

Data basics

Lin Guosheng
School of Computer Science and Engineering
Nanyang Technological University

Outline

- Types of datasets
- Data objects and attributes
- Distance and similarity
- Data normalization

Types of Datasets

■ 1. Record Data

- records in a relational database

Person:

Pers_ID	Surname	First_Name	City
0	Miller	Paul	London
1	Ortega	Alvaro	Valencia
2	Huber	Urs	Zurich
3	Blanc	Gaston	Paris
4	Bertolini	Fabrizio	Rom

Car:

Car_ID	Model	Year	Value	Pers_ID
101	Bentley	1973	100000	0
102	Rolls Royce	1965	330000	0
103	Peugeot	1993	500	3
104	Ferrari	2005	150000	4
105	Renault	1998	2000	3
106	Renault	2001	7000	3
107	Smart	1999	2000	2

no relation

Types of Datasets

■ 2. Graphs and networks



Image credit: [Medium](#)

Social Networks

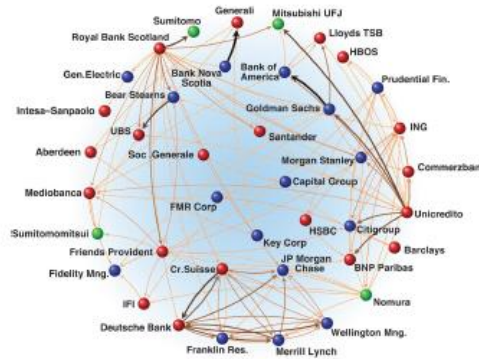


Image credit: [Science](#)

Economic Networks



Image credit: [Lumen Learning](#)

Communication Networks



Citation Networks



Image credit: [Missoula Current News](#)

Internet

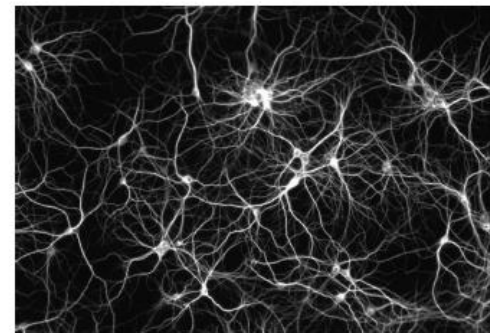


Image credit: [The Conversation](#)

Networks of Neurons

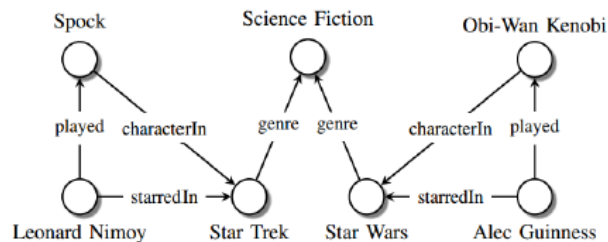


Image credit: [Maximilian Nickel et al](#)

Knowledge Graphs

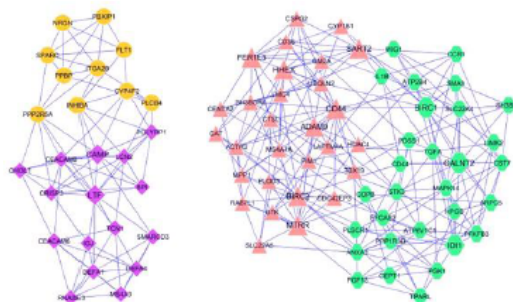


Image credit: [ese.wustl.edu](#)

Regulatory Networks

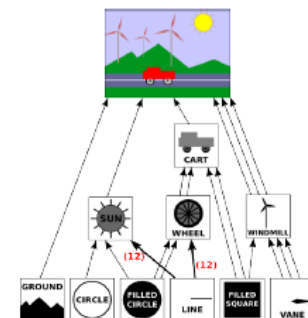


Image credit: [math.hws.edu](#)

Scene Graphs

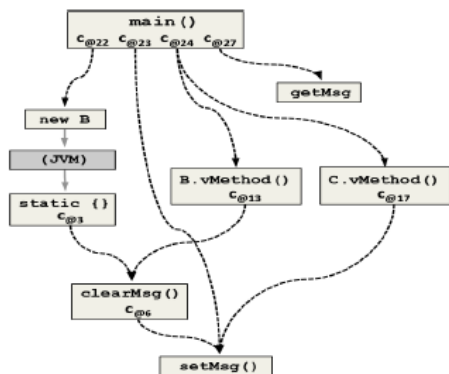


Image credit: [ResearchGate](#)

Code Graphs

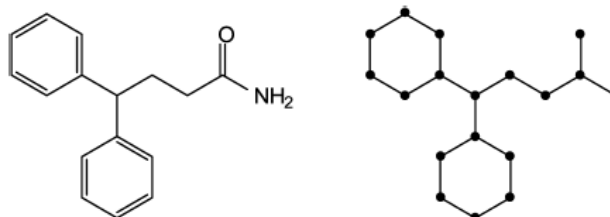


Image credit: [MDPI](#)

Molecules

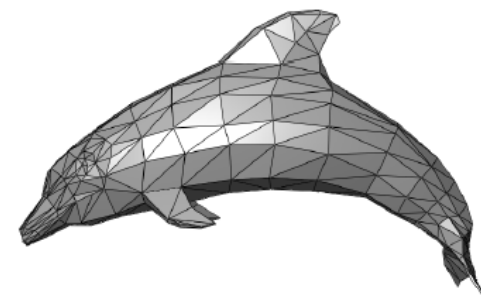


Image credit: [Wikipedia](#)

3D Shapes

Types of Datasets

- 3. Multimedia data



Images

Class: dribble



Class: kick_ball



Videos / image sequences

Types of Datasets

- 4. Text data
 - Twitter/Facebook posts
 - News
 - Wikipedia texts
 - Shopping item comments
 - Books
 - Transcripts
 - Emails
 - Documents
 - ...



Data objects and attributes

- Data objects are also called samples, examples, instances, data points, records, tuples,
- Data attributes are also called dimensions, features, variables, channels, ...
- Data sets are made up of data objects/samples
- Data objects are described by attributes/features

Car:

Car_ID	Model	Year	Value	Pers_ID
101	Bentley	1973	100000	0
102	Rolls Royce	1965	330000	0
103	Peugeot	1993	500	3
104	Ferrari	2005	150000	4
105	Renault	1998	2000	3
106	Renault	2001	7000	3
107	Smart	1999	2000	2

Each row represents a data sample;
Each column represents a data attribute.

Attribute Types


- **Numeric:** real numbers (continuous values)
 - *Prices, \$500, \$200; Image pixel intensity: [0 255]*
 - *temperature, height, or weight*
- **Nominal:** (Categorical) categories, states, or “names of things” (discrete values)
 - *Hair_color = {black, blond, brown, grey, red, white}*
 - marital status, occupation, ID numbers, zip codes
- **Binary** (discrete values)
 - Nominal attribute with only 2 states (0 and 1)
 - {true, false},
 - {1, 0} indicates one item exists or not
- **Ordinal** (discrete values)
 - Values have a meaningful order (ranking) but magnitude between successive values is not known
 - *Size = {small, medium, large}, grades={A, B, C, D},*

■ Convert raw data into numeric values

- For many data mining (machine learning) tasks, e.g., clustering, classification, regression.
- Nominal -> numeric: use one-hot encoding
- Ordinal -> numeric: use numbers to indicate ranking (1,2,3,...)
- Binary -> numeric: convert to {0, 1}

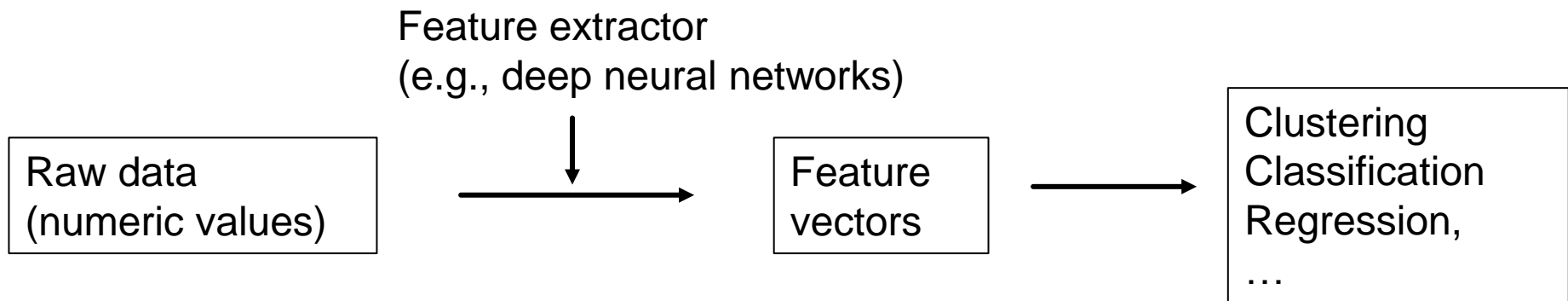
Example: convert nominal values to numeric values using one-hot encoding

id	color
1	red
2	blue
3	green
4	blue



id	color_red	color_blue	color_green
1	1	0	0
2	0	1	0
3	0	0	1
4	0	1	0

A typical pipeline for applying data mining techniques:



Feature vectors: one data sample is represented by one feature vector.

e.g., $\mathbf{x} = [x_1, x_2, x_3, x_4, \dots]$

- Vector norm

- also called vector magnitude, the length of the vector

1. Lp-norm (general):

Let $p \geq 1$ be a real number. The p -norm (also called ℓ_p -norm) of vector $\mathbf{x} = (x_1, \dots, x_n)$ is^[9]

$$\|\mathbf{x}\|_p := \left(\sum_{i=1}^n |x_i|^p \right)^{1/p}.$$

2. L1-norm:

$$\|\mathbf{x}\|_1 := \sum_{i=1}^n |x_i|.$$

3. L2-norm:

$$\|\mathbf{x}\|_2 := \sqrt{x_1^2 + \dots + x_n^2}.$$

Also called Euclidean norm,
vector length

Distance

Given two vectors: \mathbf{x}_i and \mathbf{x}_j (they have l dimensions)

1. Calculate the vector difference (residual vector): $\mathbf{r} = \mathbf{x}_i - \mathbf{x}_j$
2. apply vector norm on the vector difference:

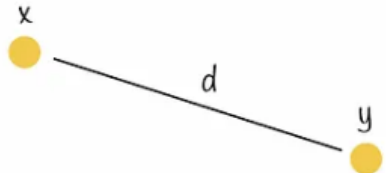
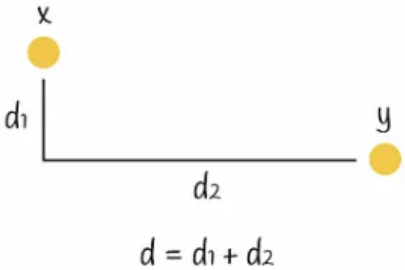
$$d_p(i, j) = \|\mathbf{r}\|_p = \|\mathbf{x}_i - \mathbf{x}_j\|_p$$

- $p = 1$: (L_1 norm) **Manhattan distance (L1 distance)**

$$d(i, j) = |x_{i1} - x_{j1}| + |x_{i2} - x_{j2}| + \cdots + |x_{il} - x_{jl}|$$

- $p = 2$: (L_2 norm) **Euclidean distance (L2 distance)**

$$d(i, j) = \sqrt{|x_{i1} - x_{j1}|^2 + |x_{i2} - x_{j2}|^2 + \cdots + |x_{il} - x_{jl}|^2}$$

Metric	Formula	Interpretation
Euclidean distance	$d = \sqrt{\sum_i^n (x_i - y_i)^2}$	
Manhattan distance	$d = \sum_i^n x_i - y_i $	

<https://towardsdatascience.com/similarity-search-knn-inverted-file-index-7cab80ccoe79>

Distance

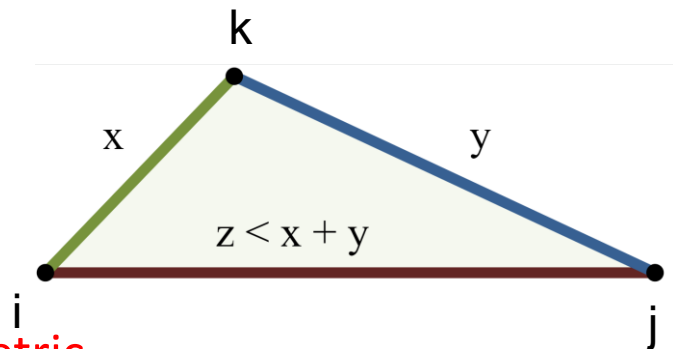
- Minkowski distance (defined by vector norm):

$$d(i, j) = \sqrt[p]{|x_{i1} - x_{j1}|^p + |x_{i2} - x_{j2}|^p + \dots + |x_{il} - x_{jl}|^p}$$

where $i = (x_{i1}, x_{i2}, \dots, x_{il})$ and $j = (x_{j1}, x_{j2}, \dots, x_{jl})$ are two l -dimensional data objects, and p is the order (defined based on L- p norm)

- It has the properties:

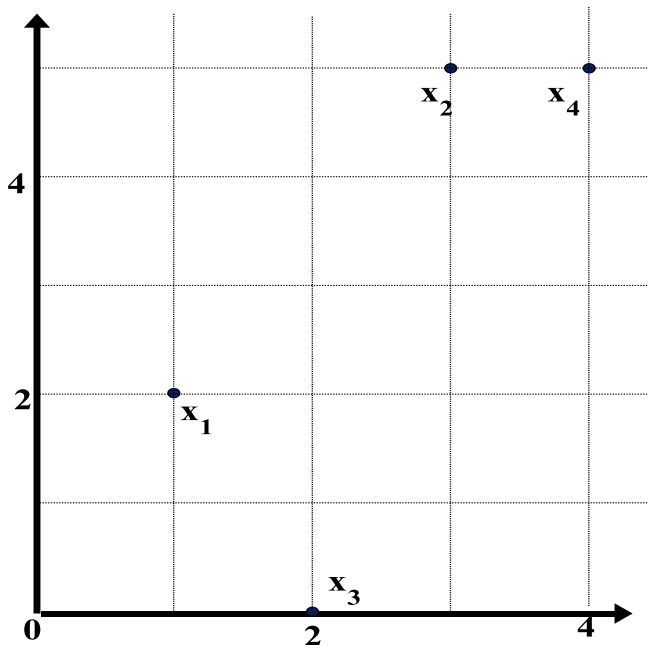
- $d(i, j) > 0$ if $i \neq j$, and $d(i, i) = 0$ (Positivity)
- $d(i, j) = d(j, i)$ (Symmetry)
- $d(i, j) \leq d(i, k) + d(k, j)$ (Triangle Inequality)



- A distance that satisfies these properties is a **metric**

■ Data matrix

- Describe a data set (data samples)
- E.g, a data matrix of n data points with d dimensions
- Each row indicates a feature vector

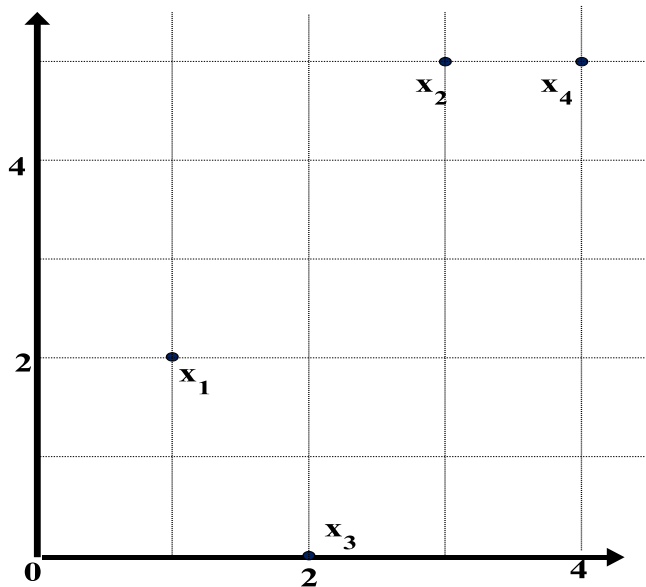


Data Matrix
 $n=4$ (data points), $d=2$ (dimensions)

point	attribute1	attribute2
$x1$	1	2
$x2$	3	5
$x3$	2	0
$x4$	4	5

Distance example

point	attribute 1	attribute 2
x1	1	2
x2	3	5
x3	2	0
x4	4	5



Manhattan distance (L_1)

L	x1	x2	x3	x4
x1	0			
x2	5	0		
x3	3	6	0	
x4	6	1	7	0

Euclidean distance (L_2)

L2	x1	x2	x3	x4
x1	0			
x2	3.61	0		
x3	2.24	5.1	0	
x4	4.24	1	5.39	0

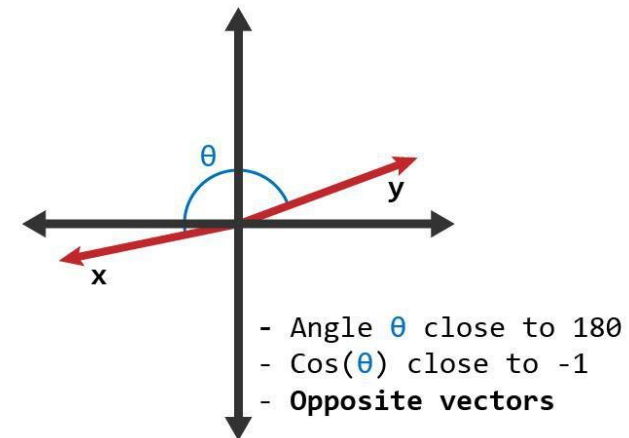
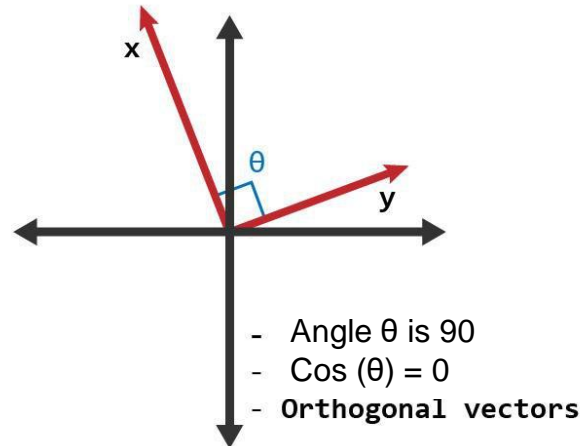
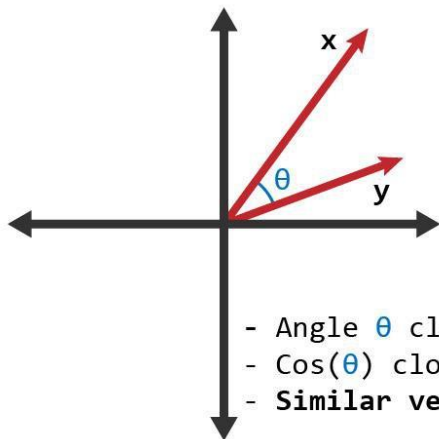
Similarity

■ Cosine similarity

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}},$$

Cosine distance = 1 - cosine similarity

Geometry illustration:



<https://www.learndatasci.com/glossary/cosine-similarity/>

Similarity example

- $D1 = [1, 1, 1, 1, 1, 0, 0]$
- $D2 = [0, 0, 1, 1, 0, 1, 1]$

First, we calculate the dot product of the vectors:

$$D1 \cdot D2 = 1 \times 0 + 1 \times 0 + 1 \times 1 + 1 \times 1 + 1 \times 0 + 0 \times 1 + 0 \times 1 = 2$$

Second, we calculate the magnitude (L2 norm) of the vectors:

$$\|D1\| = \sqrt{1^2 + 1^2 + 1^2 + 1^2 + 1^2 + 0^2 + 0^2} = \sqrt{5}$$

$$\|D2\| = \sqrt{0^2 + 0^2 + 1^2 + 1^2 + 0^2 + 1^2 + 1^2} = \sqrt{4}$$

Finally:

$$\text{similarity}(D1, D2) = \frac{D1 \cdot D2}{\|D1\| \|D2\|} = \frac{2}{\sqrt{5}\sqrt{4}} = \frac{2}{\sqrt{20}} = 0.44721$$

We can further calculate the angle between the vectors:

$$\cos(\theta) = 0.44721$$

$$\theta = \arccos(0.44721) = 63.435$$

Data normalization

- Data normalization
 - The goal of normalization is to transform attributes/features to be on a similar scale.
 - Algorithms may bias to the features which have a larger magnitude.
 - E.g., L2-distance will be dominated by large attributes

$$d(i, j) = \sqrt{|x_{i1} - x_{j1}|^2 + |x_{i2} - x_{j2}|^2 + \dots + |x_{il} - x_{jl}|^2}$$

Examples:

x1= [100, 0.1]

x2= [120, 0.01]

x3= [120, 0.1]



$d(x1, x2) \approx d(x1, x3)$

- 1. Max-Min Normalization

- rescale to a value in [0, 1]

$$x_{\text{norm}} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

- 2. Z-score normalization

- Also called standardization
- rescale to ensure the mean and the standard deviation to be 0 and 1
- More robust to outlier

$$x_{\text{stand}} = \frac{x - \text{mean}(x)}{\text{standard deviation}(x)}$$

Population Standard Deviation

$$\sigma = \sqrt{\frac{\sum (X_i - \mu)^2}{N}}$$

σ = population standard deviation

N = the size of the population

X_i = each value from the population

μ = the population mean

Example

Input dataset

user	Age	Salary
1	40	100000
2	32	80000
3	21	43000
4	24	51000
5	35	70000

Age Mean	30.4
Age Std	7.829432
Salary mean	68800
Salary std	22818.85
Age min	21
Age max	40
Salary min	43000
Salary max	100000

Z-score normalization

user	Age	Salary
1	1.2261426	1.367291
2	0.2043571	0.490822
3	-1.200598	-1.13064
4	-0.817428	-0.78006
5	0.5875267	0.052588

Max-Min Normalization

user	Age	Salary
1	1	1
2	0.5789474	0.649123
3	0	0
4	0.1578947	0.140351
5	0.7368421	0.473684