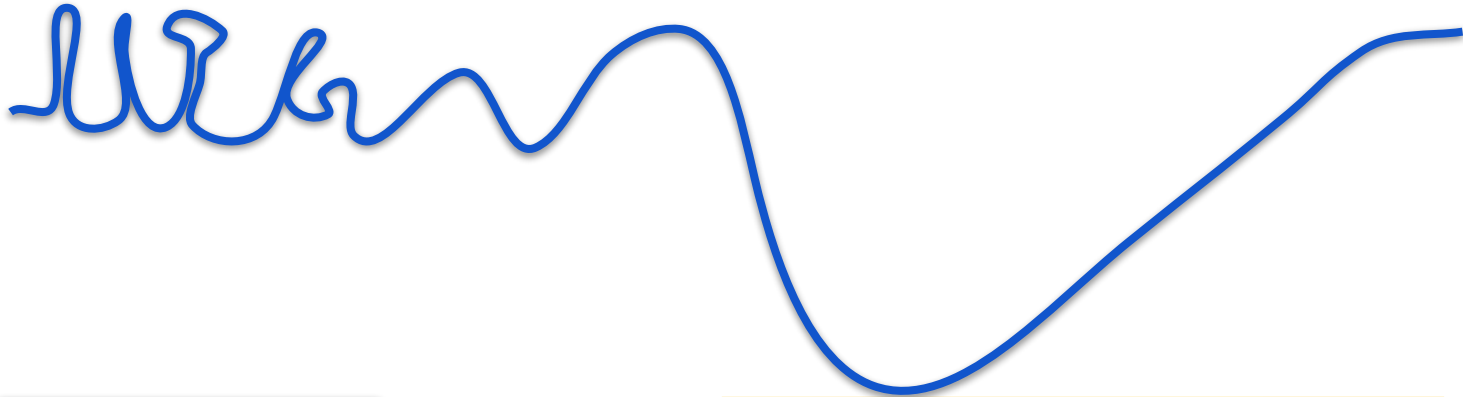


Computing with Signals



DA 623

Jan - May 2023

IIT Guwahati

Instructors: Neeraj Sharma

Lecture-30-31 [17-21st Apr]

Review:

Modeling a natural system as linear time invariant (LTI) model

Listen the below video on headphones (instead of earphones) for full effect



<https://www.youtube.com/watch?v=vTvEs15u5ek&t=97s>

HOW WE LOCALIZE SOUND

For as long as we humans have lived on Earth, we have been able to use our ears to localize the sources of sounds. Our ability to localize sounds is a matter of survival; it alerts us of danger and helps us sort out individual sounds from the usual cacophony of the acoustical world. Understanding this ability in humans and other animals is an intriguing physical,

Relying on a variety of cues, including intensity, timing, and spectrum, our brains recreate a three-dimensional image of the acoustic landscape from the sounds we hear.

William M. Hartmann

The spherical-head model is obviously a simplification. Human heads include a variety of secondary sources that can be expected to structure in the frequency-dependent ILD. Conceivably, the structure can serve as an additional cue for sound localization. As it turns out, that's what happens, but

Reading Material

Computing Edit Distance



Problem: computing edit distance

Input: two strings, s and t

Output: minimum number of character insertions, deletions, and substitutions it takes to change s into t

Examples:

"cat", "cat" \Rightarrow 0

"cat", "dog" \Rightarrow 3

"cat", "at" \Rightarrow 1

"cat", "cats" \Rightarrow 1

"a cat!", "the cats!" \Rightarrow 4

Edit (or Levenshtein) distance

Applications:

- information theory, linguistics, computational biology, and computer science, the Levenshtein distance is a string metric for measuring the difference between two sequences.
- informally, the Levenshtein distance between two words is the minimum number of single-character edits (insertions, deletions or substitutions) required to change one word into the other.
- It is named after the Soviet mathematician Vladimir Levenshtein, who considered this distance in 1965.

Concept of Memoization

Fibonacci computation

$$\text{fib}(n) = \text{fib}(n-1) + \text{fib}(n-2)$$

$$\text{fib}(1) = 1$$

$$\text{fib}(2) = 1$$

Concept of Memoization

Fibonacci computation

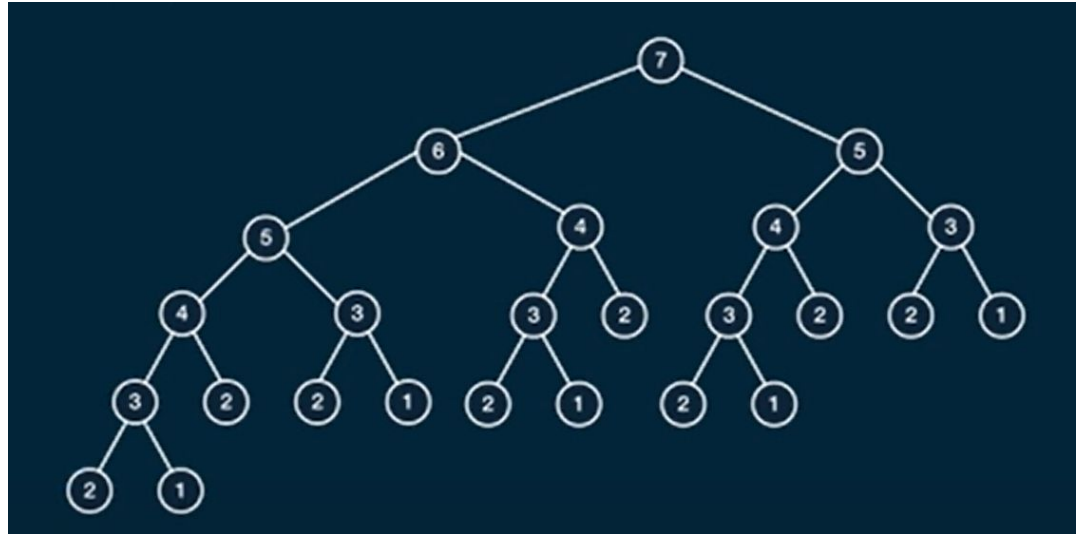
$$\text{fib}(n) = \text{fib}(n-1) + \text{fib}(n-2)$$

$$\text{fib}(1) = 1$$

$$\text{fib}(2) = 1$$

Visualizing Fibonacci computation

`compute_fibonacci(7)`



Memoization + Recursion = Dynamic
Programming

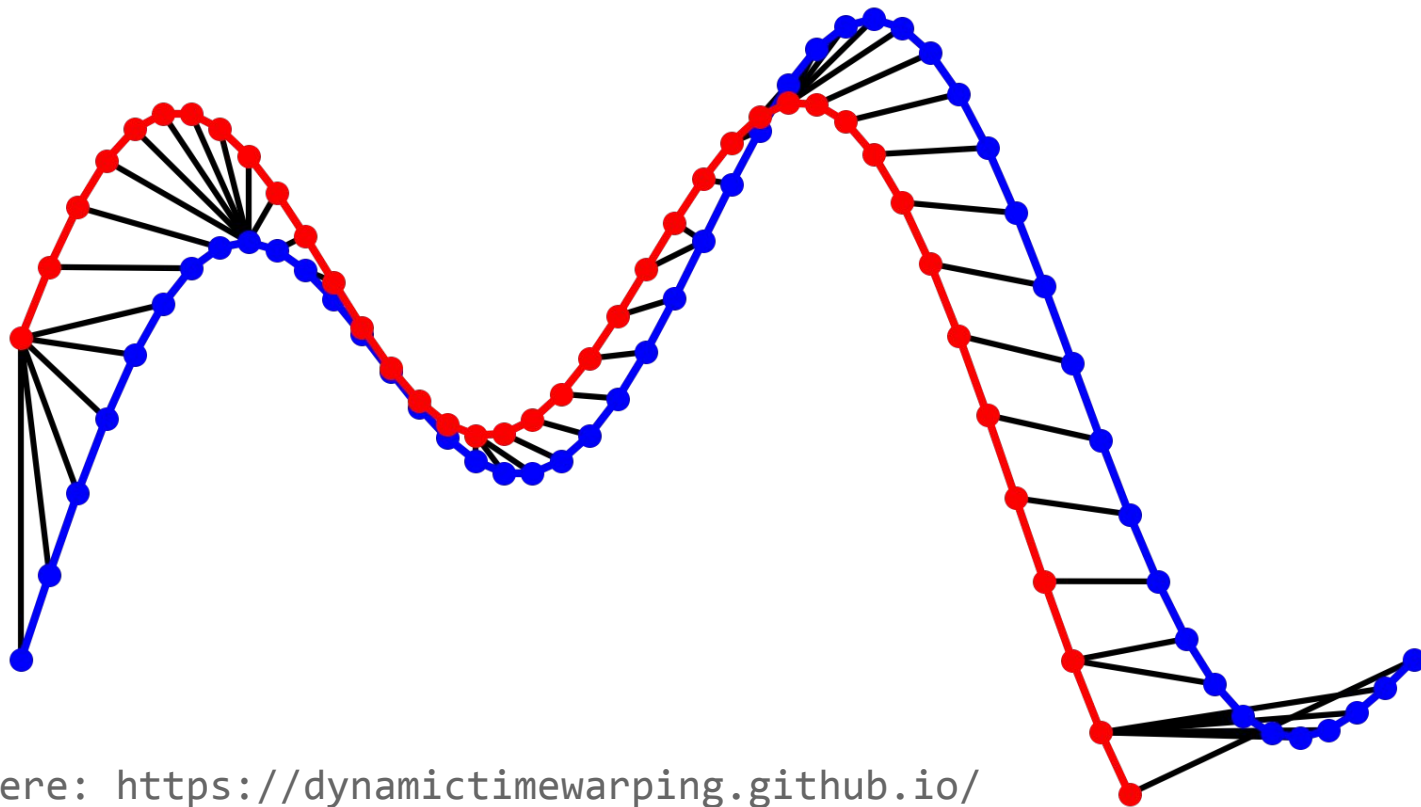
Dynamic Time Warping (DTW)

In time series analysis, dynamic time warping (DTW) is an algorithm for measuring similarity between two temporal sequences, which may vary in speed.

For instance, similarities in walking could be detected using DTW, even if one person was walking faster than the other, or if there were accelerations and decelerations during the course of an observation.

DTW has been applied to temporal sequences of video, audio, and graphics data — indeed, any data that can be turned into a one-dimensional sequence can be analyzed with DTW.

Other applications include speaker recognition and online signature recognition. It can also be used in partial shape matching applications.



More here: <https://dynamictimewarping.github.io/>

Following slides are adapted from:

Abdullah Mueen, Eamonn J. Keogh: Extracting Optimal
Performance from Dynamic Time Warping. KDD 2016: 2129-2130

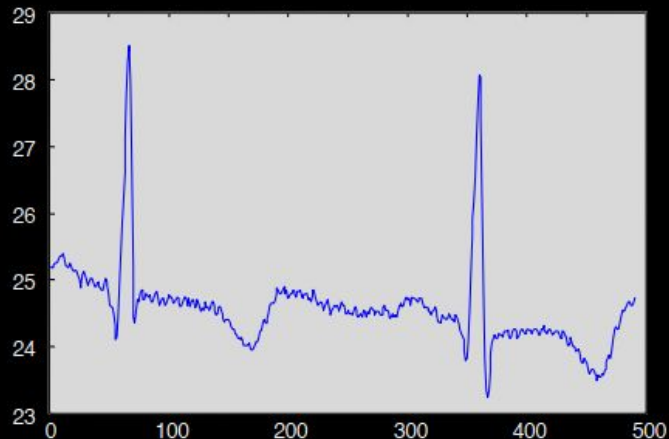
What are Time Series? 1 of 2

A time series is a collection of observations made sequentially in time.

More than most types of data, time series lend themselves to *visual* inspection and intuitions...

For example, looking at the numbers in this blue vector tells us nothing. But after *plotting* the data, we can recognize a heartbeat, and possibly even diagnose this person's disease. This tutorial will leverage the visual intuitiveness time series.

25.350
25.350
25.400
25.400
25.325
25.225
25.200
25.175
..
24.625
24.675
24.675
24.675

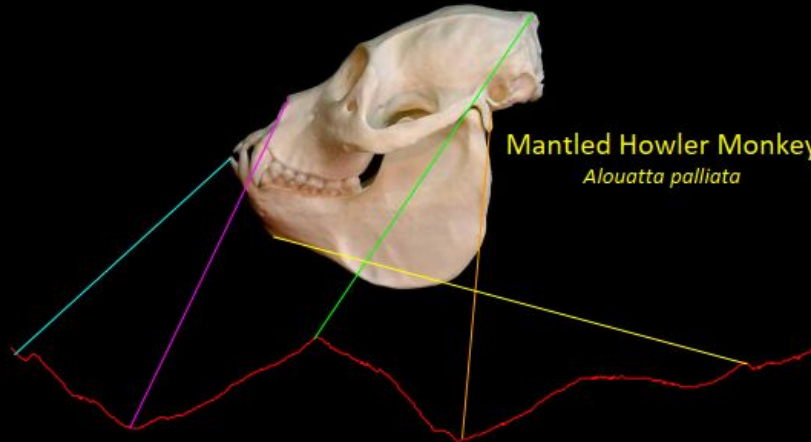
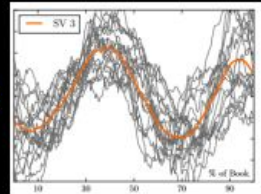


What are Time Series? 2 of 2

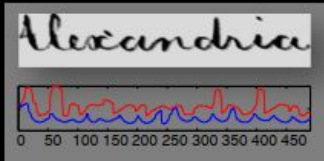
As an aside... (not the main point for today)

Many types of data that are not *true* time series can be fruitfully transformed into time series, including DNA, speech, textures, core samples, ASCII text, historical handwriting, novels and even *shapes*.

This fact greatly expands the purview of DTW

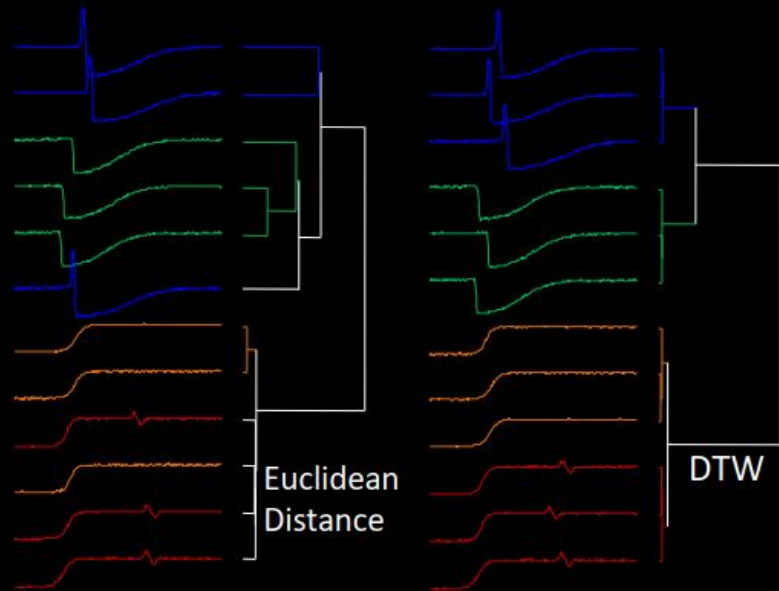


Mantled Howler Monkey
Alouatta palliata



What is Dynamic Time Warping?

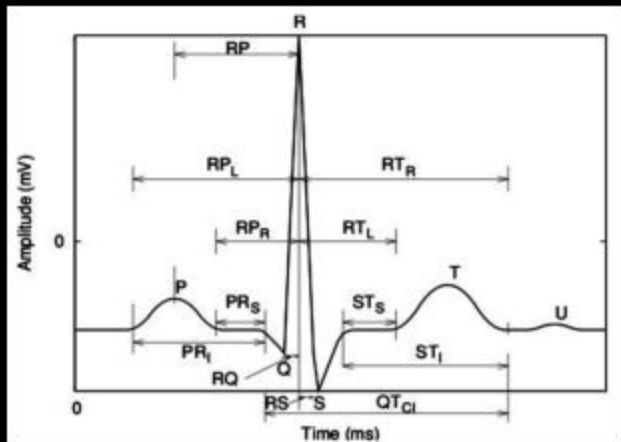
- DTW is an algorithm for measuring similarity between two time series which may vary (i.e. *warp*) in timing.
- This invariance to warping is critical in many domains, for many tasks.
- Without warping invariance, we are often condemned to very poor results.



Why Study DTW? 2 of 5

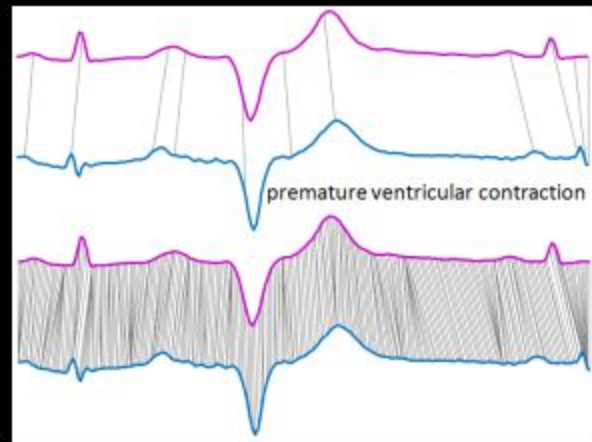
- It is almost impossible to overstate the ubiquity of DTW in data analytics
- It is used in: **robotics**, **biometrics**, **medicine**, **metrology**, bioinformatics, **video games**, **gesture recognition**, **image processing**, seismology, **music processing**, **entomology**, **anthropology**, **computational photography**, **bioacoustics**, **finance** ,...

Bazett's formula



Accuracy
75 to 95%
(10 classes)

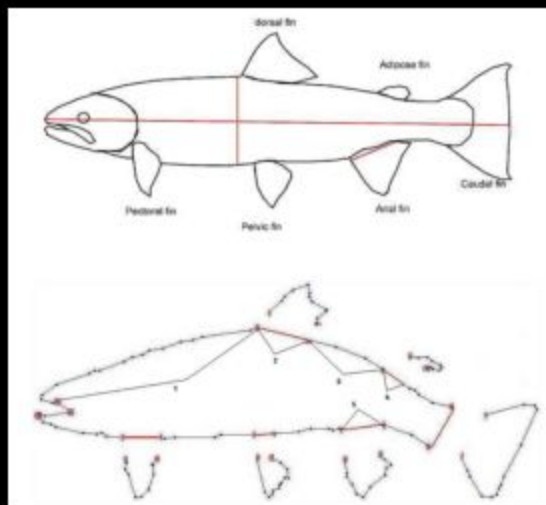
1NN DTW
Accuracy
98% plus
(10 classes)



PR Interval, PR Segment, Corrected-QT Interval, ST Segment, ST Interval, RR Interval, RQ Amplitude, R_{peak} to T_{onset} Segment RS Amplitude, Angle Q, Angle R, Angle S,...

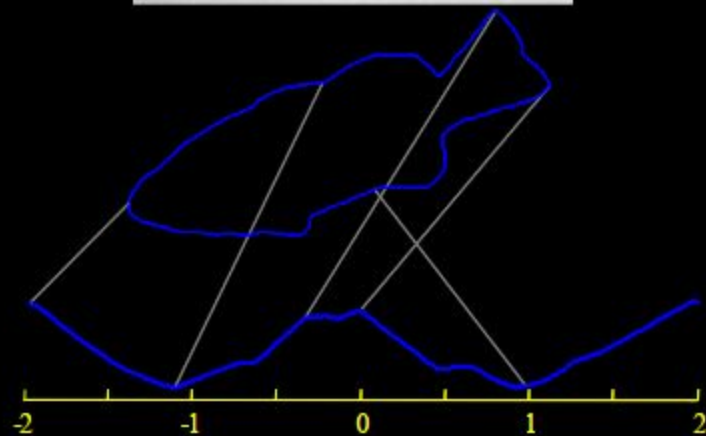
$F1 = \{7.3, 4.2, 5.2, 1.2, 6.7, \dots\}$

Parameter-free or parameter-lite,
robust to noise etc.

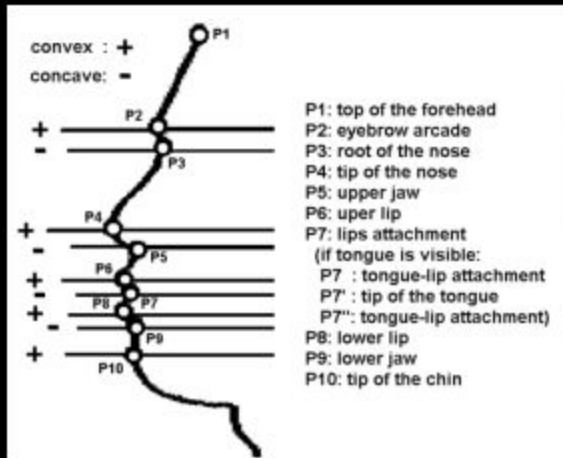


Accuracy
75.7%

1NN DTW
Accuracy
86.0%

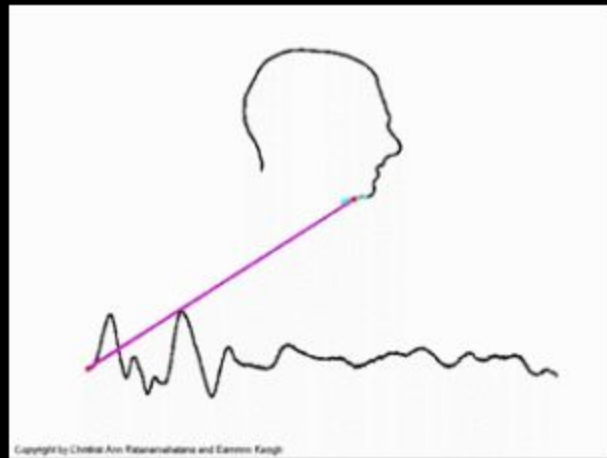


1. length between the nose and dorsal fin
 2. width of the dorsal fin
 3. distance between the dorsal fin and adipose fin
 4. width of the adipose fin
 5. width of the anal fin
- $F1=\{5.1,1.2,2.9,1.0,2.2\}$



Accuracy
70 to 80%
(10 classes)

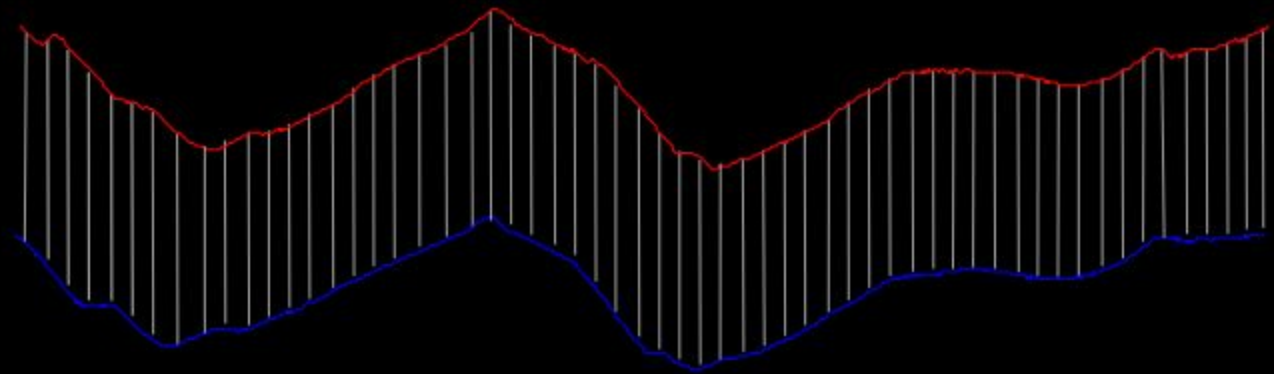
1NN DTW
Accuracy
90% plus
(10 classes)



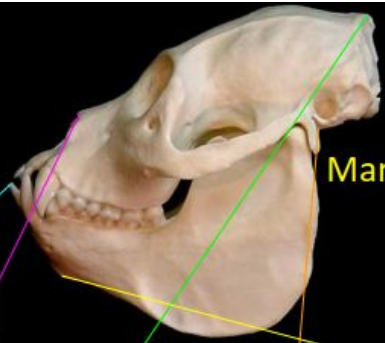
Parameter-free or parameter-lite,
robust to changes of expression..

How many fiducials? Pantic suggests
10, Campos suggests 8, Dariush
suggests 9, Liposcak suggests 12...

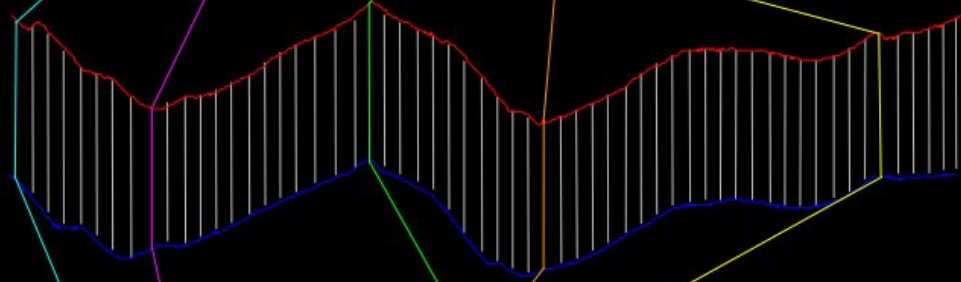
$F1 = \{7.4, 1.3, 2.1, 1.2, 4.6, 5.6, 43.3\}$



**Euclidean
Distance**



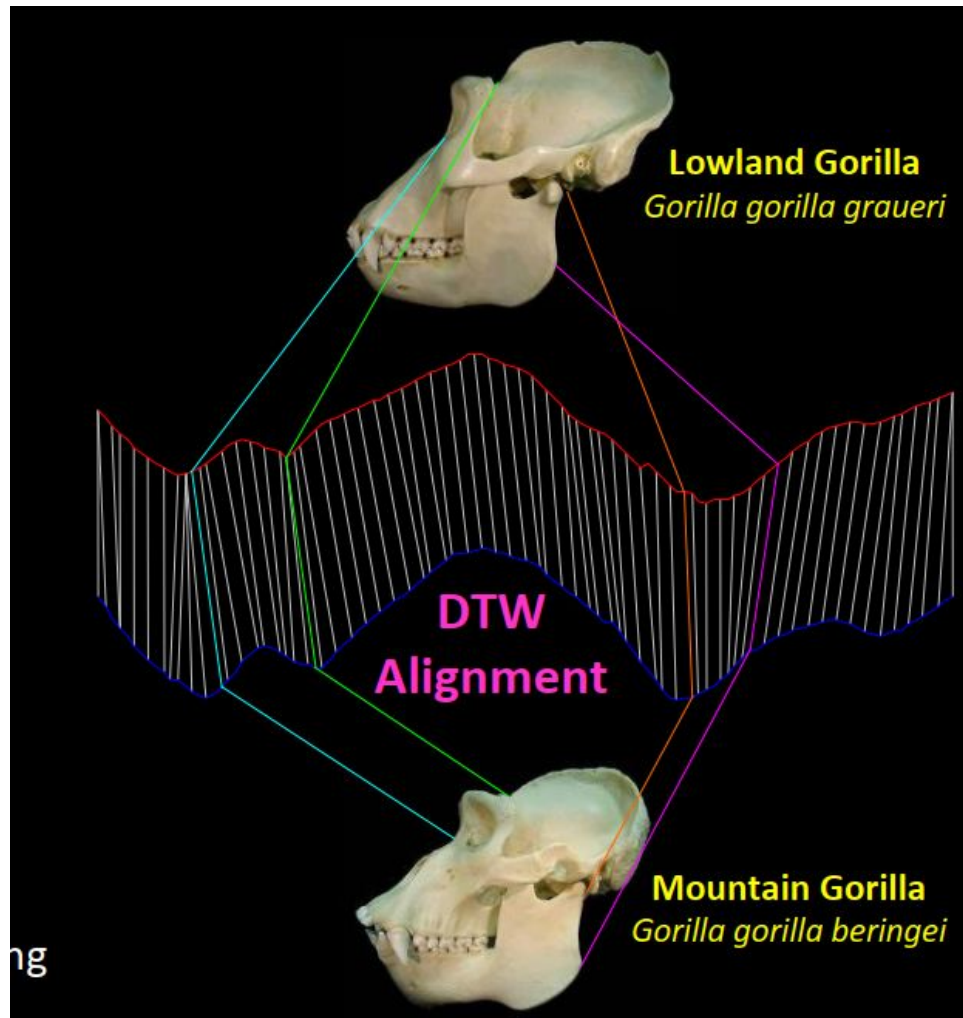
Mantled Howler Monkey
Alouatta palliata



**Euclidean
Distance**



Red Howler Monkey
Alouatta seniculus



Applications of distance measures?

Clustering

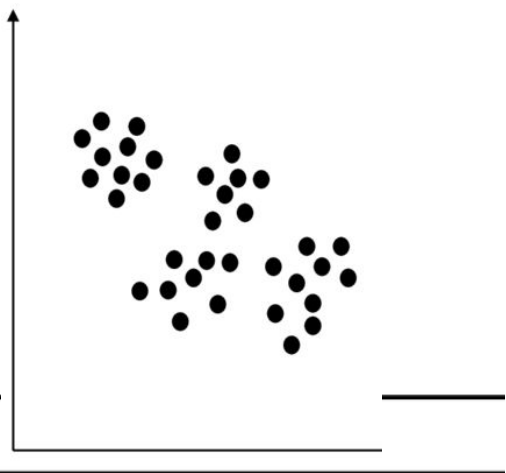
When doing learning:

“Similar data-points can be grouped together”

What if we do not have labels? Welcome to unsupervised setting.

Distance computation between data points helps.

Clustering



Algorithm 1 *k*-means algorithm

Clustering

Algorithm 1 *k*-means algorithm

1: Specify the number *k* of clusters to assign.

Clustering

Algorithm 1 k -means algorithm

- 1: Specify the number k of clusters to assign.
- 2: Randomly initialize k centroids.
- 3: **repeat**
- 4: **expectation:** Assign each point to its closest centroid.
- 5: **maximization:** Compute the new centroid (mean) of each cluster.

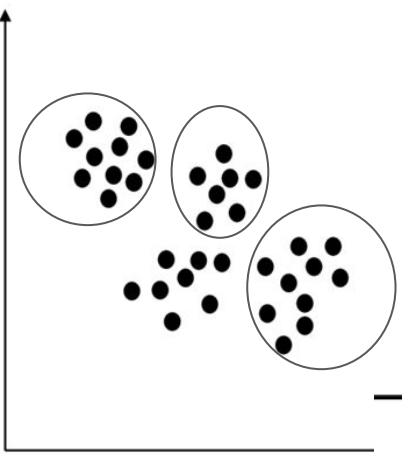
Clustering

Using distance
measures

Algorithm 1 k -means algorithm

- 1: Specify the number k of clusters to assign.
- 2: Randomly initialize k centroids.
- 3: **repeat**
- 4: **expectation:** Assign each point to its **closest** centroid.
- 5: **maximization:** Compute the new centroid (mean) of each cluster.

Clustering



Algorithm 1 k -means algorithm

- 1: Specify the number k of clusters to assign.
 - 2: Randomly initialize k centroids.
 - 3: **repeat**
 - 4: **expectation:** Assign each point to its closest centroid.
 - 5: **maximization:** Compute the new centroid (mean) of each cluster.
 - 6: **until** The centroid positions do not change.
-

Image segmentation - using clustering

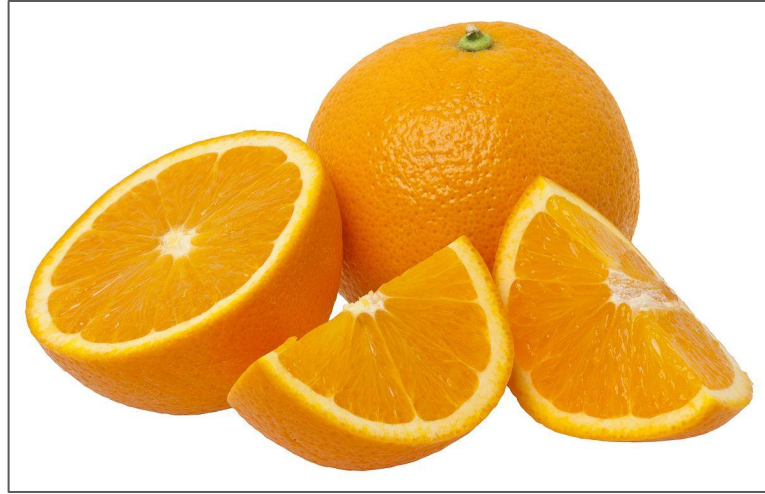
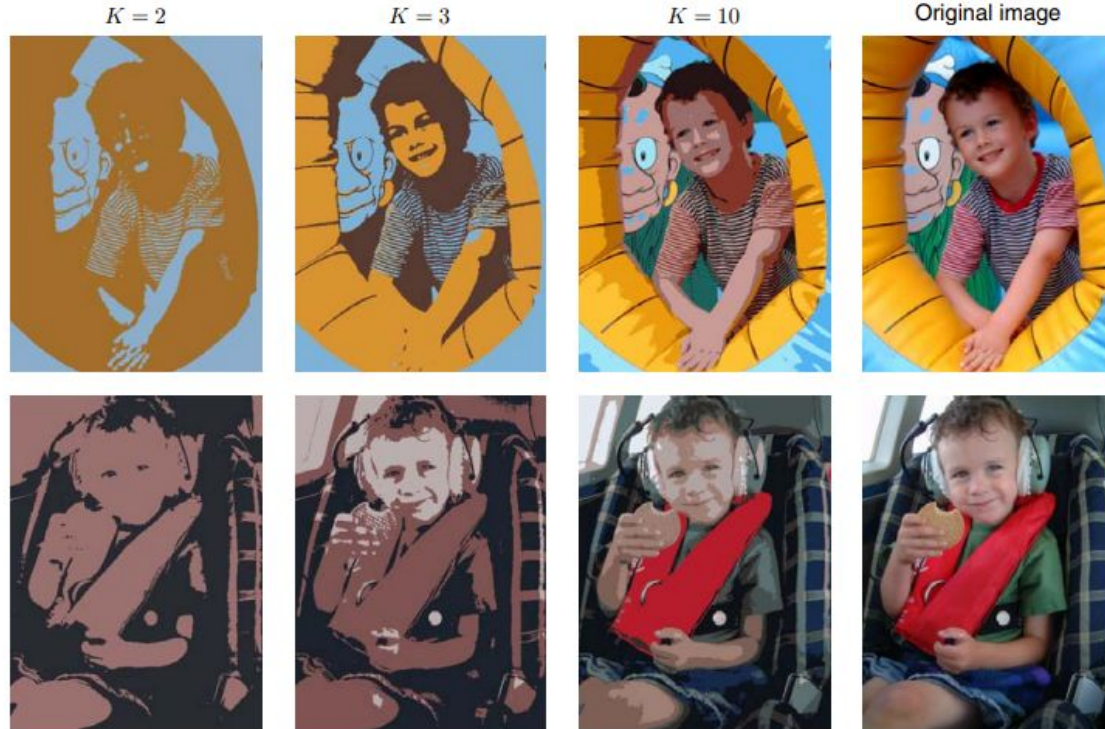


Image compression - using clustering



From C. Bishop

Clustering

Reading material:

Chapter 9: C. Bishop's book Pattern Recognition and Machine Learning

Additional:

ARTICLE

Data clustering: a review

Authors:  [A. K. Jain](#),  [M. N. Murty](#),  [P. J. Flynn](#)

Image quantization



8 bits



4 bits

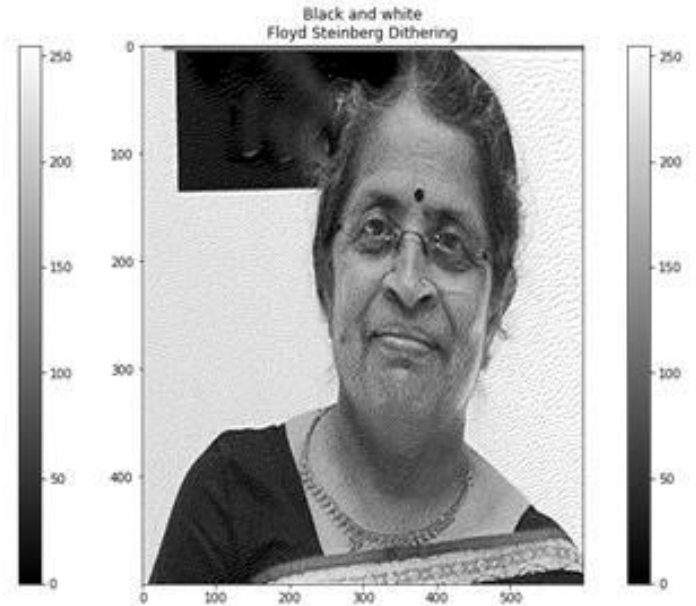
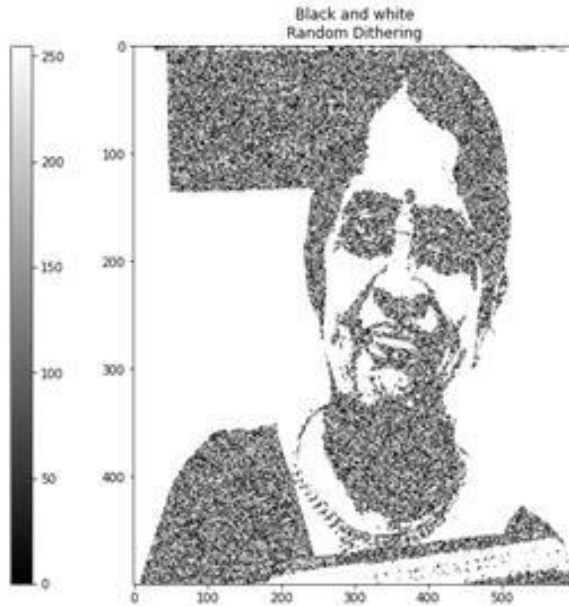


2 bits

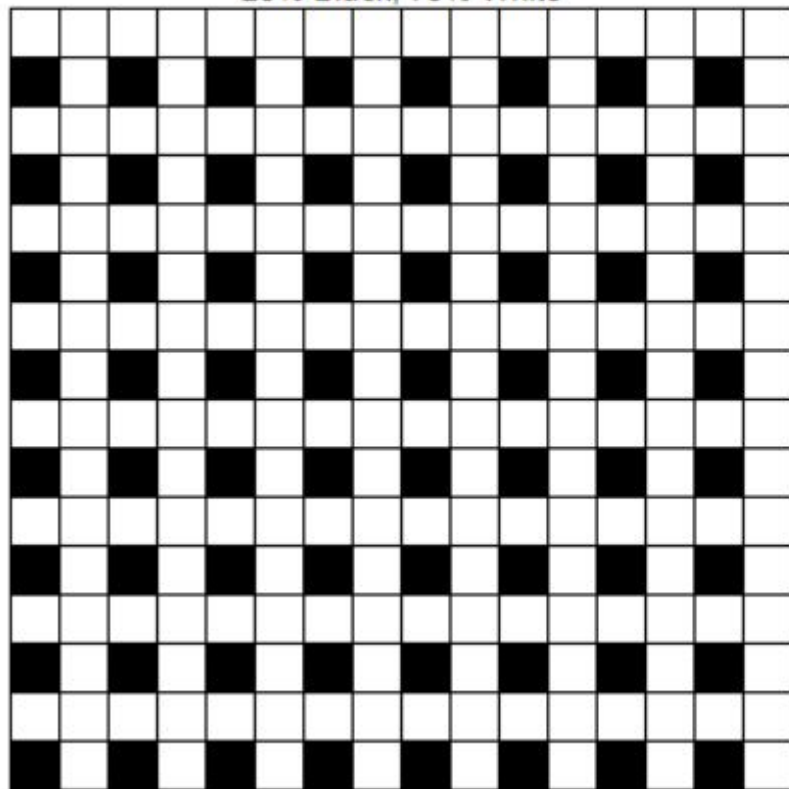


1 bit

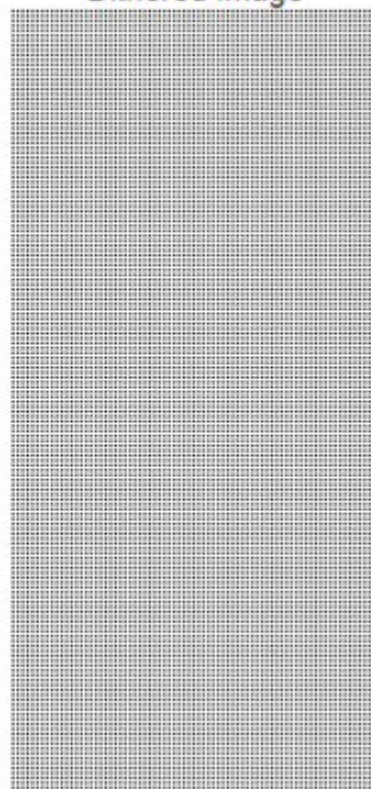
All are 1 bit images - intensity take 2 values, only



Zoomed In
25% Black, 75% White

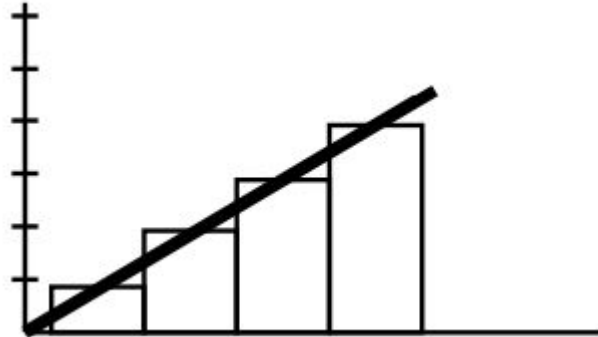


Actual Size
Dithered Image



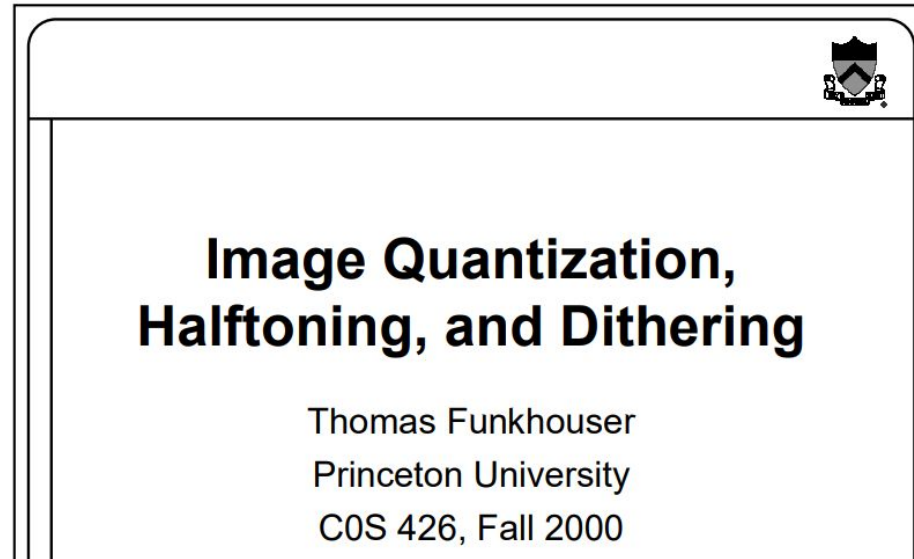
Quantization

- assigning discrete values to the continuous amplitude values taken by the signal
- The discrete values are also called levels
- If b bits are used to represent the discrete values then there are 2^b discrete levels



Quantization Error results due to limited intensity resolution.

Dithering - allows distributing the quantization error



Thank you