# Similarity, Dissimilarity, and Proximity

- Similarity measure or similarity function
  - A real-valued function that quantifies the similarity between two objects
  - Measure how two data objects are alike: The higher value, the more alike
  - Often falls in the range [0,1]: 0: no similarity; 1: completely similar
- Dissimilarity (or distance) measure

  - In some sense, the inverse of similarity: The lower, the more alike
  - Minimum dissimilarity is often 0 (i.e., completely similar)
  - Range [0, 1] or  $[0, \infty)$ , depending on the definition
- Proximity usually refers to either similarity or dissimilarity

### Data Matrix and Dissimilarity Matrix

- Data matrix
- A data matrix of n data points with *l* dimensions



$$D = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1l} \\ x_{21} & x_{22} & \dots & x_{2l} \\ ? & ? & ? \\ x_{n1} & x_{n2} & \dots & x_{nl} \end{pmatrix}$$

- Dissimilarity (distance) matrix
  - n data points, but registers only the distance d(i, j)(typically metric)



- Usually symmetric, thus a triangular matrix
- Distance functions are usually different for real, boolean, categorical, ordinal, ratio, and vector variables
- $\begin{pmatrix} 0 & & & & \\ d(2,1) & 0 & & & \\ ? & ? & ? \\ d(n,1) & d(n,2) & \dots & 0 \end{pmatrix}$
- Weights can be associated with different variables based on applications and data semantics

# Standardizing Numeric Data

• Z-score:  $z = \frac{x - \mu}{\sigma}$ 

- X: raw score to be standardized,  $\mu$ : mean of the population,  $\sigma$ : standard deviation
- the distance between the raw score and the population mean in units of the standard deviation
- negative when the raw score is below the mean, "+" when above
- An alternative way: Calculate the mean absolute deviation

$$s_f = \frac{1}{n}(|x_{1f} - m_f| + |x_{2f} - m_f| + ... + |x_{nf} - m_f|)$$

where

$$m_f = \frac{1}{n} (x_{1f} + x_{2f} + ... + x_{nf}).$$

- standardized measure (z-score):  $z_{if} = \frac{x_{if} m_f}{s}$
- Using mean absolute deviation is more robust than using standard deviation

## Example: Data Matrix and Dissimilarity Matrix

#### **Data Matrix**

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

#### **Dissimilarity Matrix (by Euclidean Distance)**

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

### Distance on Numeric Data: Minkowski Distance

Minkowski distance: A popular distance measure

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

where i = (xi1, xi2, ..., xil) and j = (xj1, xj2, ..., xjl) are two l-dimensional data objects, and p is the order (the distance so defined is also called L-p norm)

- Properties
- d(i, j) > 0 if  $i \neq j$ , and d(i, i) = 0 (Positivity)
- d(i, j) = d(j, i) (Symmetry)
- $d(i, j) \square d(i, k) + d(k, j)$  (Triangle Inequality)
- A distance that satisfies these properties is a metric
- Note: There are nonmetric dissimilarities, e.g., set differences

## Special Cases of Minkowski Distance

- p = 1: (L1 norm) Manhattan (or city block) distance
  - E.g., the Hamming distance: the number of bits that are different between two binary vectors  $d(i, j) = |x_{i1} x_{i1}| + |x_{i2} x_{i2}| + ? + |x_{ii} x_{ii}|$
- p = 2: (L2 norm) Euclidean distance

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

- $p \square \square$ : (Lmax norm, L $\square$  norm) "supremum" distance
  - The maximum difference between any component (attribute) of the vectors

$$d(i,j) = \lim_{p \to \infty} \sqrt[p]{|x_{i1} - x_{j1}|^p + |x_{i2} - x_{j2}|^p + \dots + |x_{il} - x_{jl}|^p} = \max_{f=1}^l |x_{if} - x_{jf}|$$

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# Example: Minkowski Distance at Special Cases

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

#### Manhattan (L1)

L	x1	x2	х3	x4
x1	0			
x2	5	0		
x3	3	6	0	
x4	6	1	7	0

#### **Euclidean**

(L23	x1	x2	x3	x4
x1	0			
x2	3.61	0		
х3	2.24	5.1	0	
x4	4.24	1	5.39	0

#### **Supremum**

(LI)	x1	x2	х3	x4
x1	0			
x2	3	0		
x3	2	5	0	
x4	3	1	5	0

### Proximity Measure for Binary Attributes

A contingency table for binary data

	Object j			
		1	0	sum
Obinet:	1	q	r	q + r
Object i	0	s	t	s+t
	sum	a+s	r+t	p

- Distance measure for symmetric binary variables  $d(i, j) = \frac{r+s}{q+r+s+t}$
- Distance measure for asymmetric binary variables:  $d(i, j) = \frac{r+s}{q+r+s}$
- Jaccard coefficient (*similarity* measure for asymmetric binary variables):  $sim_{Jaccard}(i, j) = \frac{q}{q + r + s}$
- Note: Jaccard coefficient is the same as "coherence" (a concept discussed in Pattern Discovery)

$$coherence(i,j) = \frac{sup(i,j)}{sup(i) + sup(j) - sup(i,j)} = \frac{q}{(q+r) + (q+s) - q}$$

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### Example: Dissimilarity between Asymmetric Binary Variables

Jim

Name	Gender	Fever	Cough	Test-1	Test-2	Test-3	Test-4
Jack	M	Y	N	P	N	N	N
Mary	F	Y	N	P	N	P	N
Jim	M	Y	P	N	N	N	N

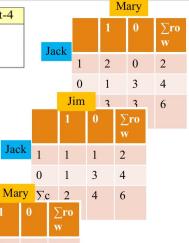
- Gender is a symmetric attribute (not counted in)
- The remaining attributes are asymmetric binary
- Let the values Y and P be 1, and the value N be 0

• Distance: 
$$d(i, j) = \frac{r+s}{q+r+s}$$
  

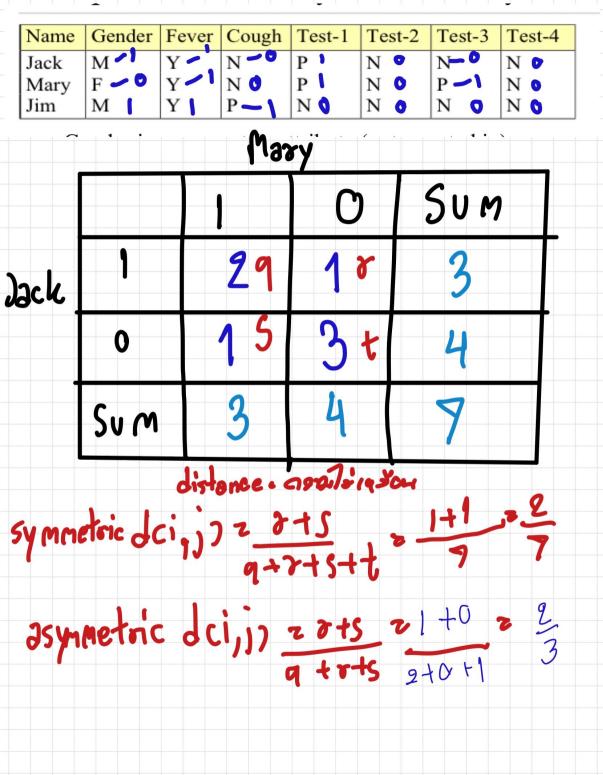
$$d(jack, mary) = \frac{0+1}{2+0+1} = 0.33$$

$$d(jack, jim) = \frac{1+1}{1+1+1} = 0.67$$

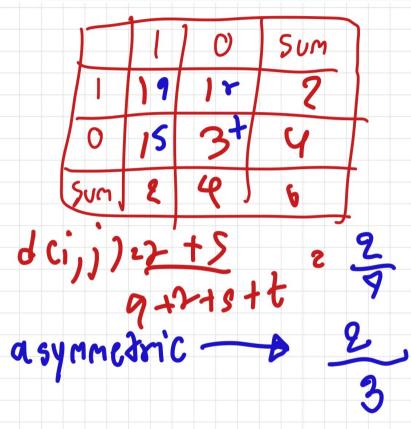
$$d(jim, mary) = \frac{1+2}{1+1+2} = 0.75$$



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Name	Gender	Fever	Cough	Test-1	Test-2	Test-3	Test-4
Jack	M	Y	N 💋	P	N O	NO	N 🔮
Mary	F 🛡	Y	N _	P	N 🌭	P	N
Jim	M I	Y	P	N 🖠	No	NO	N 0



# Proximity Measure for Categorical Attributes

- Categorical data, also called nominal attributes
  - Example: Color (red, yellow, blue, green), profession, etc.
- Method 1: Simple matching
  - m: # of matches, p: total # of variables  $d(i,j) = \frac{p-m}{p}$
- Method 2: Use a large number of binary attributes
  - Creating a new binary attribute for each of the *M* nominal states

