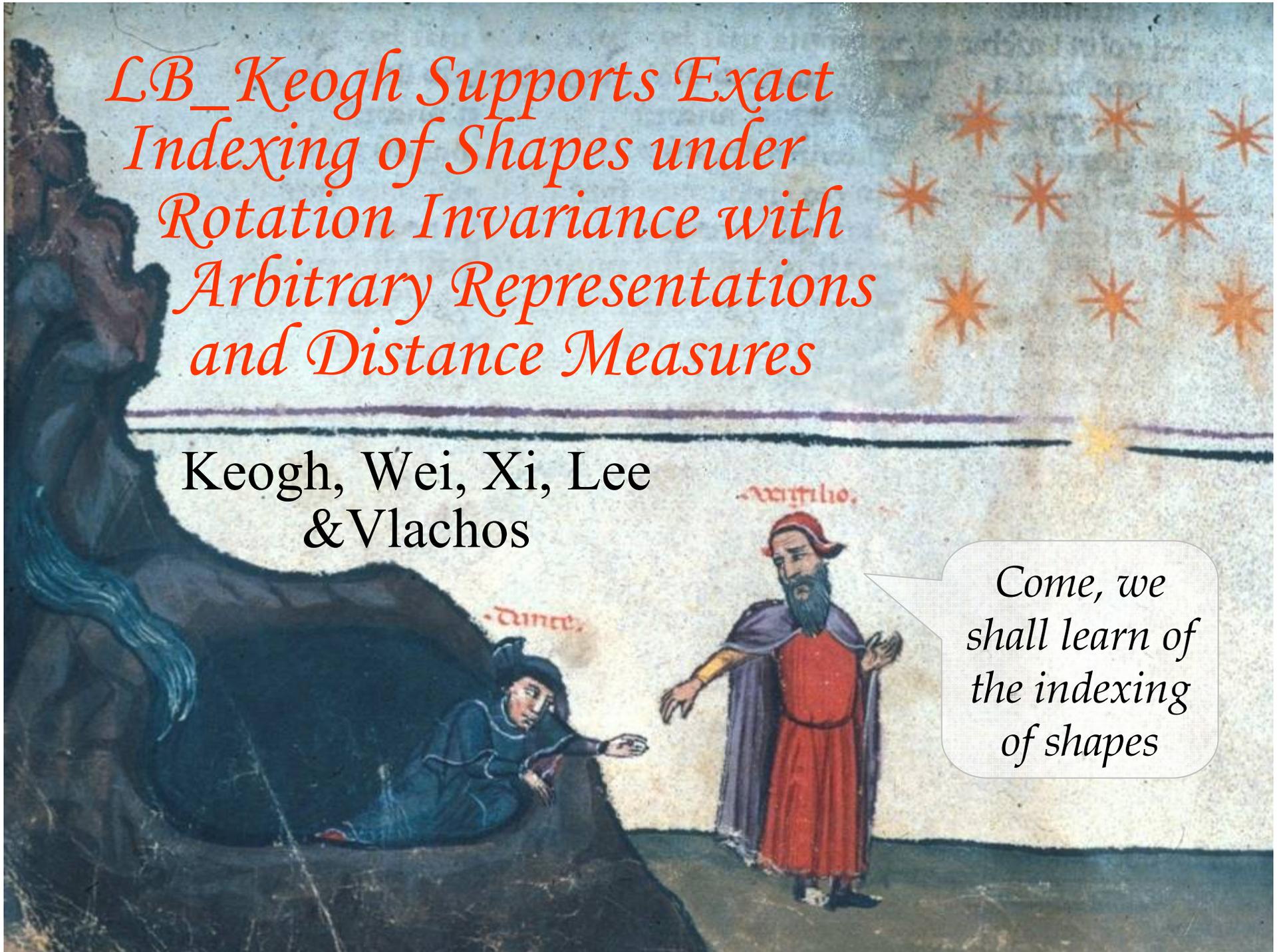


*LB\_Keogh Supports Exact  
Indexing of Shapes under  
Rotation Invariance with  
Arbitrary Representations  
and Distance Measures*

Keogh, Wei, Xi, Lee  
& Vlachos

*Come, we  
shall learn of  
the indexing  
of shapes*



*Set forth these figures as I have conceived their shape...\**

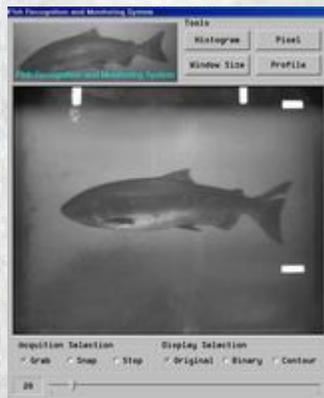
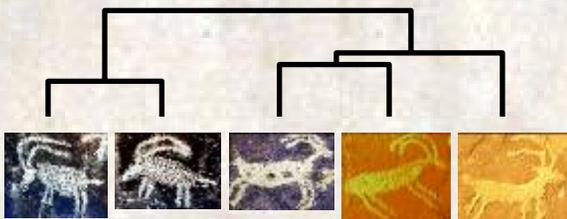
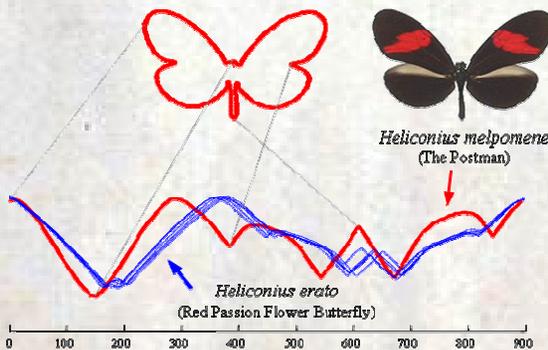
# Outline of Talk

- The utility of shape matching
- Shape representations
- Shape distance measures
- Lower bounding rotation invariant measures with the LB\_Keogh
- Accuracy experiments
- Efficiency experiments
- Conclusions

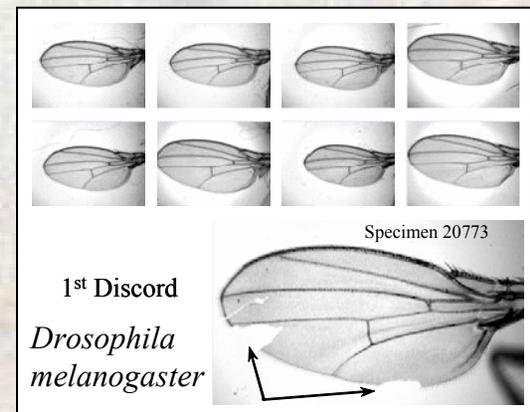
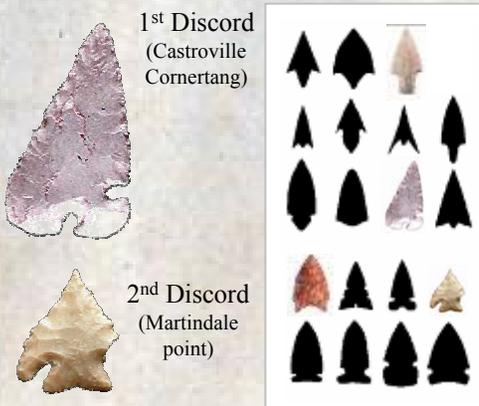


*\*Paradiso Canto XVIII 85*

# The Utility of Shape Matching I



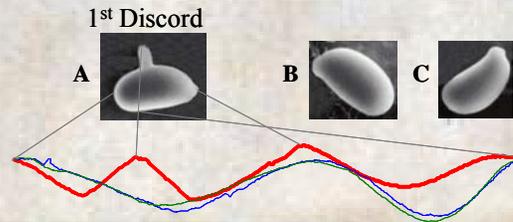
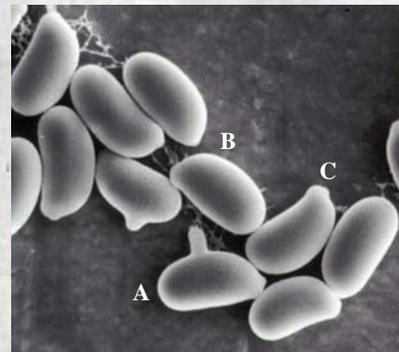
...discovering insect mimicry,  
clustering petroglyphs, finding unusual  
arrowheads, tracking fish migration,  
finding anomalous fruit fly wings...



# The Utility of Shape Matching II



*...automatically annotating old manuscripts, mining medical images, biometrics, spatial mining of horned lizards, indexing nematodes...*

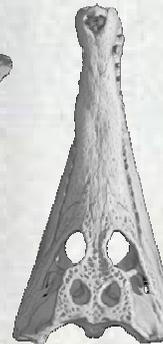
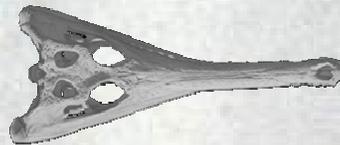


# Shape Representations I

For virtually all shape matching problems, *rotation* is the problem

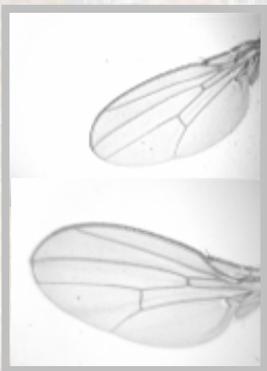


If I asked you to group these reptile skulls, *rotation* would not confuse you



There are two ways to be rotation invariant

- 1) Landmarking: Find the one “true” rotation
- 2) Rotation invariant features



# Landmarking

- **Domain Specific Landmarking**

Find some fixed point in your domain, eg. the nose on a face, the stem of leaf, the tail of a fish ...

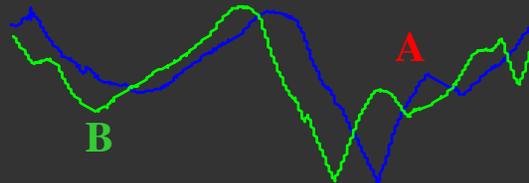
- **Generic Landmarking**

Find the major axis of the shape and use that as the canonical alignment

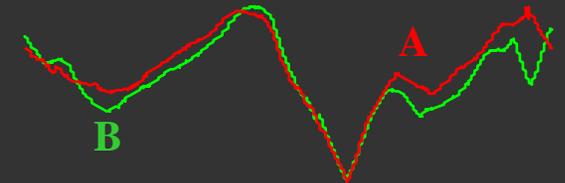


Generic Landmark Alignment

Generic Landmark Alignment



Best Rotation Alignment



*The only problem with landmarking is that it does not work*

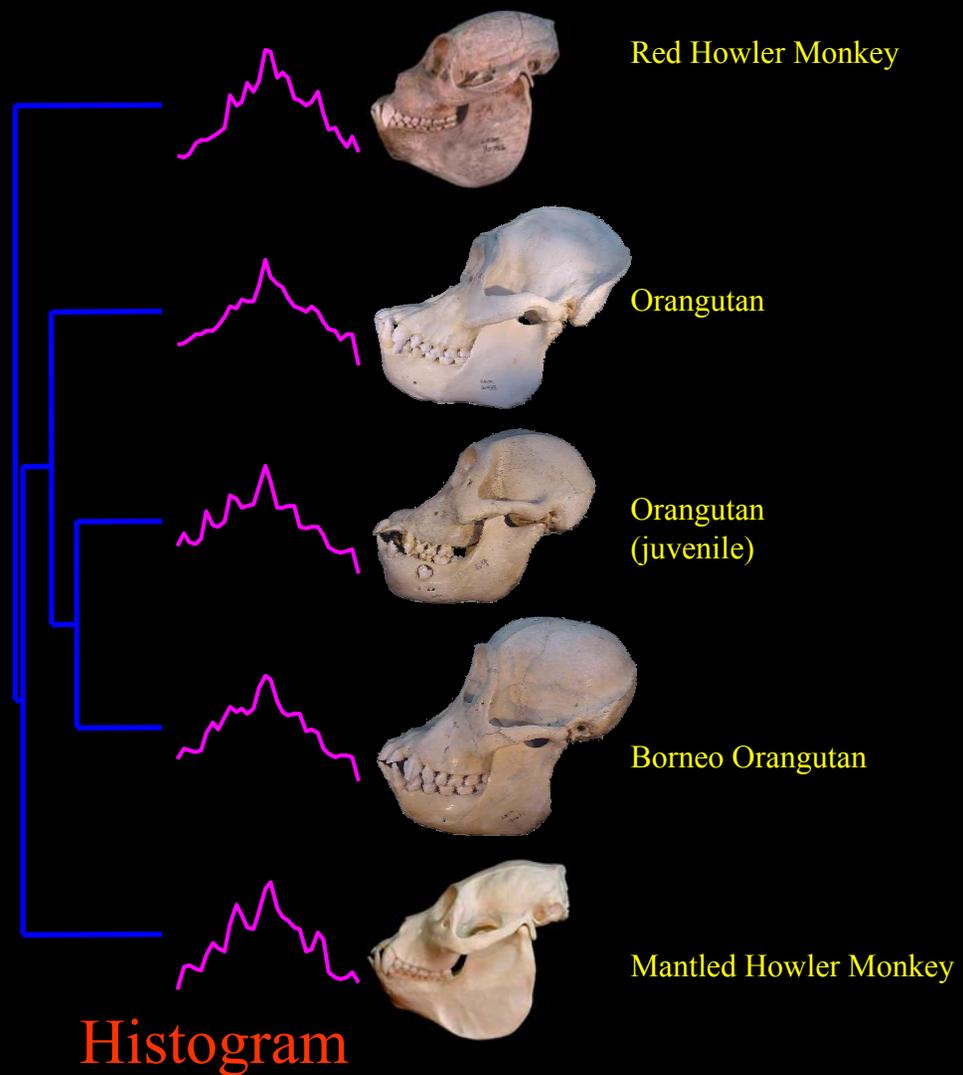
# Rotation invariant features

## Possibilities include:

Ratio of perimeter to area, fractal measures, elongatedness, circularity, min/max/mean curvature, entropy, perimeter of convex hull and histograms



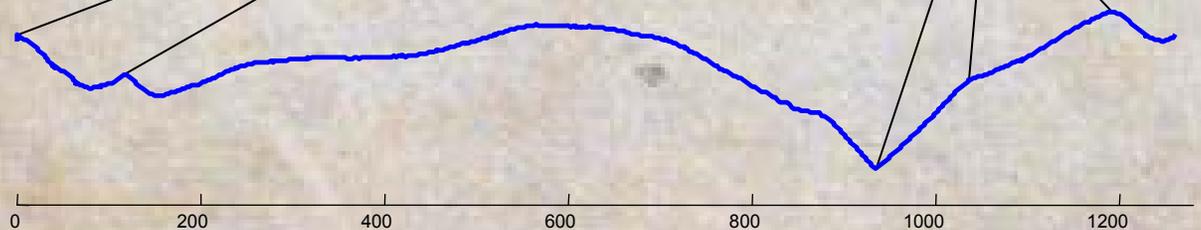
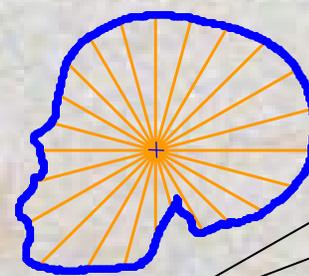
*The only problem with rotation invariant features is that in throwing away rotation information, you must invariably throw away useful information*



We can convert shapes into a 1D signal. Thus can we remove information about *scale* and *offset*.

*Rotation* we must deal with in our algorithms...

...so it seemed to change its shape, from running lengthwise to revolving round...\*



There are many other 1D representations of shape, and our algorithm can work with *any* of them

\*Dante Alighieri. The Divine Comedy Paradiso -- Canto XXX, 90.



# Shape Distance Measures

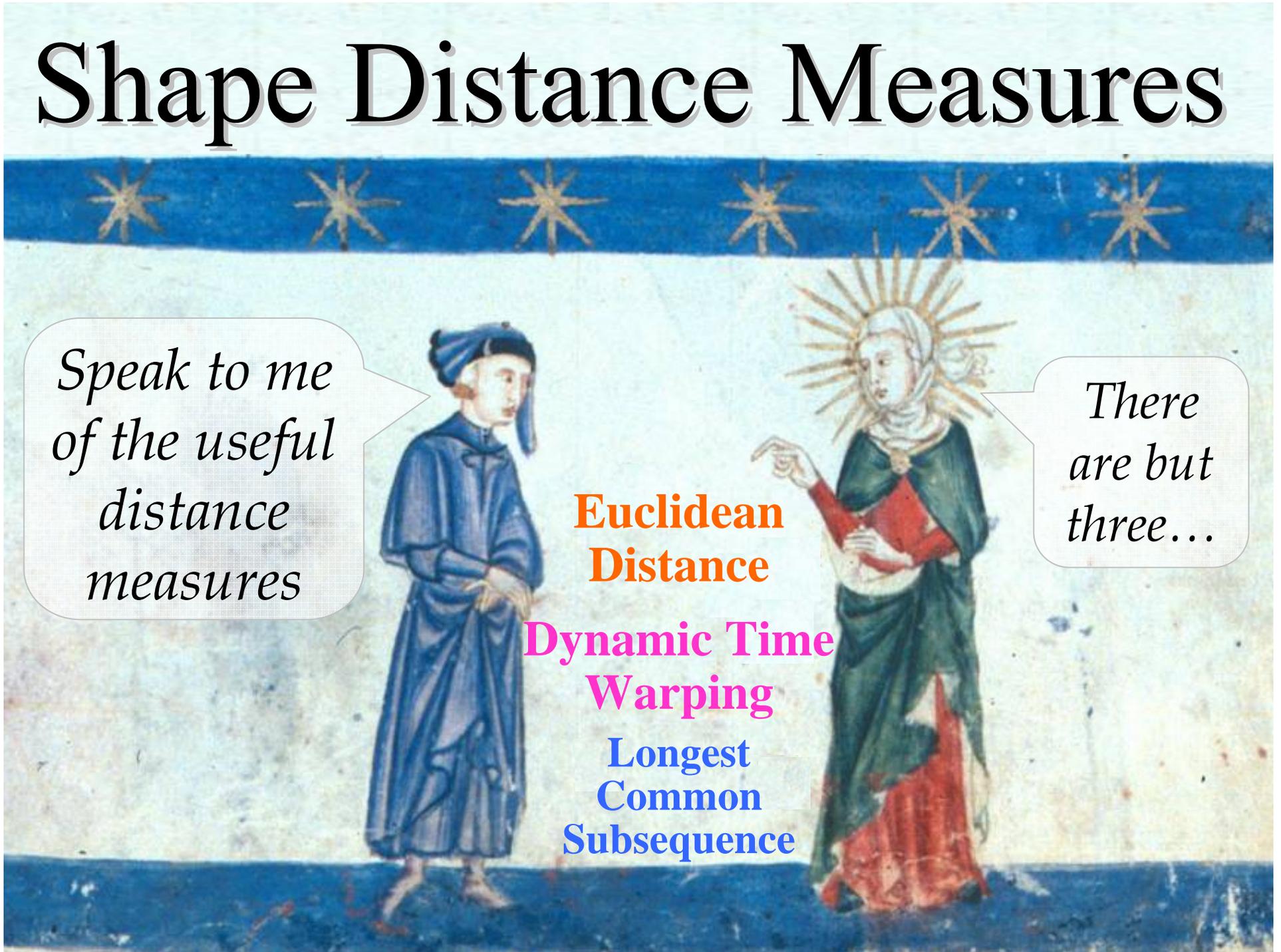
*Speak to me  
of the useful  
distance  
measures*

**Euclidean  
Distance**

**Dynamic Time  
Warping**

**Longest  
Common  
Subsequence**

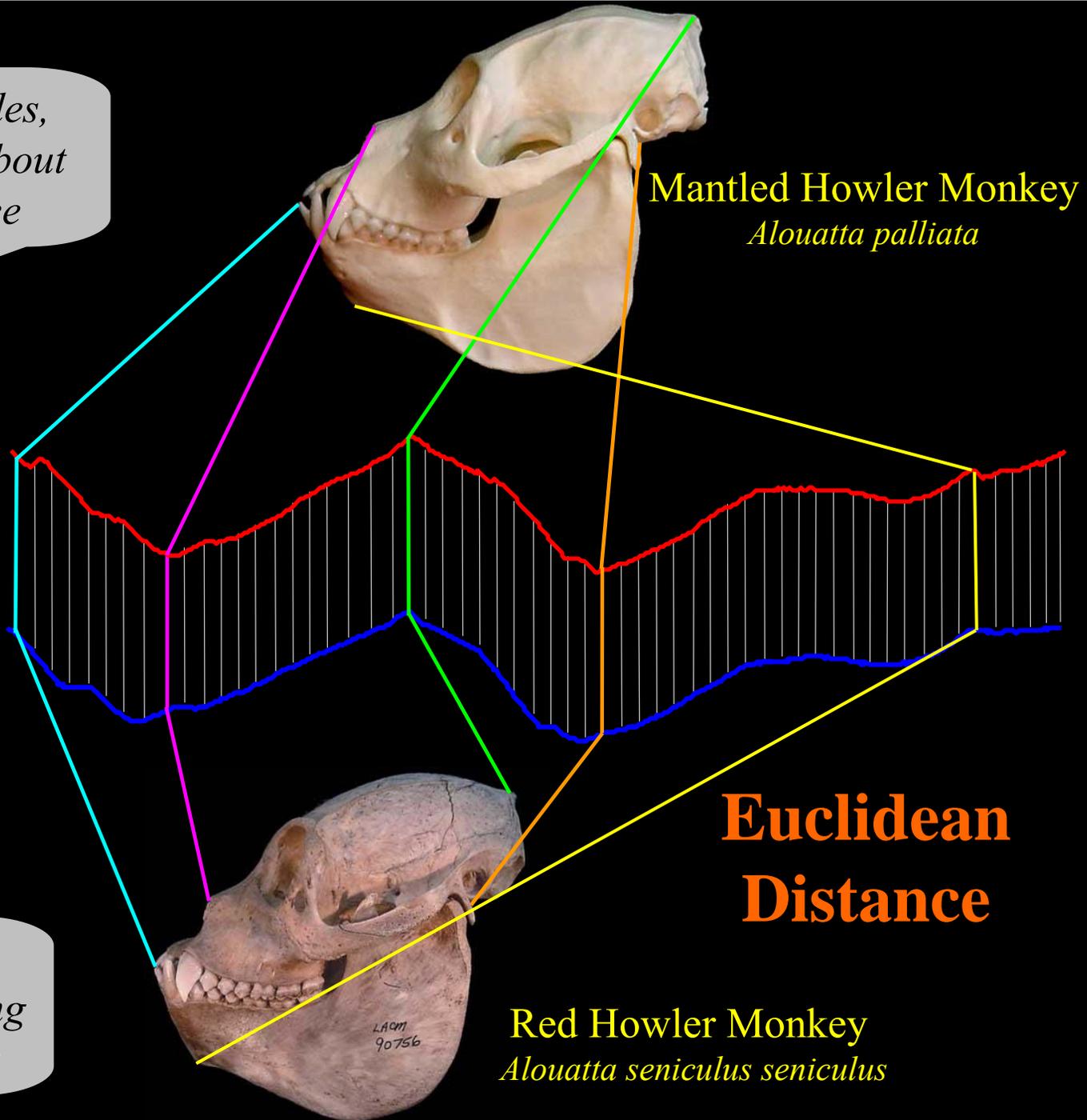
*There  
are but  
three...*



For the next ten slides,  
temporarily forget about  
rotation invariance



Euclidean Distance  
works well for matching  
many kinds of shapes

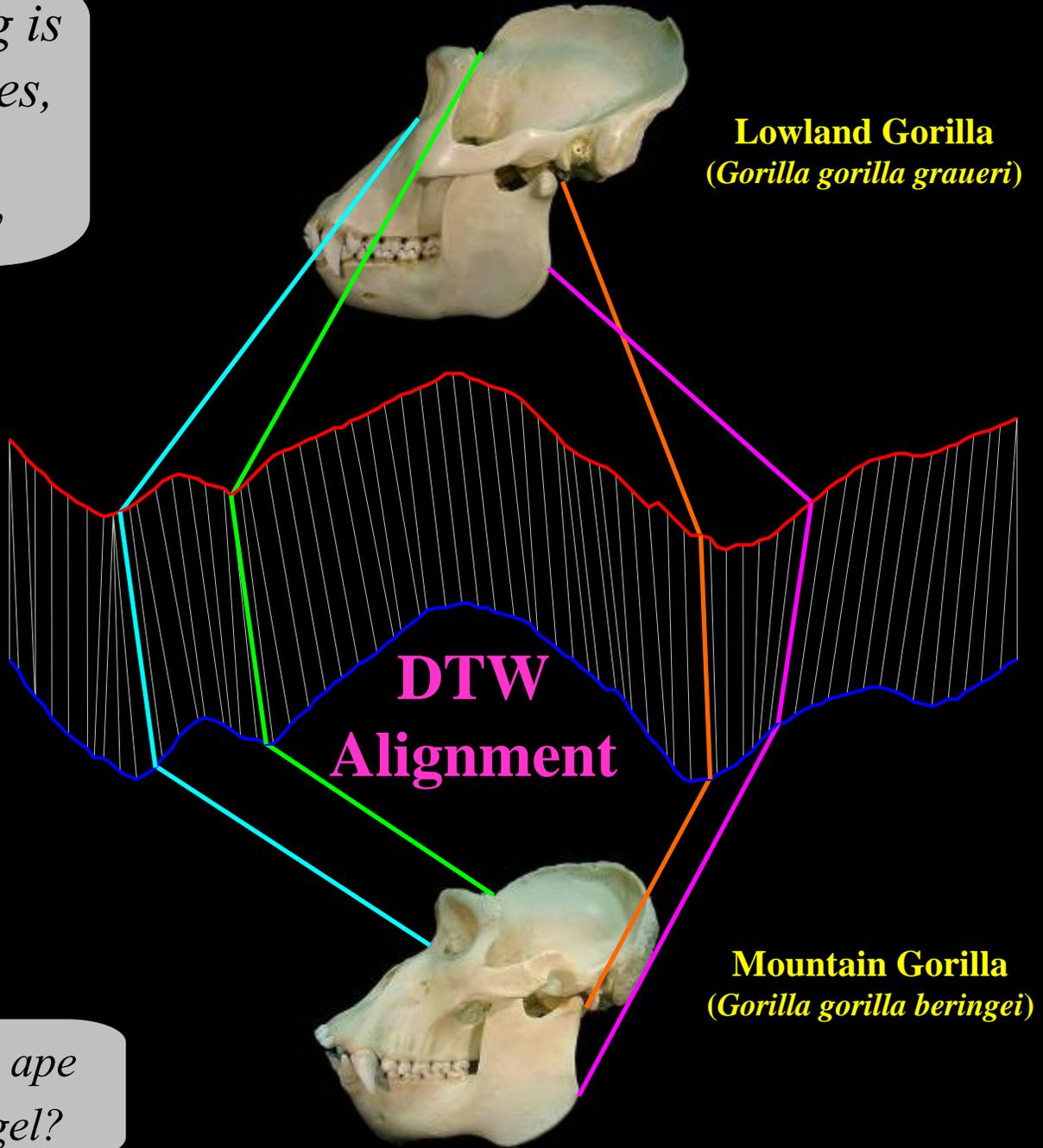


**Euclidean  
Distance**

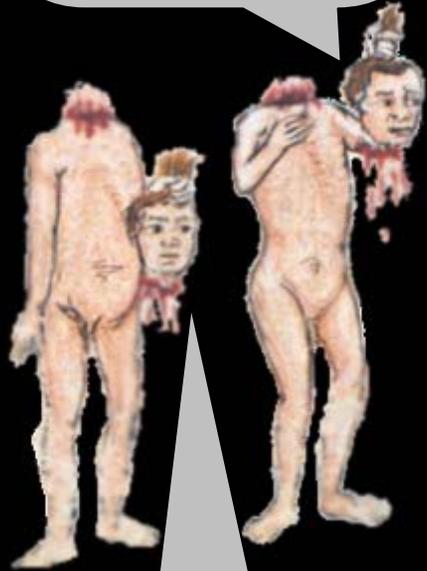
*Dynamic Time Warping is useful for natural shapes, which often exhibit intraclass variability*



*Is man an ape or an angel?*

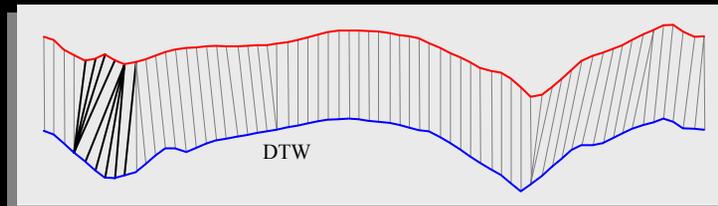
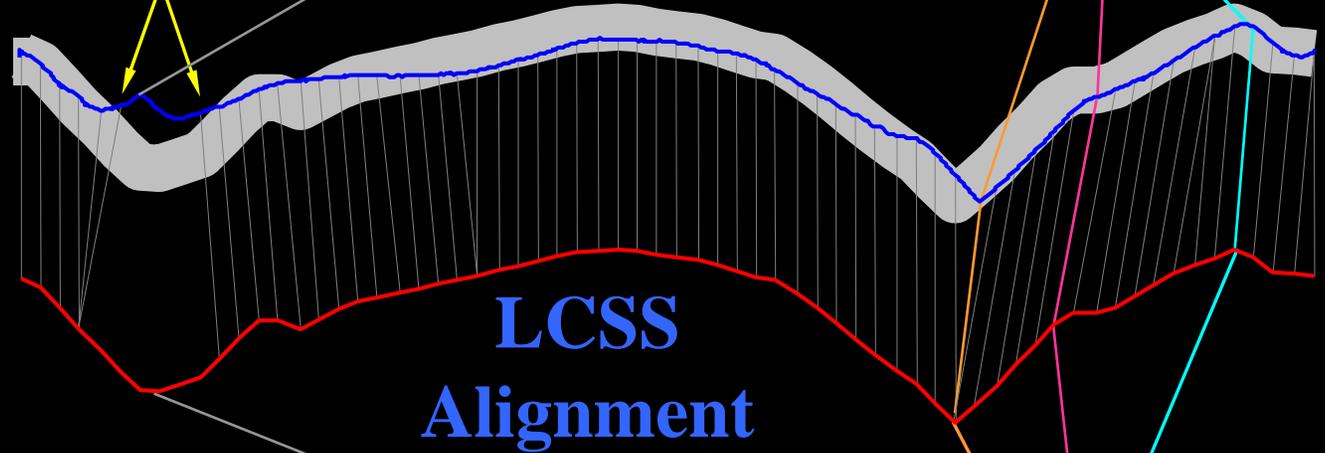


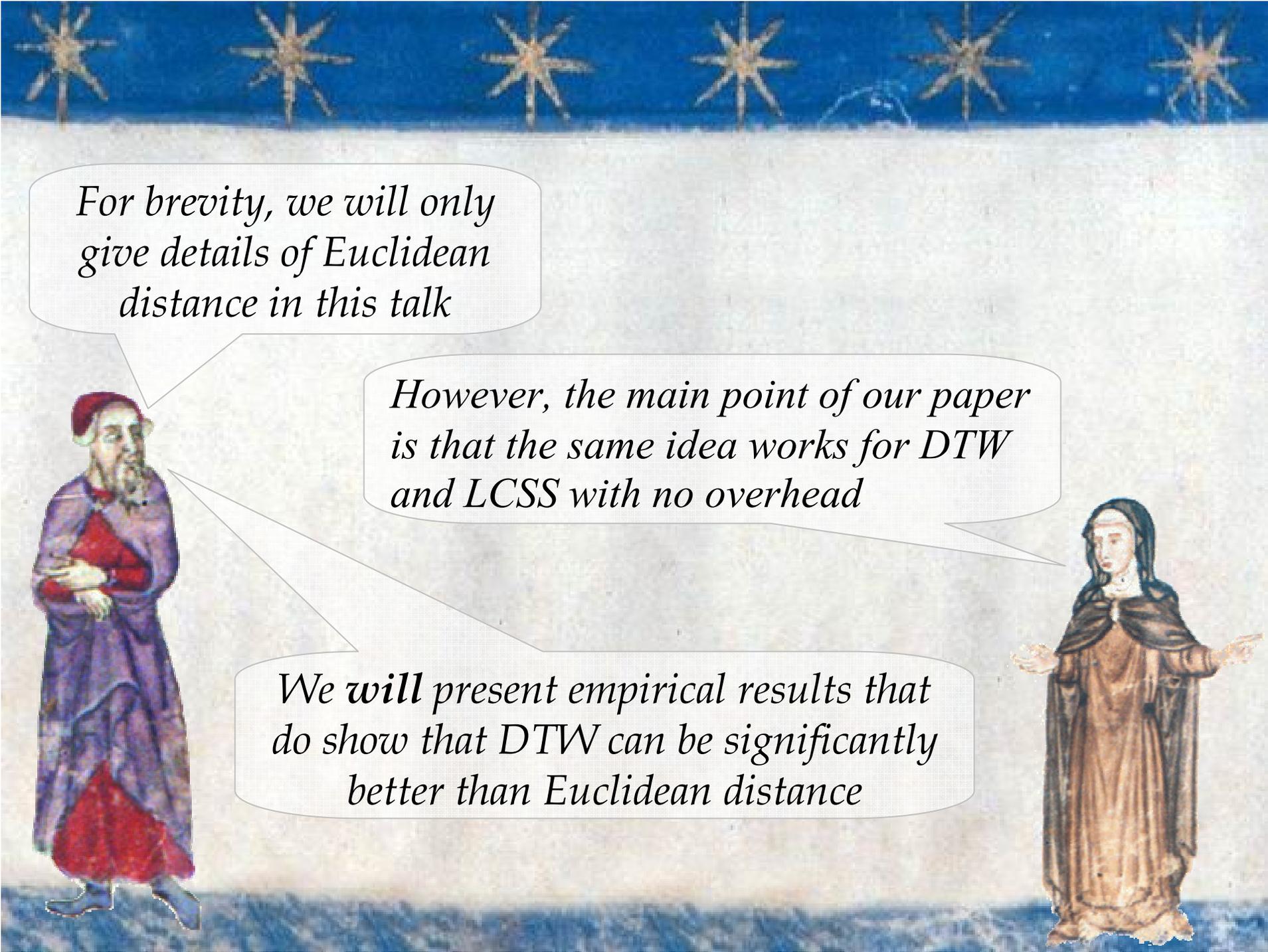
Matching skulls is an important problem



LCSS can deal with missing or occluded parts

This region will not be matched



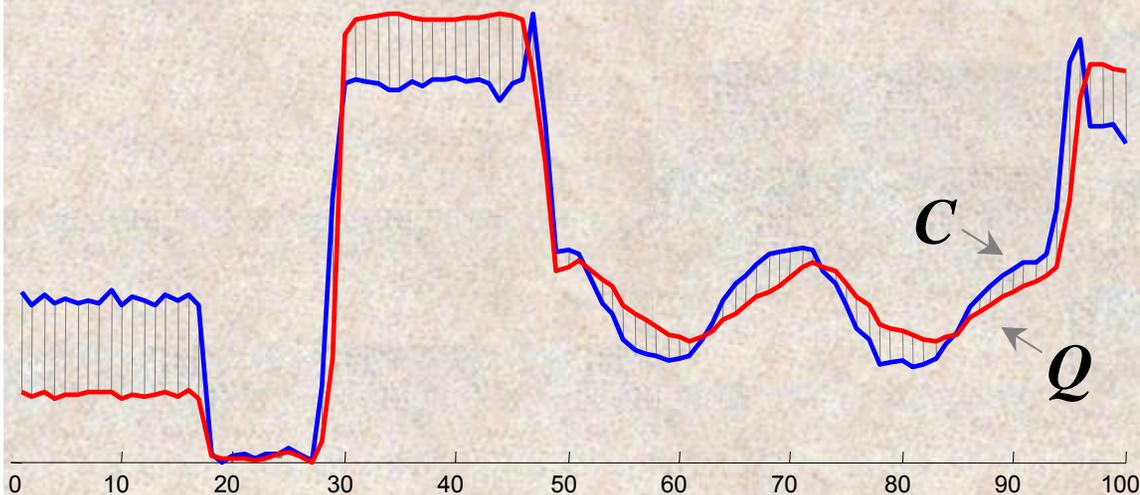


*For brevity, we will only give details of Euclidean distance in this talk*

*However, the main point of our paper is that the same idea works for DTW and LCSS with no overhead*

*We will present empirical results that do show that DTW can be significantly better than Euclidean distance*

# Euclidean Distance Metric



Given two time series  $Q = q_1 \dots q_n$  and  $C = c_1 \dots c_n$ , the Euclidean distance between them is defined as:

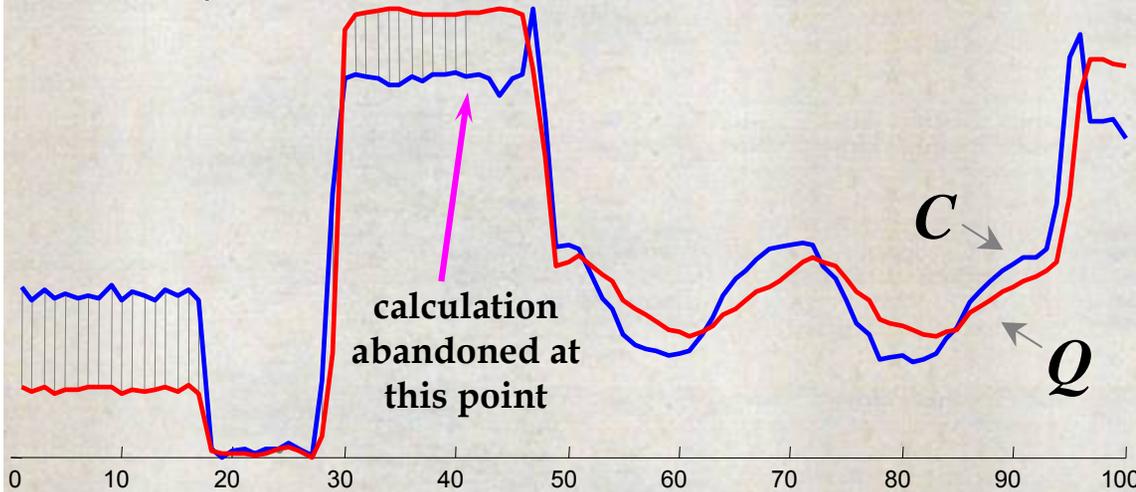
$$D(Q, C) \equiv \sqrt{\sum_{i=1}^n (q_i - c_i)^2}$$

I notice that you Z-normalized the time series first

The next slide shows a useful optimization



# Early Abandon Euclidean Distance



During the computation, if current sum of the squared differences between each pair of corresponding data points exceeds  $r^2$ , we can safely **abandon** the calculation

I see, because incremental value is always a lower bound to the final value, once it is greater than the best-so-far, we may as well abandon

**Abandon** all hope ye who enter here



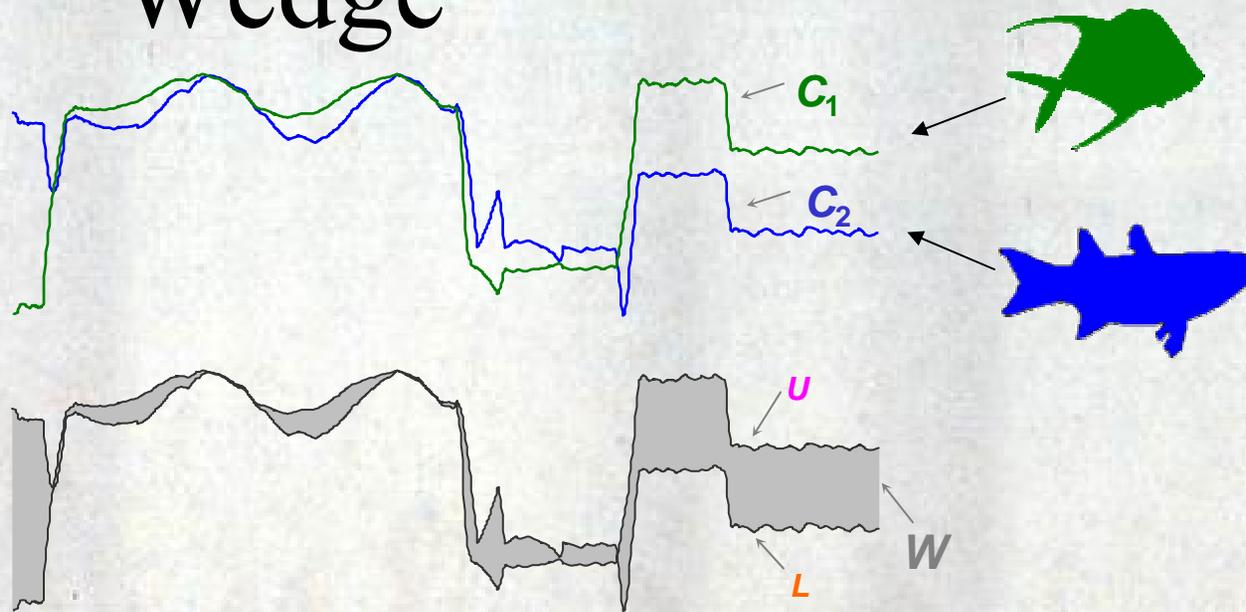
*Most indexing techniques work by grouping objects into logical units, and defining a lower bound distance to the units*

*For example, for indexing cities we can use MBRs and the classic MIN-DIST function of Guttman*

*Here we will use “wedges” as the logical unit, and LB\_Keogh as the lower bound distance*



# Wedge



Suppose two shapes get converted to time series...



Having candidate sequences  $C_1, \dots, C_k$ , we can form two new sequences  $U$  and  $L$  :

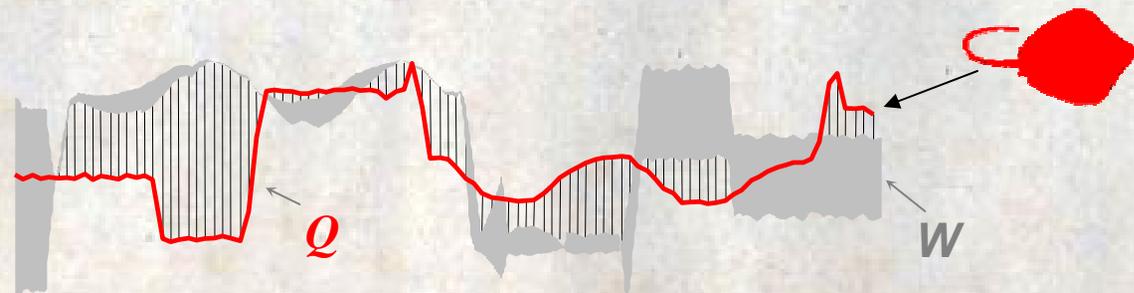
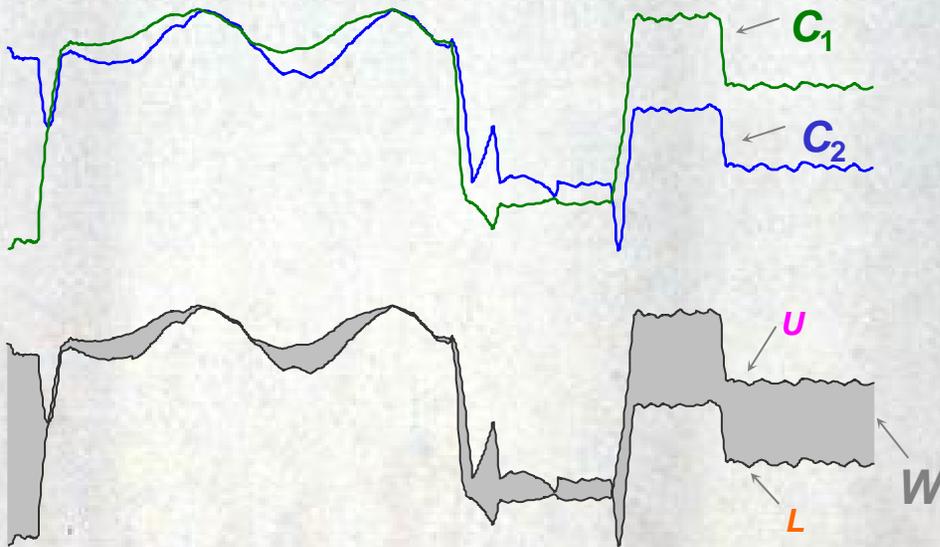
$$U_i = \max(C_{1i}, \dots, C_{ki})$$

$$L_i = \min(C_{1i}, \dots, C_{ki})$$

They form the smallest possible bounding envelope that encloses sequences  $C_1, \dots, C_k$ .

We call the combination of  $U$  and  $L$  a *wedge*, and denote a wedge as  $W$ .  $W = \{U, L\}$

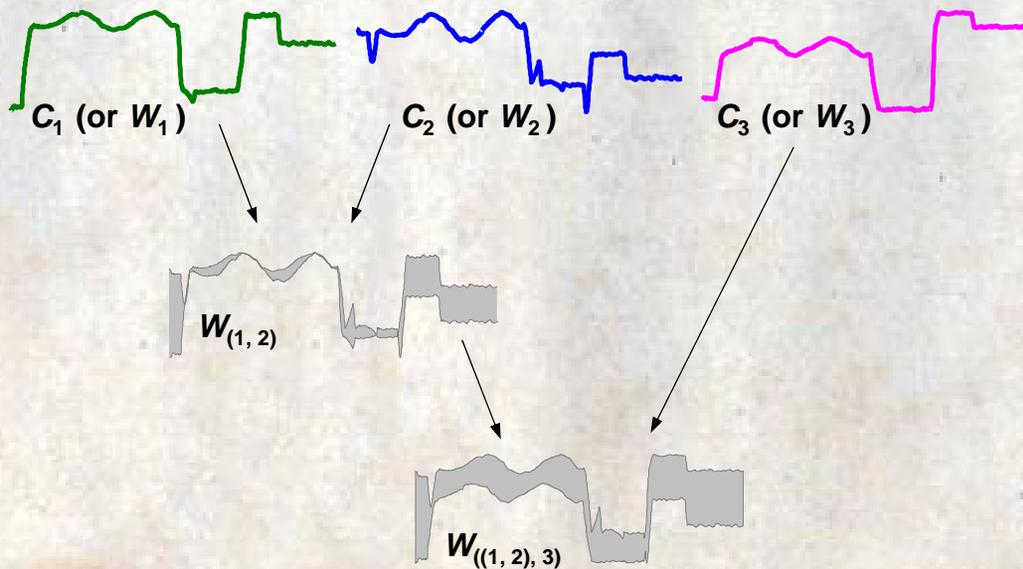
A lower bounding measure between an arbitrary query  $Q$  and the set of candidate sequences contained in a wedge  $W$ , is the  $LB\_Keogh$



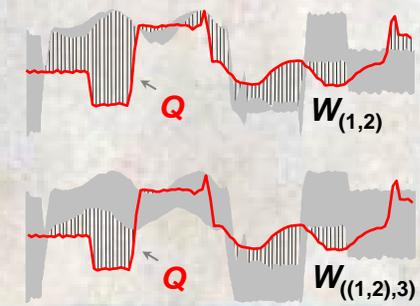
$$LB\_Keogh(Q, W) = \sqrt{\sum_{i=1}^n \begin{cases} (q_i - U_i)^2 & \text{if } q_i > U_i \\ (q_i - L_i)^2 & \text{if } q_i < L_i \\ 0 & \text{otherwise} \end{cases}}$$

# Generalized Wedge

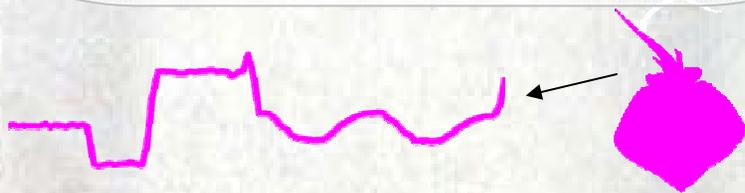
- Use  $W_{(1,2)}$  to denote that a wedge is built from sequences  $C_1$  and  $C_2$ .
- Wedges can be hierarchically nested. For example,  $W_{((1,2),3)}$  consists of  $W_{(1,2)}$  and  $C_3$ .



*Of course, fatter wedges mean looser lower bounds...*



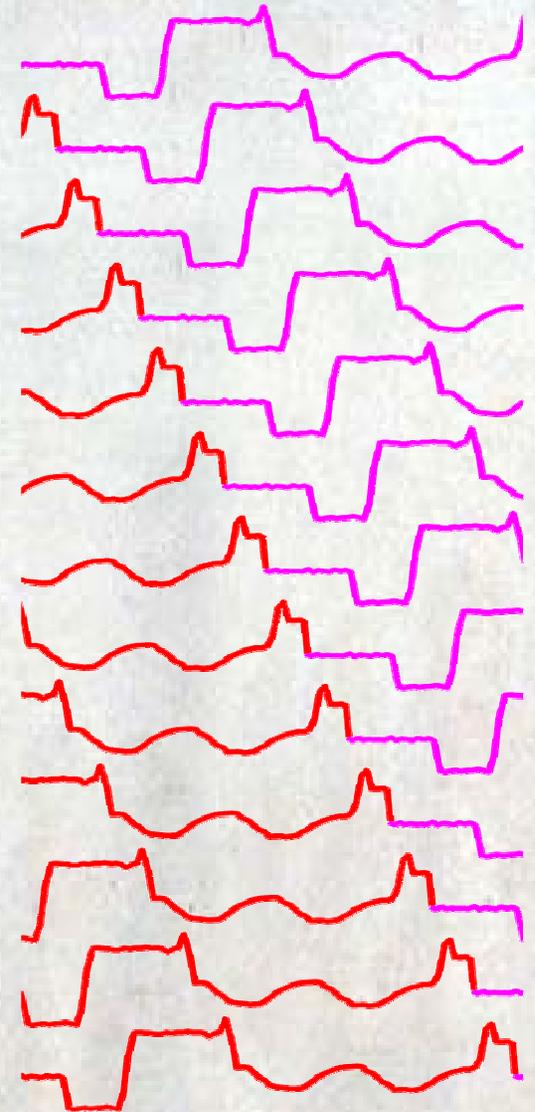
*We are finally ready to explain our idea for rotation invariance, an idea we have sidestepped to this point. Suppose we have a shape as before...*



*We can create every possible rotation of the shape, by considering every possible circular shift of the time series, as shown at my left...*

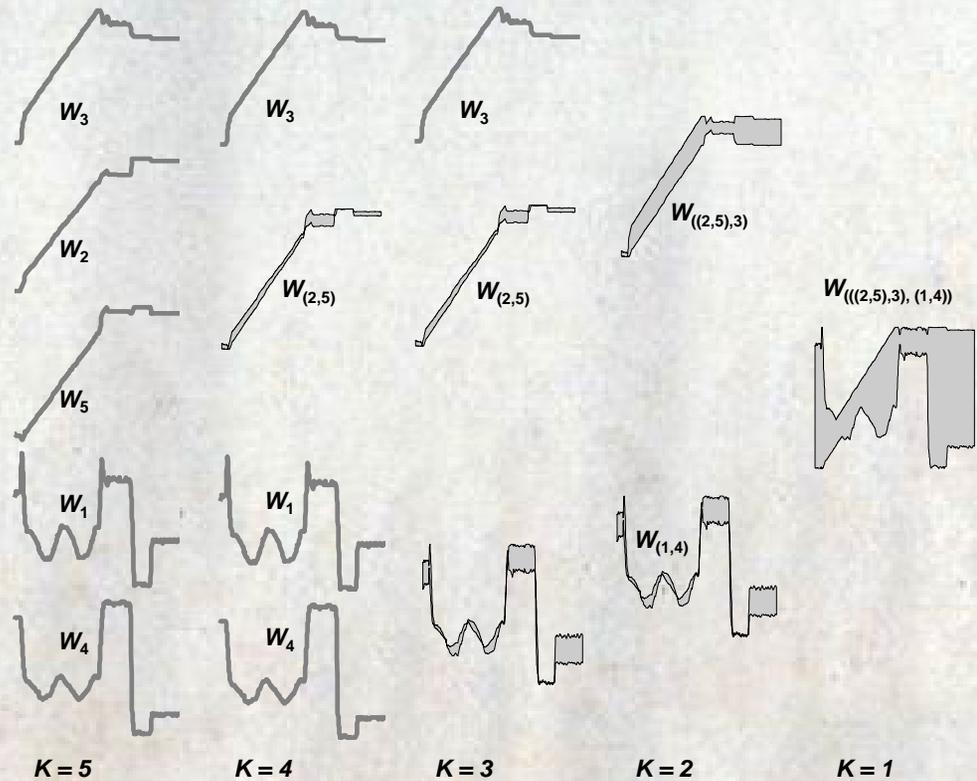
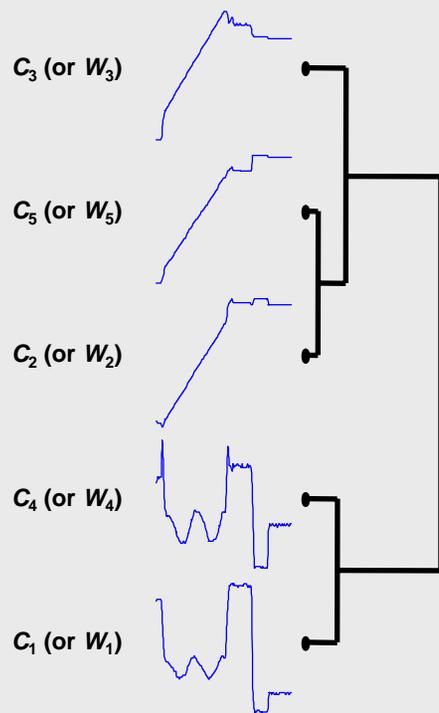
*But we already know how to index such time series by using wedges!*

*We just need to figure out the best wedge making policy..*



*It sucks being a grad student*

# Hierarchical Clustering



**Which wedge set to choose ?**

*Once we have all possible rotations of all the objects we want to index inserted into wedges, we can simply use any LB\_Keogh indexer*

*Since the introduction of LB\_Keogh indexing at this conference 4 years ago, at least 50 groups around the world have used/extended/adapted the idea, making this work easily reimplementable*

*What are the disadvantages of using LB\_Keogh?*

*There are Nun*





*"LB\_Keogh has provided a convincing lower bound" T. Rath*

*"LB\_Keogh can significantly speed up DTW." Suzuki*

*"LB\_Keogh is the best...". Zhou & Wong*

*"LB\_Keogh offers the tightest lower bounds". M. Cardle.*

*"LB\_Keogh makes retrieval of time-warped time series feasible even for large data sets". Muller et. al.*

*"LB\_Keogh can be effectively used, resulting in considerably less number of DTW computations." Karydis*

*"exploiting LB\_Keogh, we can guarantee indexability". Bartolini et. al.*

*"LB\_Keogh, the best method to lower bound.." Capitani.*

*"LB\_Keogh is fast, because it cleverly exploits global constraints that appear in dynamic programming"*

*Christos Faloutsos.*

***By using the LB\_Keogh framework, we can leverage off the wealth of work in the literature***

# All our Experiments are Reproducible!

*People that do irreproducible experiments should be boiled alive*

*Agreed!  
All our  
data is  
publicly  
available*



# We tested on many diverse datasets

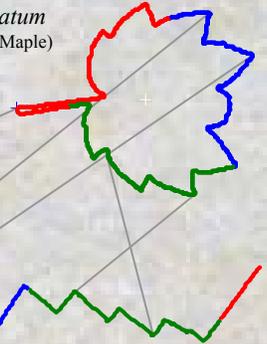
...and I recognized  
the face <sup>¥</sup>



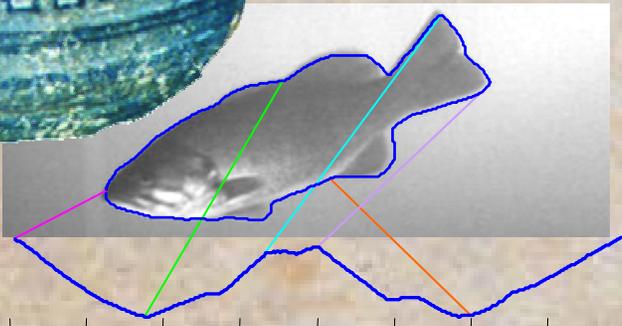
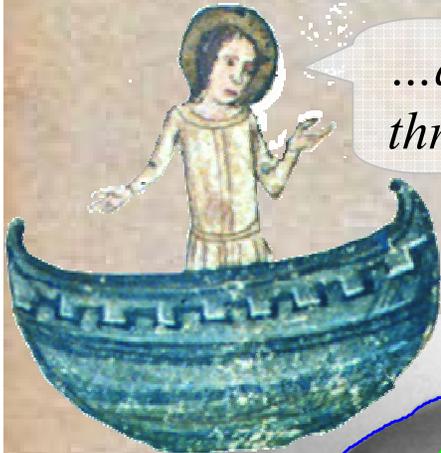
Leaf of mine, in whom I found pleasure <sup>ĩ</sup>



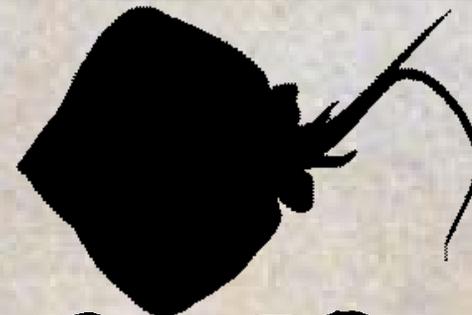
*Acer circinatum*  
(Oregon Vine Maple)



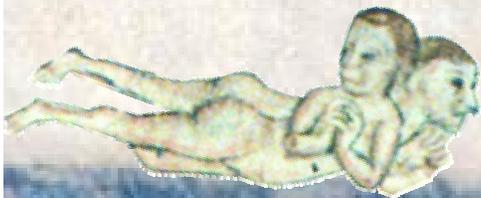
...as a fish dives  
through water <sup>£</sup>



...the shape of that cold  
animal which stings and  
lashes people with its tail <sup>\*</sup>



<b>Name</b>	Classes	Instances	Euclidean Error (%)	DTW Error (%) $\{R\}$	Other Techniques
Face	16	2240	3.839	<b>3.170</b> $\{3\}$	
Swedish Leaves	15	1125	13.33	<b>10.84</b> $\{2\}$	
Chicken	5	446	19.96	19.96 $\{1\}$	20.5 Discrete strings
MixedBag	9	160	4.375	4.375 $\{1\}$	Chamfer 6.0, Hausdorff 7.0
OSU Leaves	6	442	33.71	<b>15.61</b> $\{2\}$	
Diatoms	37	781	27.53	27.53 $\{1\}$	26.0 Morphological Curvature Scale Spaces
Plane	7	210	0.95	<b>0.0</b> $\{3\}$	0.55 Markov Descriptor
Fish	7	350	11.43	<b>9.71</b> $\{1\}$	36.0 Fourier /Power Cepstrum



*Note that DTW is sometimes worth the little extra effort*

*Implementation details should not matter, for example the results reported should be the same if reimplemented in Red Hat Linux*

*We therefore use a cost model that is independent of hardware/software/buffer size etc. See the paper for details*

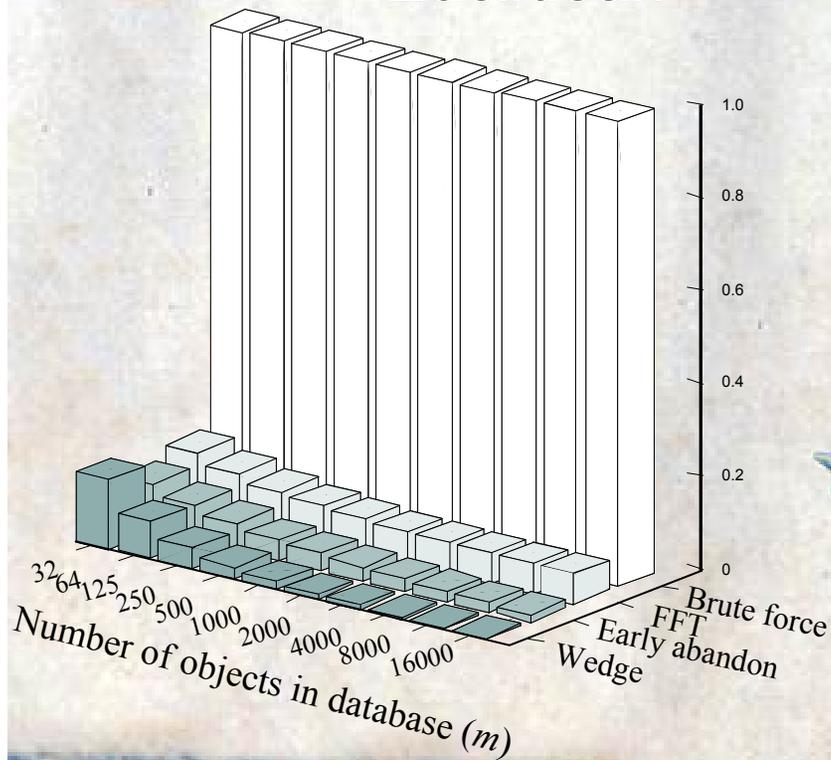
*We compare to brute force, and were possible a Fourier based approach (it can't handle DTW)*



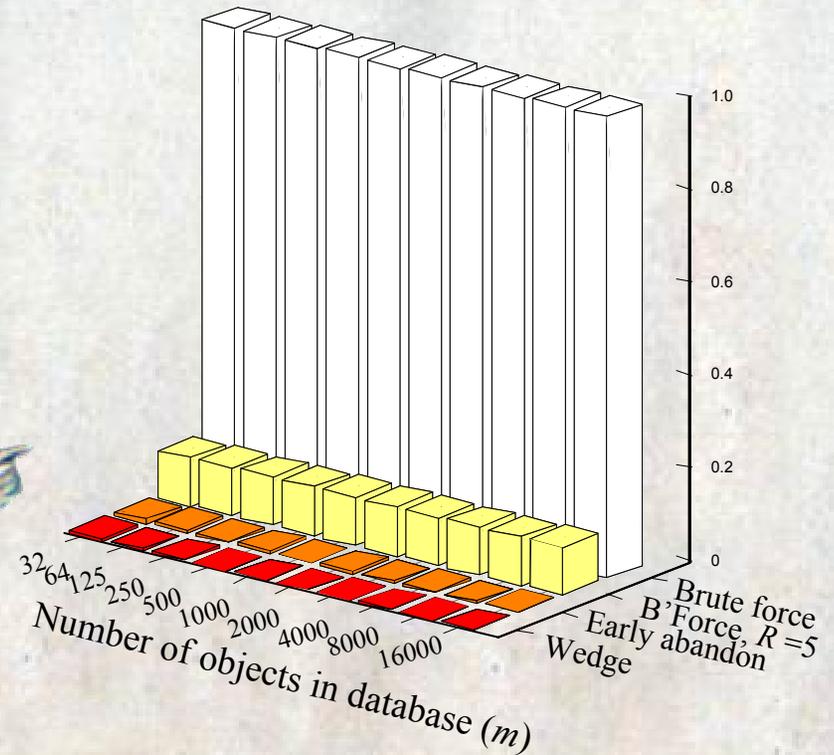
# Main Memory Experiments

- Projectile point database
- Increasingly larger datasets
- One-nearest-neighbor queries

## Euclidean



## DTW

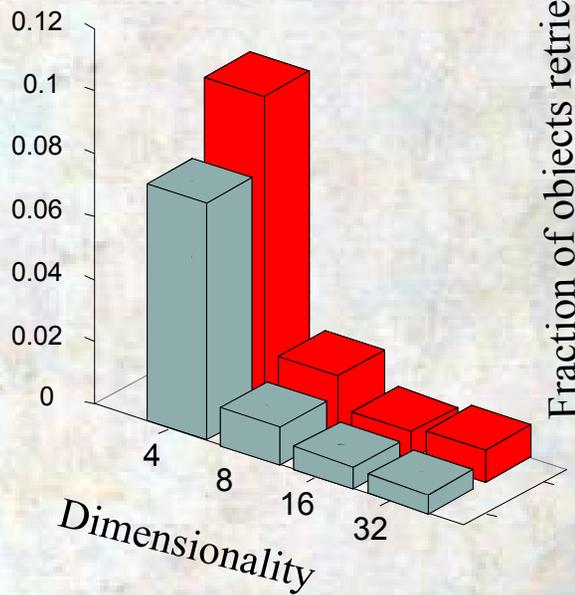


# Indexing Experiments

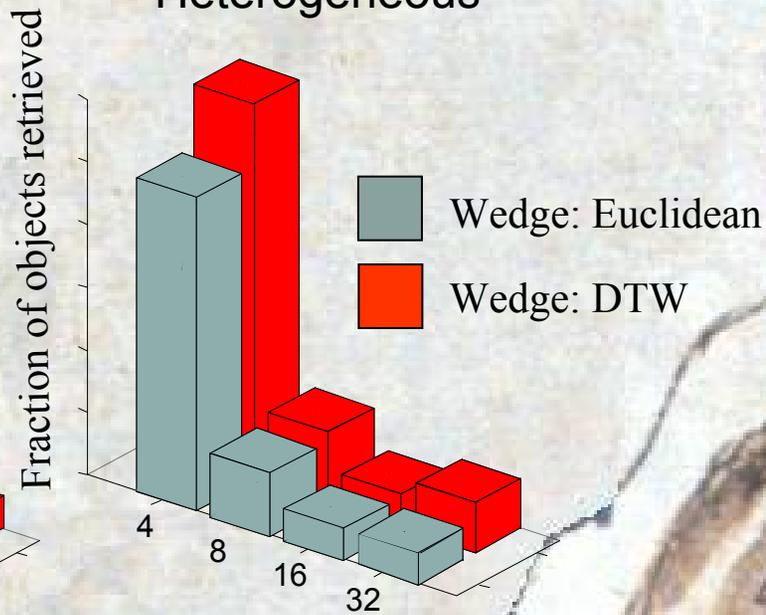
- Projectile point/Heterogeneous databases
- Increasingly large dimensionality
- One-nearest-neighbor queries



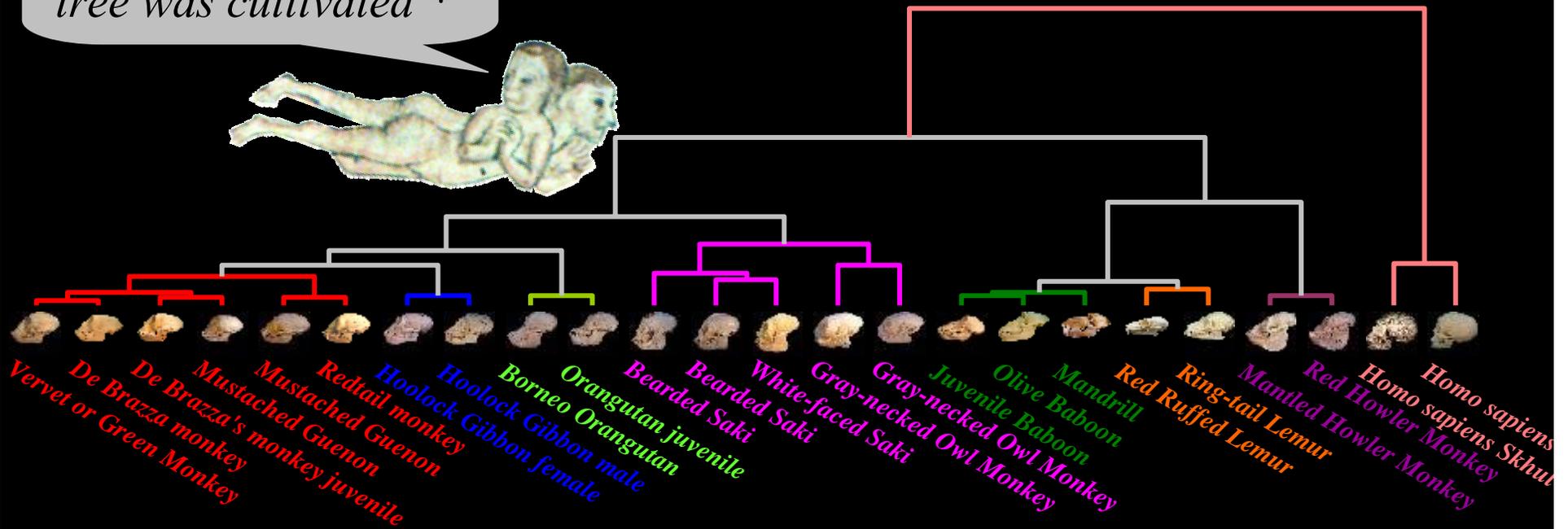
Projectile Points



Heterogeneous



... from its stock this tree was cultivated \*



All these are in the genus *Cercopithecus*, except for the skull identified as being either a Vervet or Green monkey, both of which belong in the Genus of *Chlorocebus* which is in the same Tribe (**Cercopithecini**) as *Cercopithecus*.

Tribe *Cercopithecini*

*Cercopithecus*

- De Brazza's Monkey, *Cercopithecus neglectus*
- Mustached Guenon, *Cercopithecus cephus*
- Red-tailed Monkey, *Cercopithecus ascanius*

*Chlorocebus*

- Green Monkey, *Chlorocebus sabaceus*
- Vervet Monkey, *Chlorocebus pygerythrus*

These are the same species  
*Bunopithecus hooloc* (Hoolock Gibbon)

These are in the Genus **Pongo**

All these are in the family **Cebidae**  
Family *Cebidae* (*New World monkeys*)

Subfamily *Aotinae*

*Aotus trivirgatus*

Subfamily *Pitheciinae sakis*

*Black Bearded Saki, Chiropotes satanas*

*White-nosed Saki, Chiropotes albinasus*

All these are in the tribe

**Papionini**

Tribe *Papionini*

Genus *Papio* – baboons

Genus *Mandrillus*- Mandrill

These are in the family **Lemuridae**

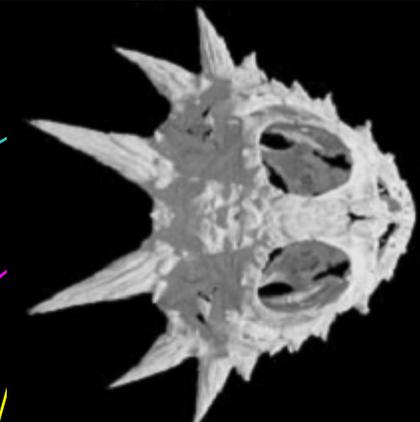
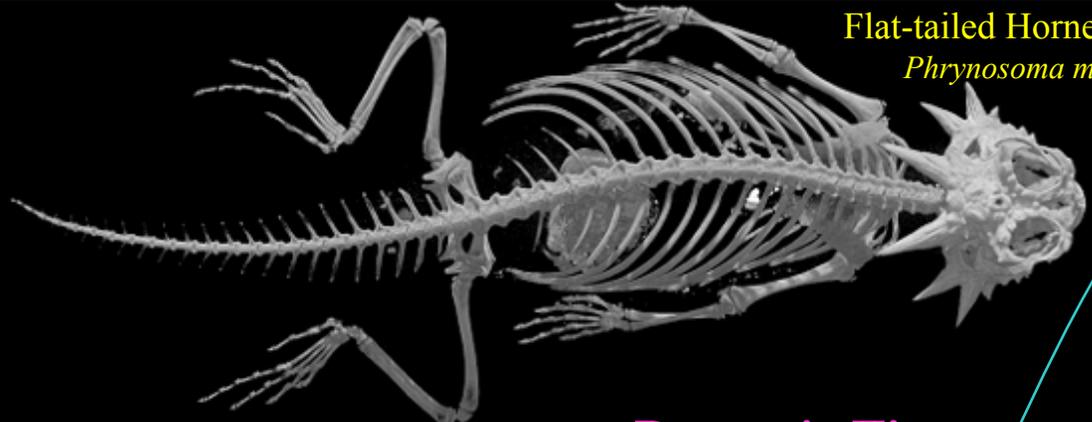
These are in the genus **Alouatta**

These are in the same species

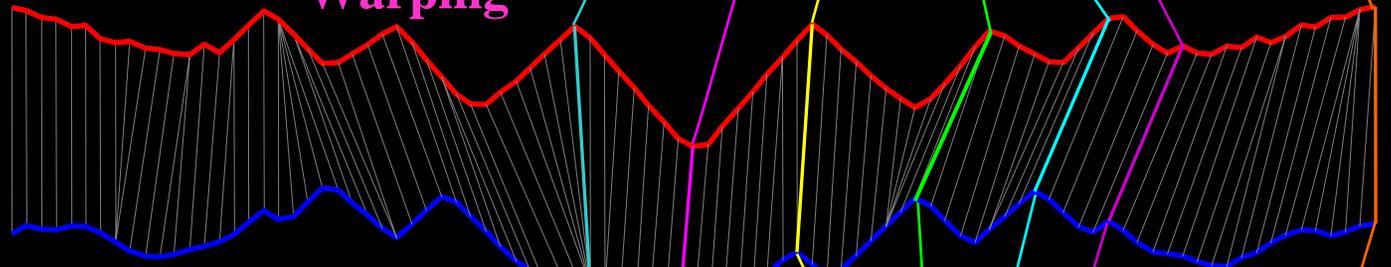
**Homo sapiens** (Humans)

\*Purgatorio -- Canto XXIV 117

Flat-tailed Horned Lizard  
*Phrynosoma mcallii*



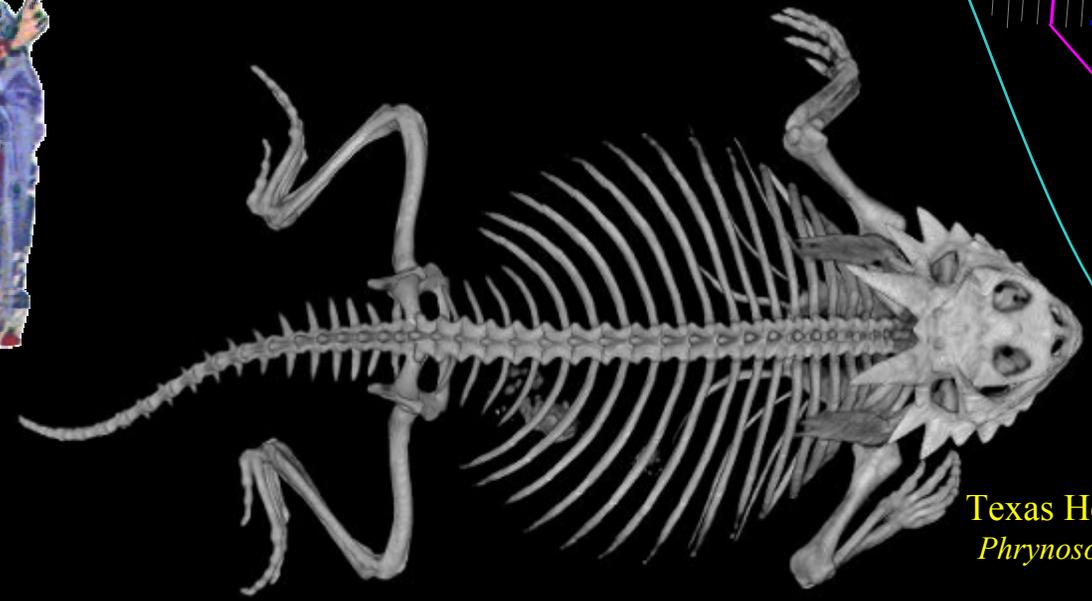
**Dynamic Time  
Warping**



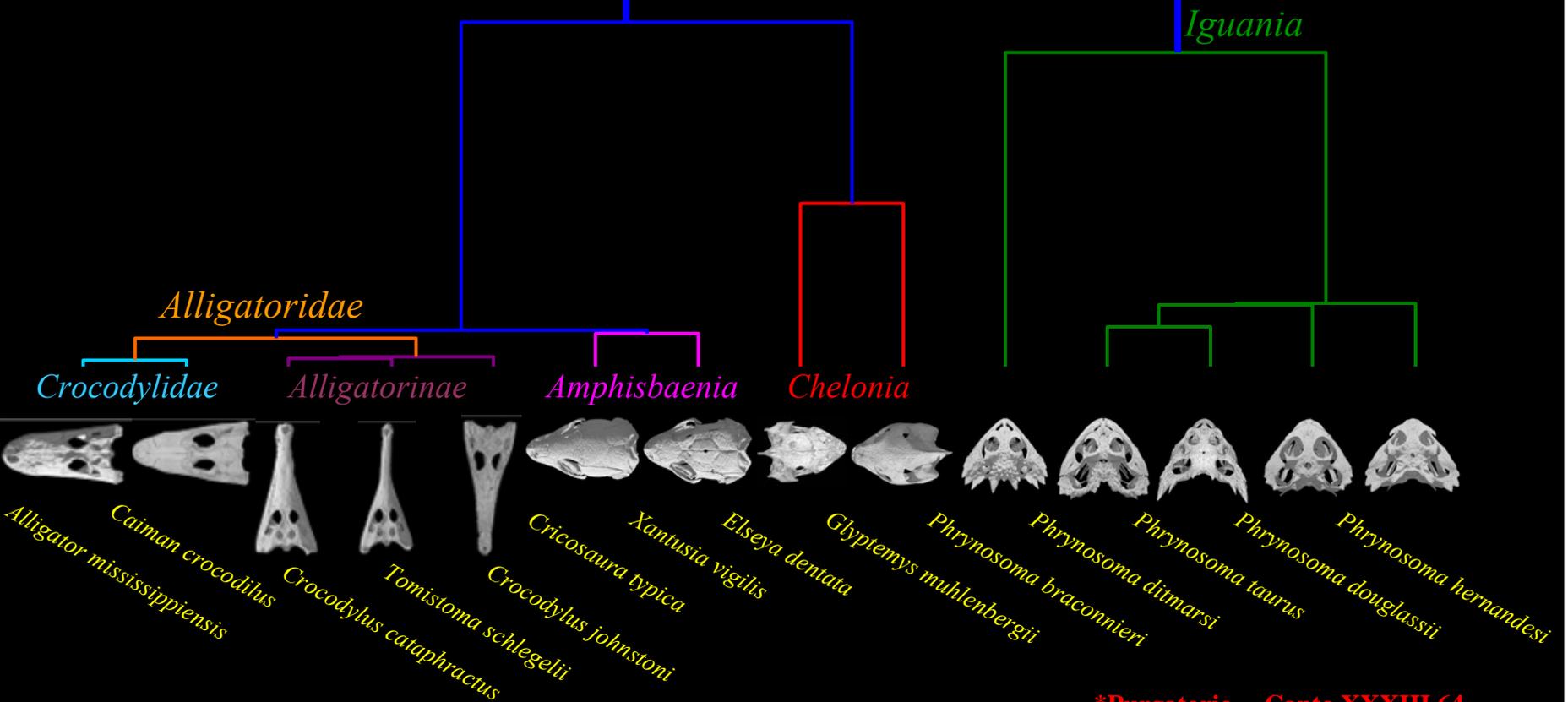
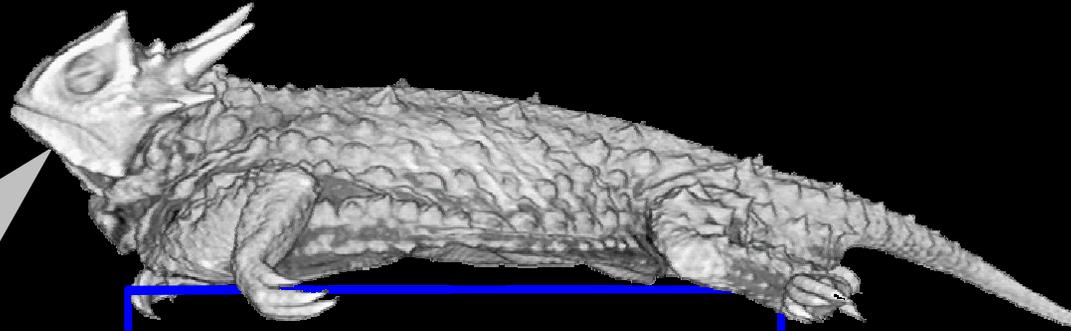
Unlike the  
primates, reptiles  
require warping...



Texas Horned Lizard  
*Phrynosoma cornutum*



There is a special reason why this tree is so tall and inverted at its top\*



\*Purgatorio -- Canto XXXIII 64

# Petroglyph Mining

- They appear worldwide
- Over a million in America alone
- Surprisingly little known about them

Petroglyphs are images incised in rock, usually by prehistoric, peoples. They were an important form of pre-writing symbols, used in communication from approximately 10,000 B.C.E. to modern times. **Wikipedia**

*who so sketched out  
the shapes there?\**

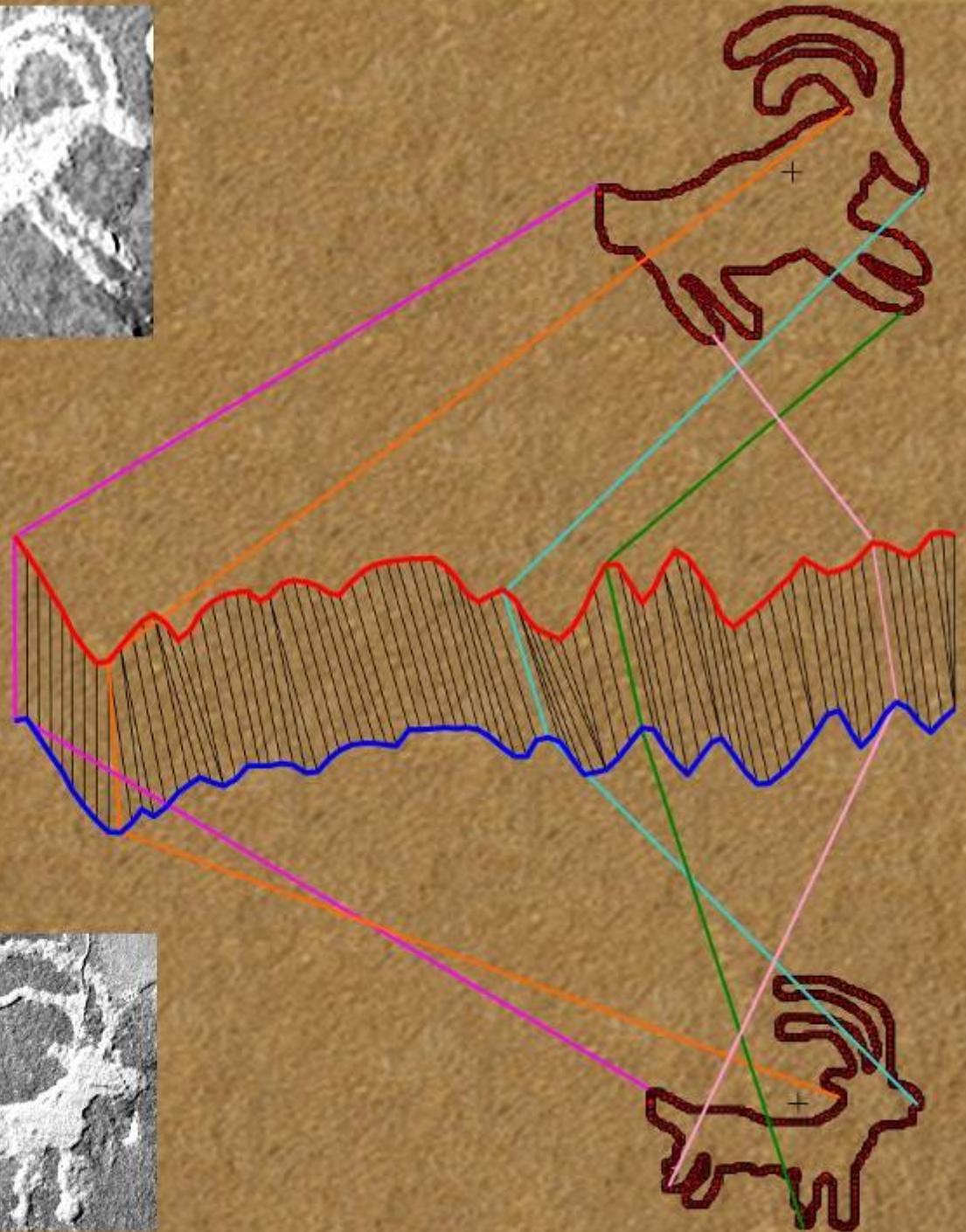


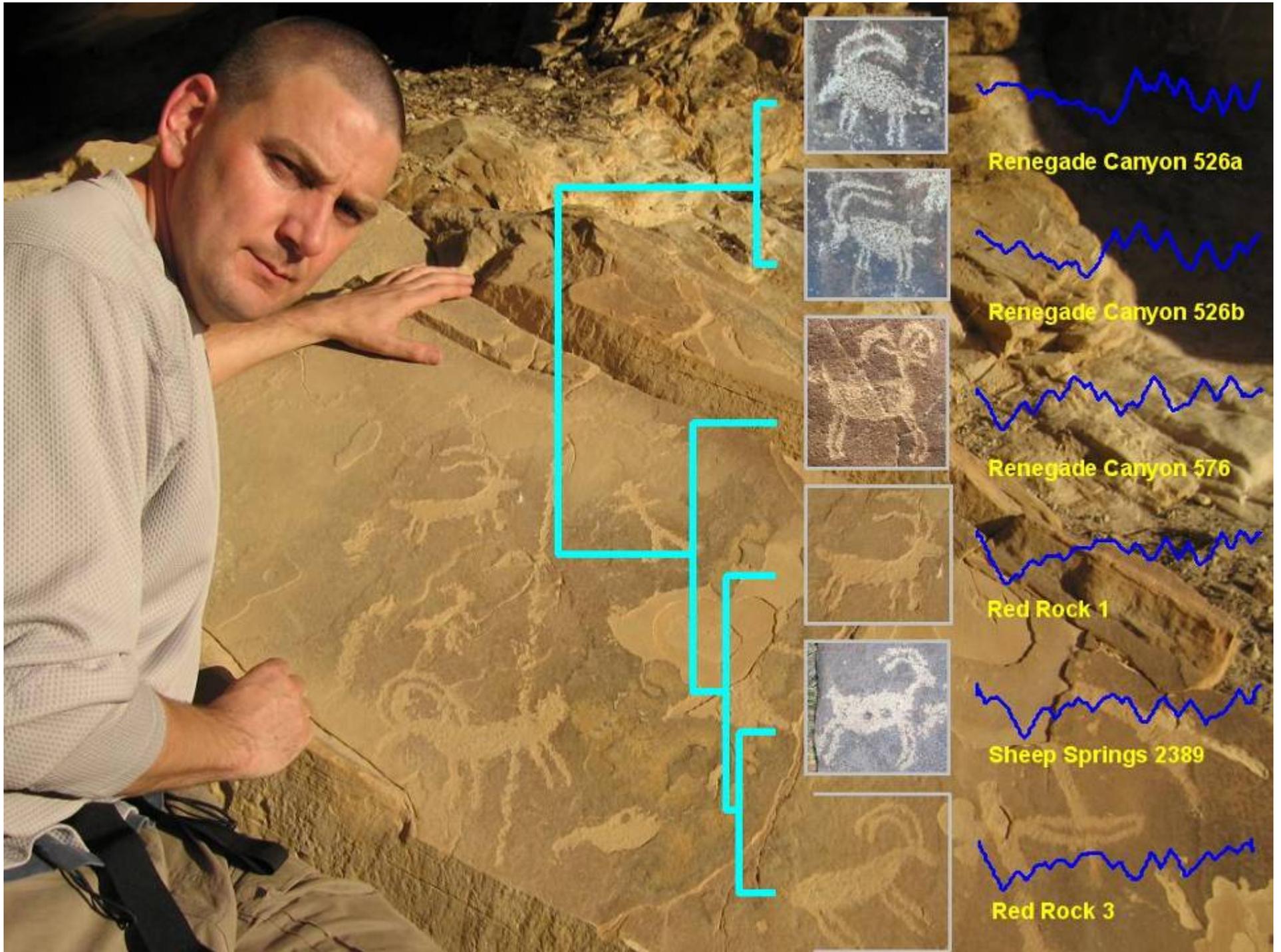
*.. they would  
strike the subtlest  
minds with awe\**

**\* Purgatorio -- Canto XII 6**

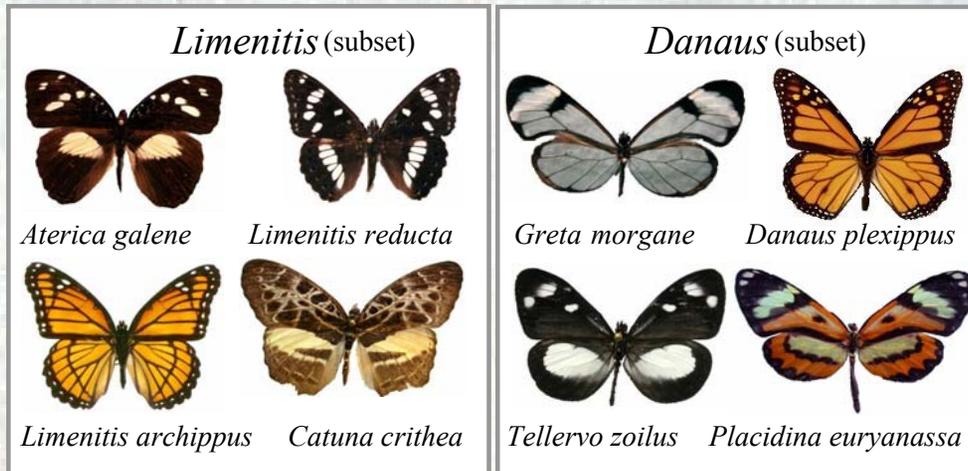


*Such complex shapes probably need DTW*



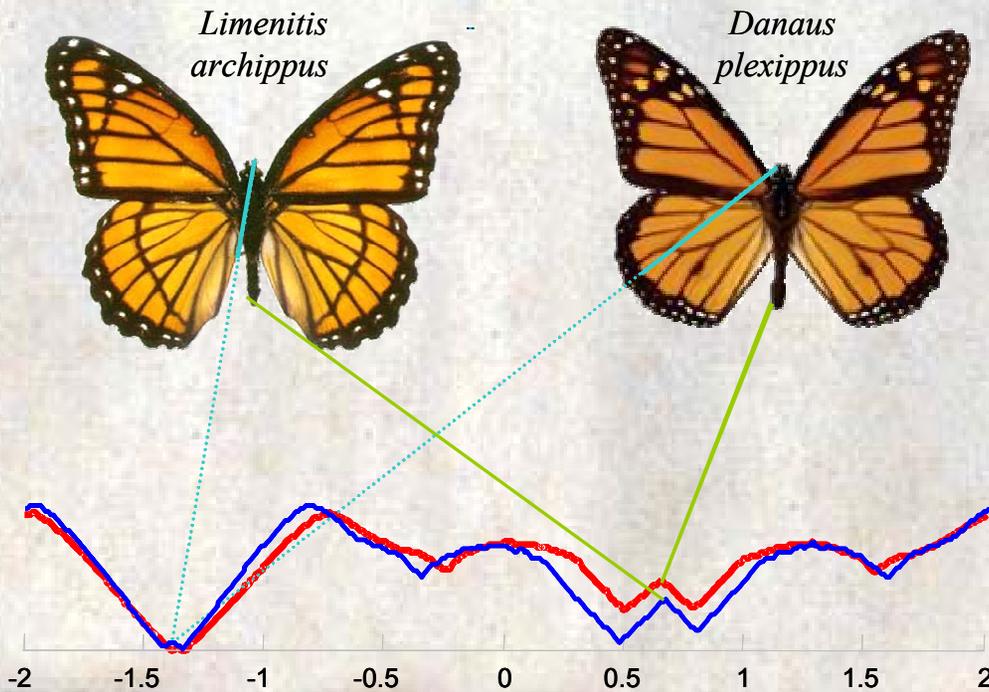


# Future Work: Data Mining



*We did not want to work on shape data mining until we could do fast matching, that would have been ass backwards*

*.. so similar in act and coloration that I will put them both to one\**



**\* Inferno -- Canto  
XXIII 29**

# Questions?

Feel free to email us with questions  
Eamonn Keogh: Project Leader  
[eamonn@cs.ucr.edu](mailto:eamonn@cs.ucr.edu)

Li Wei: Lower Bounding  
[wli@cs.ucr.edu](mailto:wli@cs.ucr.edu)

Michail Vlachos: Public  
Nudity and Index  
Structures  
[vlachos@us.ibm.com](mailto:vlachos@us.ibm.com)

Sang Hee Lee:  
Anthropology and  
Primatology  
[shlee@ucr.edu](mailto:shlee@ucr.edu)

Xiaopeng Xi:  
Image Processing  
[xxi@cs.ucr.edu](mailto:xxi@cs.ucr.edu)

