non-linear projection.
  - Points lie on an  $N-1$  surface within the original  $N$  dimensional space.
- So consider points in 3-D .....

# Correlation Space (II)

- Subtracting mean - translation.
- Length one - project onto sphere.
- Correlation is then:
  - Cosine of angle between vectors (points).



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# Useful Connection ...

- Euclidean distance is inversely proportional to correlation in correlation space.

$$\begin{aligned}\sqrt{\sum_{x,y} (A[x,y] - B[x,y])^2} &= \sqrt{\sum_{x,y} A[x,y]^2 + \sum_{x,y} B[x,y]^2 - 2A[x,y]B[x,y]} \\ &= \sqrt{1+1 - 2 \sum_{x,y} A[x,y]B[x,y]} \\ &= \sqrt{2 - 2A \cdot B} \\ &= \sqrt{2 - 2\text{Corr}(A,B)}\end{aligned}$$

- Nearest-neighbor classifiers in correlation space maximize correlation