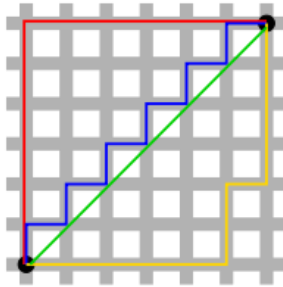


COMS20017 – Algorithms & Data



January 2025

Majid Mirmehdi

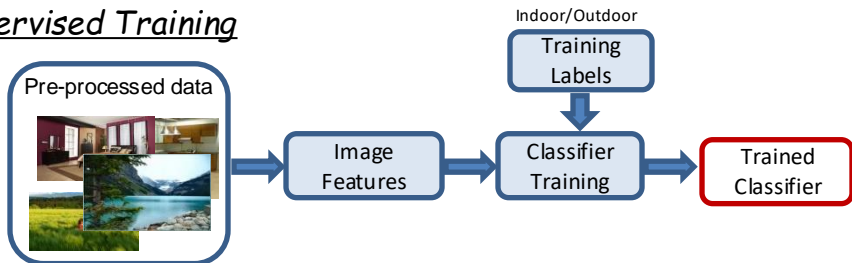
with a few slides from Rui Ponte Costa & Dima Damen

Lecture MM-02

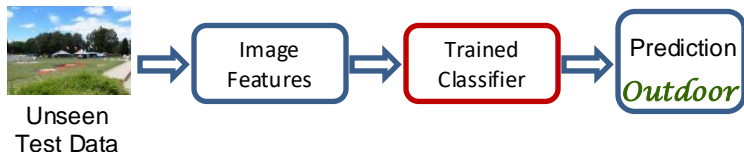
Last lecture: Typical Data Analysis Problem

1. Pre-processing
2. Feature Selection
3. Classification

Supervised Training



Testing



This lecture



Analog Signal



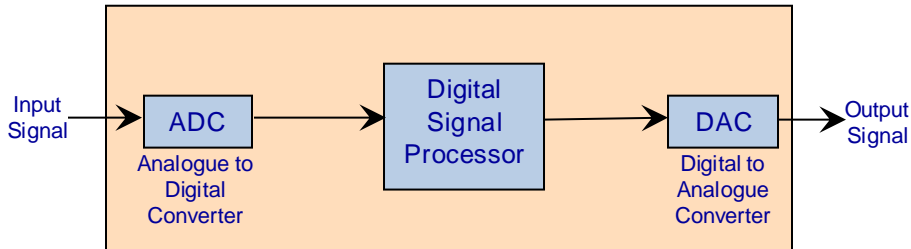
Digital Signal

- **Data acquisition**
- **Data characteristics: distance measures**
- Data characteristics: summary statistics [*reminder*]
- Data normalisation and outliers

Data Acquisition – Example Data Journey



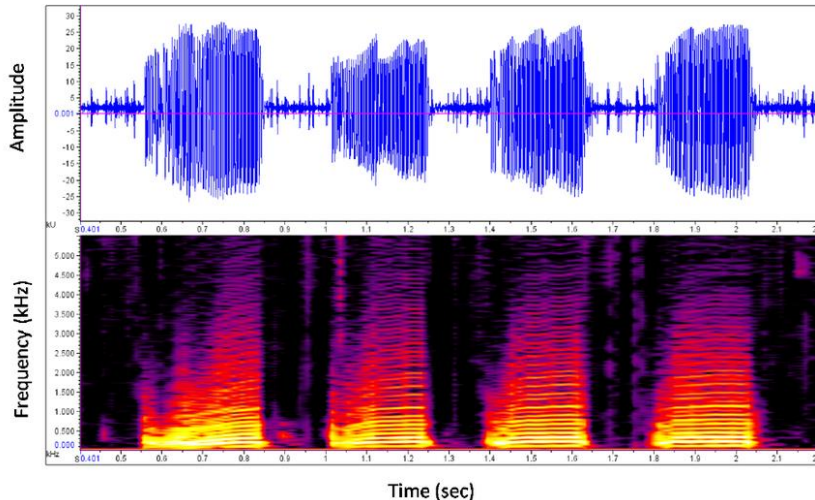
<https://www.vectorstock.com/>



Data Acquisition - Analogue to Digital Conversion

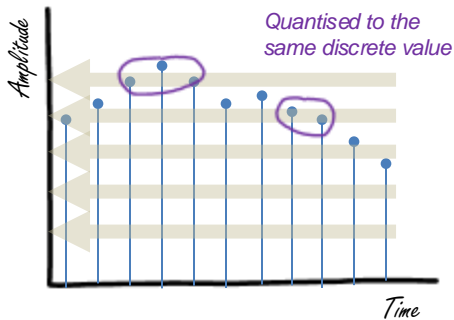
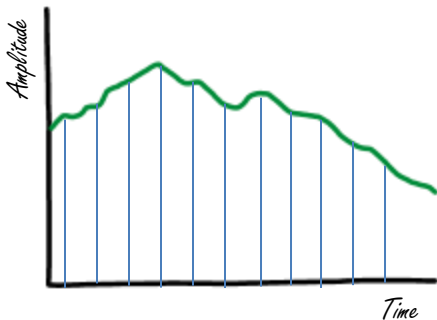
Analogue to Digital conversion involves *Sampling & Quantisation*

e.g. a 1D Audio Signal



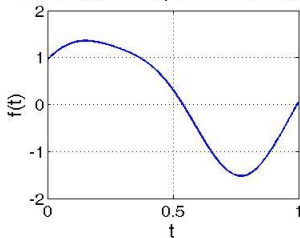
Data Acquisition - Analogue to Digital Conversion

Analogue to Digital conversion involves *Sampling* & *Quantisation*

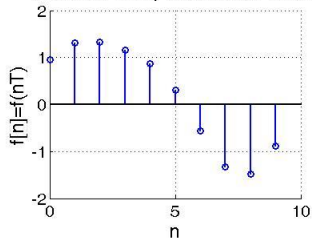


Sample and Quantise

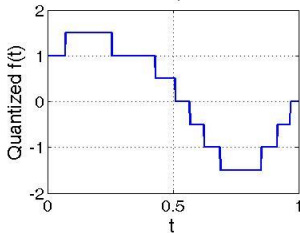
Continuous Time, Continuous Value



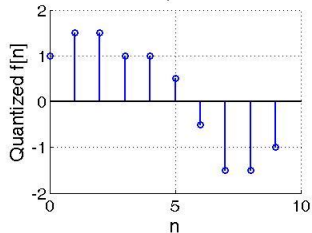
Discrete Time, Continuous Value



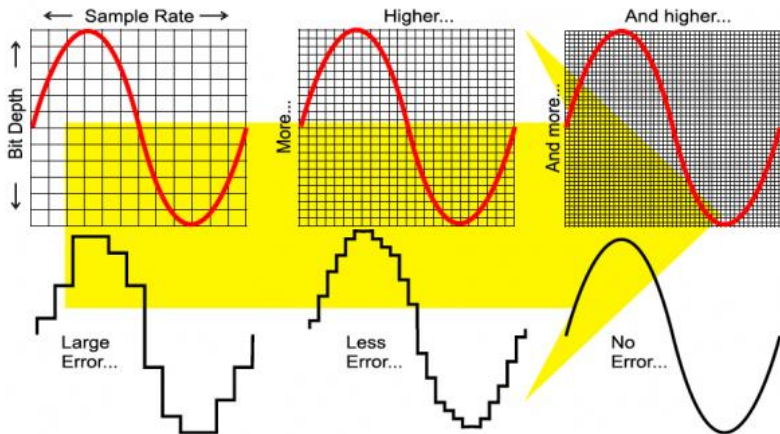
Continuous Time, Discrete Value



Discrete Time, Discrete Value



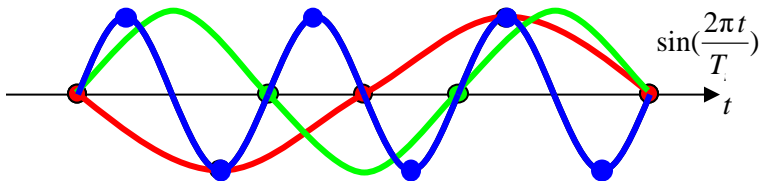
Sample and Quantise



Nyquist-Shannon Sampling Theory

"An analogue signal containing components up to some maximum frequency u (Hz) may be completely reconstructed by regularly spread samples, provided the sampling rate is at least $2u$ samples per second"

Also referred to as the Nyquist-Shannon criterion: sampling rate s should be at least twice the highest spatial frequency u .

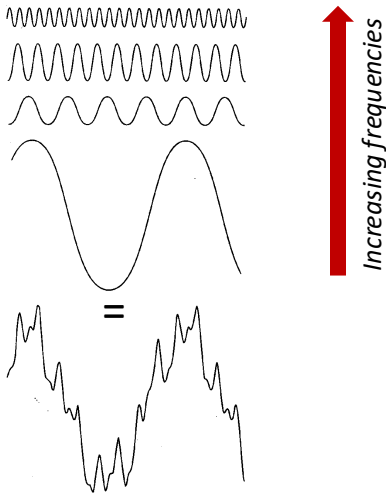


$$\text{sampling period} \quad T \leq \frac{1}{2u}$$

$$\text{equivalent to sampling rate} \quad s \geq 2u$$

Nyquist-Shannon Sampling Theory

"An analogue signal containing components up to some maximum frequency u (Hz) may be completely reconstructed by regularly spread samples, provided the sampling rate is at least $2u$ samples per second"



Data Acquisition - Analogue to Digital Conversion

Examples of sampling and quantisation of standard audio formats:

- Speech (e.g. phone call)
 - Sampling: 8 KHz samples
 - Quantisation: 8 bits / sample
- Audio CD and Streaming
 - Sampling: 44 KHz samples
 - Quantisation: 16 bits / sample
 - Stereo (2 channels)

Higher sampling and quantisation levels achieves better signal quality, but at the expense of larger memory and storage.

Data Acquisition - Analogue to Digital Conversion

Examples of sampling and quantisation of Images (multi-dimensional):

- Sampling: Resolution in digital photography
- Quantisation: Representation of each pixel in the image
 - 8 Mega Pixel Camera: 3264 x 2448 pixels
 - Colour images: 3 channels - Red, Green, Blue (8 bits per colour)
 - Greyscale images: 1 channel - intensity = $aR+bG+cB$ where $a+b+c=1.0$
 - Binary images: Black/White - 1 bit per pixel

Sampling – visual example

The effect of sparser sampling...is **ALIASING**



256x256



64x64



32x32

Anti-aliasing is achieved by filtering to remove frequencies above the Nyquist limit.

Quantisation – visual example

This results from representing a continuously varying function $f(x)$ with a discrete one using quantisation levels



16 levels



6 levels



2 levels

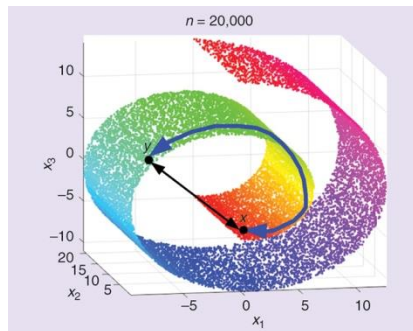
Next...



- Data acquisition
- **Data characteristics: distance measures**
- Data characteristics: summary statistics [*reminder*]
- Data normalisation and outliers

Data Characteristics: Distance Measures

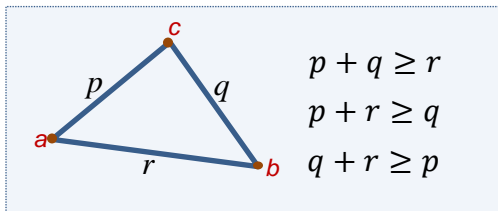
- Distance is measure of separation between data.
- Distance is important as it:
 - enables data to be ordered
 - allows numeric calculations
 - enables measuring similarity and dissimilarity
- Without defining a distance measure, almost all statistical and machine learning algorithms will not function!
- Can be defined between single-dimensional data, multi-dimensional data or data sequences.



Properties for a Distance Measure

A valid distance measure $D(a,b)$ between two components a and b has the following properties

- non-negative: $D(a,b) \geq 0$
- symmetric: $D(a,b) = D(b,a)$
- reflexive: $D(a,b) = 0 \iff a = b$
- satisfies triangular inequality: $D(a,b) \leq D(a,c) + D(c,b)$



Distance (Numerical)

To find the distance between numerical data points $\mathbf{x} = (x_1, x_2, \dots, x_n)$ and $\mathbf{y} = (y_1, y_2, \dots, y_n)$ in Euclidean space \mathbb{R}^n , the **Minkowski Distance** of order p (p -norm distance) is defined as:

$$D(\mathbf{x}, \mathbf{y}) = \left(\sum_{i=1}^n |x_i - y_i|^p \right)^{\frac{1}{p}}$$

- $p = 1$
- 1-norm distance (L_1)

$$D(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^n |x_i - y_i|$$

- Also known as the *Manhattan Distance*
- *Not the shortest path possible...*



Distance (Numerical)

To find the distance between numerical data points $\mathbf{x} = (x_1, x_2, \dots, x_n)$ and $\mathbf{y} = (y_1, y_2, \dots, y_n)$ in Euclidean space \mathbb{R}^n , the **Minkowski Distance** of order p (p -norm distance) is defined as:

$$D(\mathbf{x}, \mathbf{y}) = \left(\sum_{i=1}^n |x_i - y_i|^p \right)^{\frac{1}{p}}$$

- $p = 2$
- 2-norm distance (L_2)
- Also known as the *Euclidean Distance*

$$D(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{i=1}^n |x_i - y_i|^2}$$

Can be expressed in vector form:

$$\begin{aligned} D(\mathbf{x}, \mathbf{y}) &= \|\mathbf{x} - \mathbf{y}\| \\ &= \sqrt{(\mathbf{x} - \mathbf{y})^T (\mathbf{x} - \mathbf{y})} \end{aligned}$$



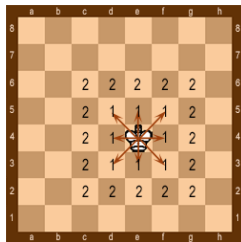
Distance (Numerical)

To find the distance between numerical data points $\mathbf{x} = (x_1, x_2, \dots, x_n)$ and $\mathbf{y} = (y_1, y_2, \dots, y_n)$ in Euclidean space \mathbb{R}^n , the **Minkowski Distance** of order p (p -norm distance) is defined as:

$$D(\mathbf{x}, \mathbf{y}) = \left(\sum_{i=1}^n |x_i - y_i|^p \right)^{\frac{1}{p}}$$

- $p = \infty$
- ∞ -norm distance (L_∞)
- Also known as the *Chebyshev Distance*

$$\begin{aligned} D(\mathbf{x}, \mathbf{y}) &= \lim_{p \rightarrow \infty} \left(\sum_{i=1}^n |x_i - y_i|^p \right)^{\frac{1}{p}} \\ &= \max (|x_1 - y_1|, |x_2 - y_2|, \dots, |x_n - y_n|) \end{aligned}$$



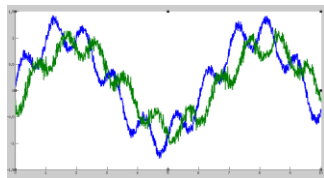
If 2 dimensions where two points have cartesian coordinates, then $D = \max (|x_2 - x_1|, |y_2 - y_1|)$

Distance (Numerical Series)

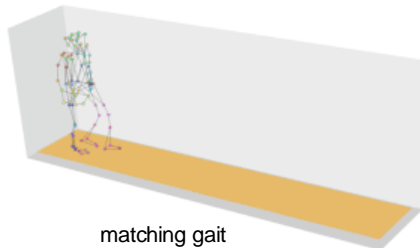
- Time Series: successive measurements made over a time interval

p-norm distances can only

- compare time series of the same length
- very sensitive to signal transformations:
 - shifting
 - amplitude scaling
 - uniform time scaling



matching audio signal of two people saying the same word

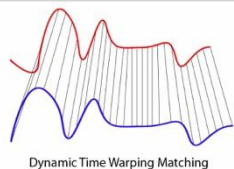
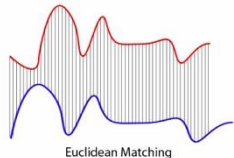


matching gait

Distance (Numerical Time Series)

Dynamic Time Warping (Berndt and Clifford, 1994)

- Replaces Euclidean one-to-one comparison with many-to-one
- Recognises similar shapes even in the presence of shifting, length, and scaling
- Dynamic Time Warping (DTW) can be defined **recursively** to tell us how two signals align with each other:



For two time series $\mathbf{X} = (x_1, \dots, x_n)$ and $\mathbf{Y} = (y_1, \dots, y_m)$

$$DTW(\mathbf{X}, \mathbf{Y}) = D(x_1, y_1) + \min\{DTW(\mathbf{X}, \text{REST}(\mathbf{Y})), DTW(\text{REST}(\mathbf{X}), \mathbf{Y}), DTW(\text{REST}(\mathbf{X}), \text{REST}(\mathbf{Y}))\}$$

$$\text{where } \text{REST}(\mathbf{X}) = (x_2, \dots, x_n)$$

DTW builds a distance matrix between two time series and then finds the minimum path (alignment cost) for an optimal match.

OPTIONAL: for more details, watch: <https://www.youtube.com/watch?v=ERKDHZyZDwA> (2 parts)

Distance (Symbolic)

- Distance is not always between numerical data
- Distance between symbolic data is less well-defined (e.g. text data)
- Distance in text could be:
 - syntactic
 - semantic

I will send you some **cashh**|

Distance (Symbolic)

Syntactic - e.g. Hamming Distance

- Defined over symbolic data of *the same* length
- Measures the number of substitutions required to change one string/number into another

➤ $\begin{matrix} B & r & i & s & t & o & l \\ B & u & r & t & t & o & n \end{matrix}$ $D(\text{'Bristol'}, \text{'Burtton'}) = 4$

➤ $\begin{matrix} 5 & 2 & 4 & 3 \\ 6 & 2 & 1 & 3 \end{matrix}$ $D(5243, 6213) = 2$

➤ $\begin{matrix} 1011101 \\ 1001001 \end{matrix}$ $D(1011101, 1001001) = 2$

- Used in coding theory and error correcting codes
- For binary strings, Hamming Distance is the same as taking L_1 absolute difference of bits and summing them

Distance (Symbolic)

Syntactic - e.g. Edit Distance

- Defined on text data of *any* length
- Measures the *minimum* number of 'operations' required to transform one sequence of characters into another
- 'Operations' can be: insertion, substitution, deletion
- e.g. $D(\text{'fishing'}, \text{'first'}) = 5$

'fishing' $\xrightarrow{\text{insertion}}$ 'firshing' $\xrightarrow{\text{substitution}}$ 'firsting' $\xrightarrow{3x \text{ deletion}}$ 'first'

- used in spelling correction, DNA string comparisons, etc.

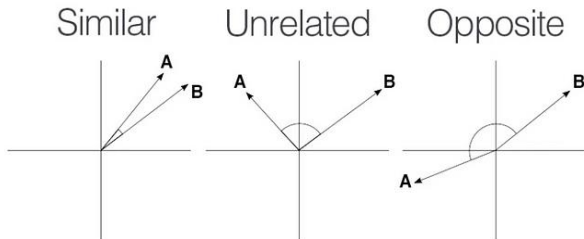
Distance

Cosine Similarity and Cosine Distance

- Cosine similarity is a metric that determines how **two vectors** (words, sentences, features) are **similar** to each other.
- Cosine distance measures how **different** two vectors are.

$$\text{Similarity}(A, B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$

$$\text{Distance}(A, B) = 1 - \text{Similarity}(A, B)$$



Cosine Similarity/Distance – Example 1

Find Cosine Similarity and Distance between two vectors

$\mathbf{x} = \{4, 2, 0, 3\}$ and $\mathbf{y} = \{1, 0, 1, 0\}$

$$\mathbf{x} \cdot \mathbf{y} = 4 * 1 + 2 * 0 + 0 * 1 + 3 * 0$$

$$\|\mathbf{x}\| = \sqrt{16 + 4 + 0 + 9} = 5.385$$

$$\|\mathbf{y}\| = \sqrt{1 + 0 + 1 + 0} = 1.414$$

$$\text{Similarity}(\mathbf{x}, \mathbf{y}) = \frac{4}{5.385 * 1.414} = 0.525$$

$$\text{Distance}(\mathbf{x}, \mathbf{y}) = 1 - 0.525 = 0.475$$

Cosine Similarity/Distance – Example 2

Find Cosine Similarity and Distance between two documents that contain these words:

Doc1 = {Computer Science at Bristol is simple}

Doc2 = {Amongst all courses Computer Science isn't simple}

Generate vectorised representations of the texts:

Amongst all courses Computer Science at Bristol is isn't simple

$$\text{Doc1} = \mathbf{x} = \{0,0,0,1,1,1,1,1,0,1\}$$

$$\text{Doc2} = \mathbf{y} = \{1,1,1,1,1,0,0,0,1,1\}$$

$$\mathbf{x} \cdot \mathbf{y} = 3$$

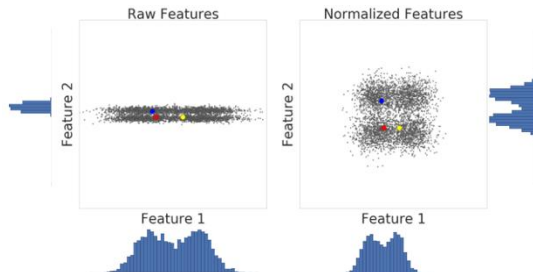
$$\|\mathbf{x}\| = \sqrt{6}$$

$$\|\mathbf{y}\| = \sqrt{7}$$

$$\text{Similarity}(\mathbf{x}, \mathbf{y}) = \frac{3}{\sqrt{42}} = 0.463$$

$$\text{Distance}(\mathbf{x}, \mathbf{y}) = 1 - 0.463 = 0.537$$

Next lecture



- Data acquisition
- Data characteristics: distance measures
- **Data characteristics: summary statistics [reminder]**
- **Data normalisation and outliers**