

# Lecture 26: MDS / Canonical Forms

COMPSCI/MATH 290-04

Chris Tralie, Duke University

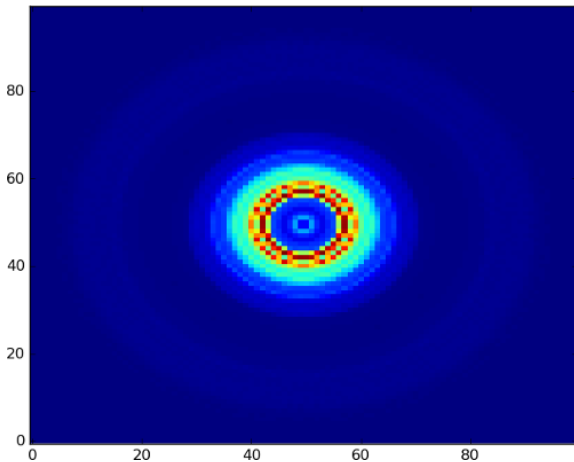
4/19/2016

# Announcements

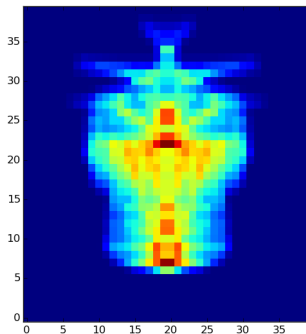
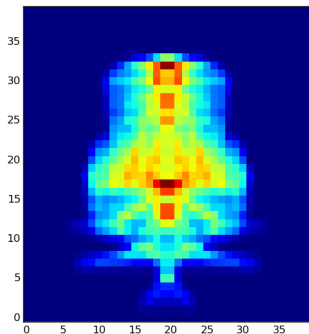
- ▷ Group Assignment 3 Final Deadline Tuesday 4/26
- ▷ Guest Lecture Thursday
- ▷ No office hours Thursday

# Spin Images

Why did they all look so boring and unlike the objects in question?



# Spin Images



I made a mistake on the assignment! First principal axis is vertical axis in image

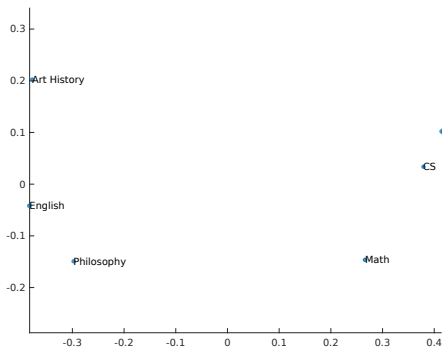
# Table of Contents

- ▶ Multidimensional Scaling
- ▷ Canonical Forms

# Academic Majors Distances: Your Choices

	Art History	English	Math	CS	ECE	Philosophy
Art History	0	0.36	0.74	0.8	0.81	0.37
English	0.36	0	0.7	0.8	0.82	0.29
Math	0.74	0.7	0	0.31	0.32	0.59
CS	0.8	0.8	0.31	0	0.2	0.71
ECE	0.81	0.82	0.32	0.2	0	0.77
Philosophy	0.37	0.29	0.59	0.71	0.77	0

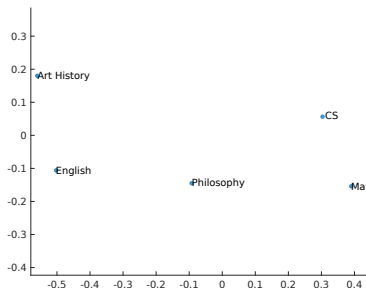
Multidimensional Scaling down to  $\mathbb{R}^2$



# Academic Majors Distances: Chris's Choices

	Art History	English	Math	CS	ECE	Philosophy
Art History	0	0.3	1	0.9	1	0.5
English	0.3	0	0.9	0.8	1	0.3
Math	1	0.9	0	0.3	0.2	0.3
CS	0.9	0.8	0.3	0	0.1	0.4
ECE	1	1	0.2	0.1	0	0.6
Philosophy	0.5	0.3	0.3	0.4	0.6	0

Multidimensional Scaling down to  $\mathbb{R}^2$



# Multidimensional Scaling

- ▷ Given an  $N \times N$  symmetric discrete similarity matrix  $D$  (i.e.  $D_{ij} = D_{ji}$ )
- ▷ Given a Euclidean dimension  $K$

Find a point cloud  $X \in \mathbb{R}^{N \times K}$  so that

$$D_{ij} \approx \sqrt{\sum_{k=1}^K (X[i, k] - X[j, k])^2}$$



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In other words, find a point cloud in Euclidean  $K$ -space that *best approximates* the distances

# MDS: Euclidean Dimension Reduction

$$D_{ij} \approx \sqrt{\sum_{k=1}^K (X[i, k] - X[j, k])^2}$$

What if  $D_{ij}$  comes from a Euclidean space of dimension  $d > k$ ?  
Can we solve this using something else we learned in the course?

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Can we solve this using something else we learned in the course?

This is equivalent to PCA!! If we let  $k = d$ , then we can represent distances exactly

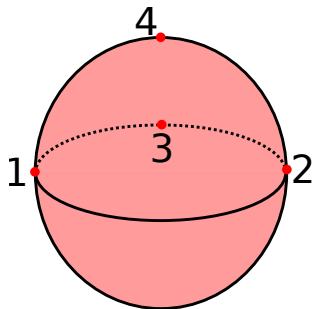
# MDS: Non-Euclidean Space Reduction

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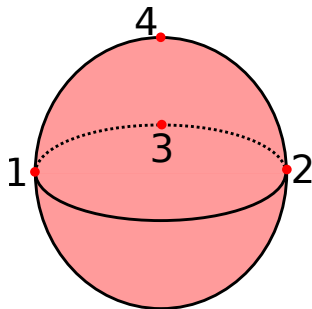


	$v_1$	$v_2$	$v_3$	$v_4$
$v_1$				
$v_2$				
$v_3$				
$v_4$				

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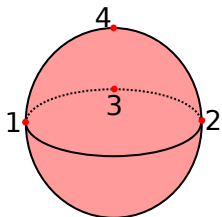
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$v_1$	0	2	1	1
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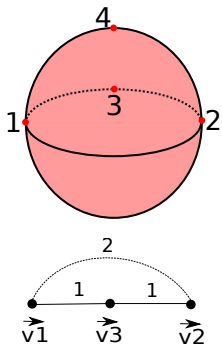
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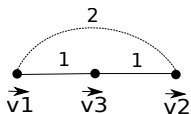
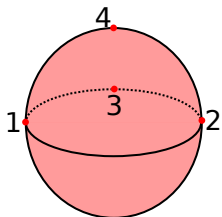
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$v_1, v_3, v_2$  along a line



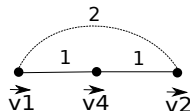
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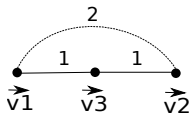
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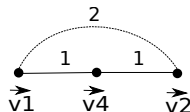


$v_1, v_4, v_2$  also along a line!

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$v_1, v_3, v_2$  along a line

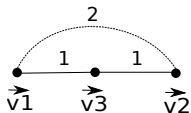


$v_1, v_4, v_2$  also along a line!

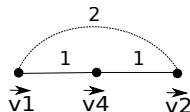
This implies that  $v_4$  and  $v_3$  must collapse to the same point in any Euclidean space.

- ▷ In other words, distances along the sphere cannot be perfectly realized using a Euclidean space of any finite dimension!

# MDS: Non-Euclidean Space Reduction



$v_1, v_3, v_2$  along a line



$v_1, v_4, v_2$  also along a line!

This implies that  $v_4$  and  $v_3$  must collapse to the same point in any Euclidean space.

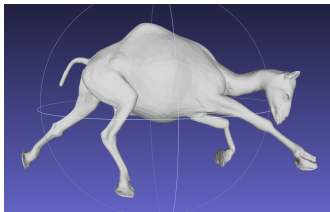
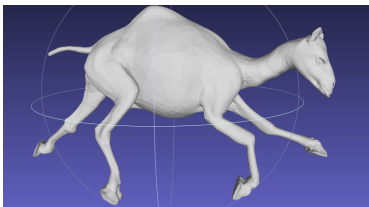
- ▷ In other words, distances along the sphere cannot be perfectly realized using a Euclidean space of any finite dimension!
- ▷ (But let's do our best and see what we come up with)

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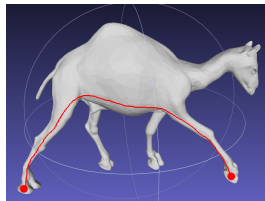
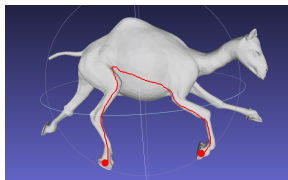
# Nonrigid Shape Alignment

How do I align these two camels??



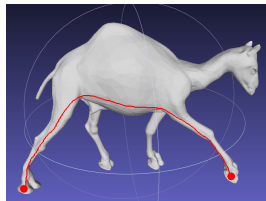
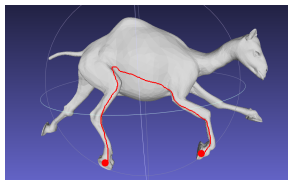
# Geodesic Distances

Geodesic distances are invariant to *isometries* (aka bending without stretching)



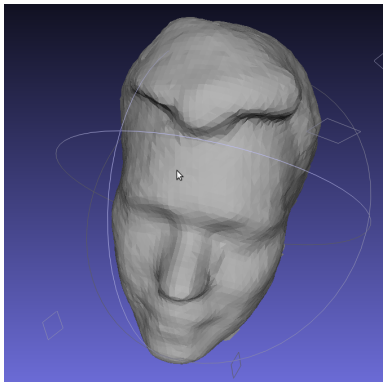
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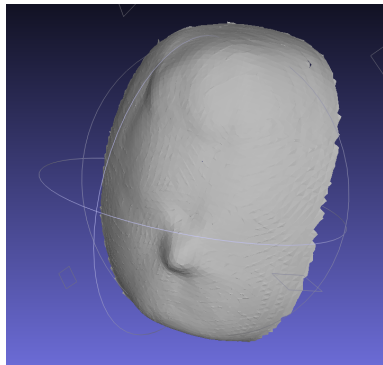
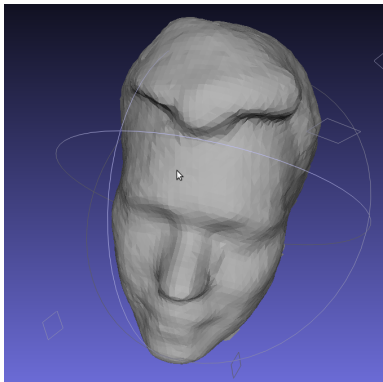
What if we try to apply MDS to the distance matrix we get from geodesic distances?

# Face Example

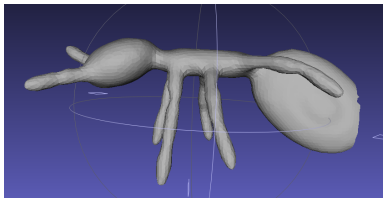




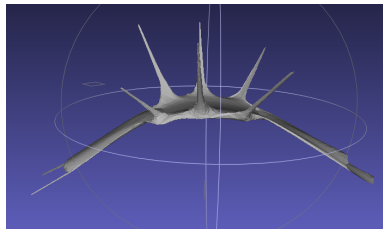
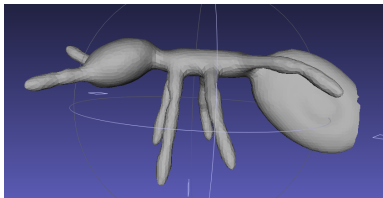
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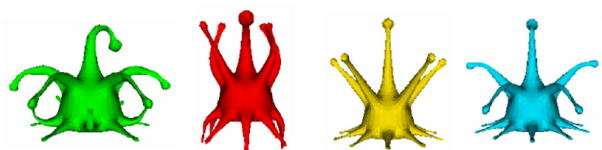
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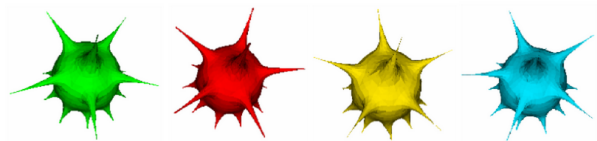
# Face Example



# More Examples



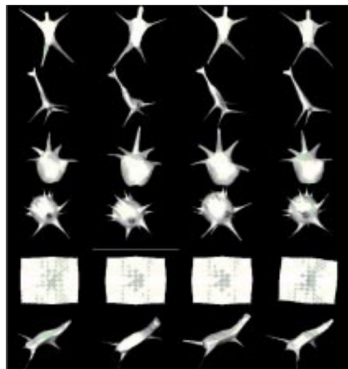
Near-isometric deformations of a shape



Canonical forms

Bronstein

# Lots More Examples



Elad Kimmel 2001: “Bending Invariant Representations for Surfaces”