Data Mining: Similarity Measures

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Similarity and Dissimilarity

- Similarity
 - Numerical measure of how alike two data objects are.
 - Is higher when objects are more alike.
 - Often falls in the range [0,1].
- Dissimilarity
 - Numerical measure of how different two data objects are.
 - Lower when objects are more alike.
 - Minimum dissimilarity is often 0.
 - Upper limit varies.
- Proximity refers to a similarity or dissimilarity



Similarity/Dissimilarity for Simple Attributes



$$d = \begin{cases} 0, & p = q \\ 1, & p \neq q \end{cases} \quad s = 1 - d$$

• Ordinal attributes: map n distinct values to integers from 0 to n-1

$$d = \frac{|p-q|}{n-1} \qquad s = 1-d$$

• Interval or ratio attributes: d = |p - q| $s = \frac{1}{1+d}$

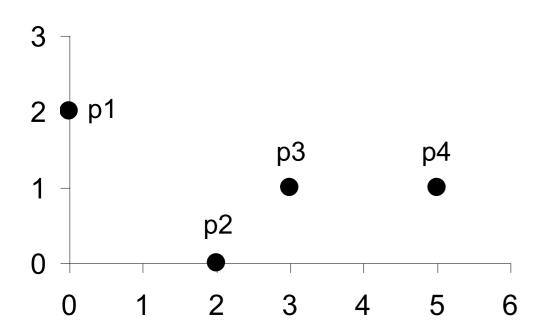
Euclidean distance

Euclidean distance between two objects p and q with n attributes

$$d(\mathbf{p}, \mathbf{q}) = \sqrt{\sum_{k=1}^{n} (p_k - q_k)^2}$$

- Distance of a ruler
- Standardization is necessary, if scales differ

Euclidean Distance



point	Х	У
p1	0	2
p2	2	0
р3	3	1
p4	5	1

	p1	p2	р3	р4
p1	0	2.828	3.162	5.099
p2	2.828	0	1.414	3.162
р3	3.162	1.414	0	2
p4	5.099	3.162	2	0

distance matrix

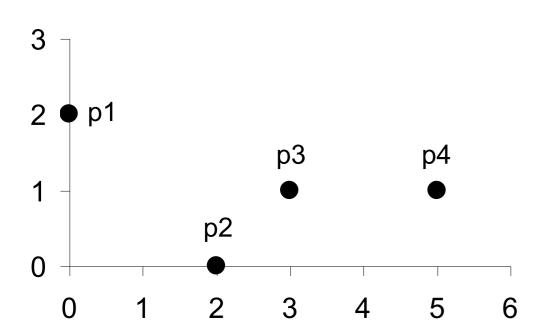
Minkowski distance

Generalization of Euclidean distance:

$$d(\mathbf{p}, \mathbf{q}) = \sqrt[r]{\sum_{k=1}^{n} |p_k - q_k|^r}$$

- r = 1: city block (Manhattan, taxicab, L₁ norm) distances
 - reduces to Hamming distance, which just counts the number of differences, in case of binary variables
- r = 2 corresponds to Euclidean distance
- $r=\infty$: supremum (L_{max} , L_{∞}) or Chebyshev distance
 - maximum distance between any component of the vectors
 - distance kings have to travel on a chess board

Manhattan Distance (r = 1)

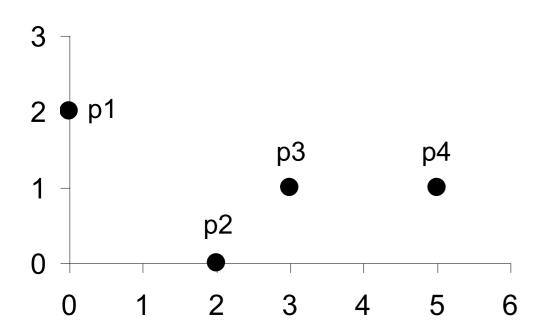


point	X	У
p1	0	2
p2	2	0
р3	3	1
p4	5	1

	p1	p2	р3	p4
p1 0		4	4	6
p2 4		0	2	4
р3	4	2	0	2
р4	6	4	2	0

distance matrix

Supremum Distance $(r = \infty)$

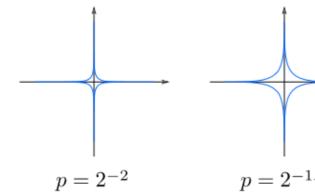


point	v	V
point	X	У
p1	0	2
p2	2	0
р3	3	1
р4	5	1

	p1	p2	р3	p4
p1	0	2	3	5
p2	2	0	1	3
р3	3	1	0	2
р4	5	3	2	0

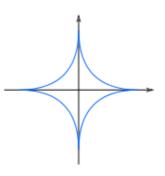
distance matrix

Unit circle



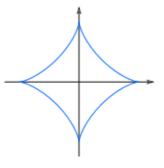
= 0.25

$$p = 2^{-1.5} \\ = 0.354$$

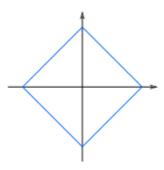


$$p = 2^{-1}$$

= 0.5

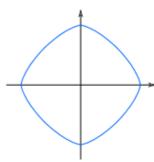


$$p = 2^{-0.5} = 0.707$$



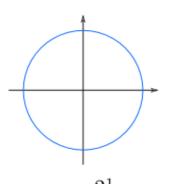
$$p = 2^0$$

= 1

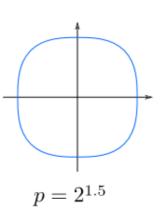


$$p = 2^{0.5}$$

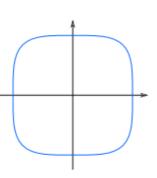
= 1.414



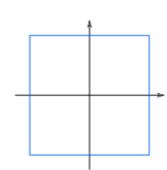
$$\begin{aligned} p &= 2^1 \\ &= 2 \end{aligned}$$



$$p = 2.828$$



$$\begin{aligned} p &= 2^2 \\ &= 4 \end{aligned}$$



$$\begin{aligned} p &= 2^{\infty} \\ &= \infty \end{aligned}$$

Common properties of a distance

- Distances, such as the Euclidean distance, have some well-known properties
 - 1. Positive definiteness: $d(\mathbf{p}, \mathbf{q}) \ge 0$ for all \mathbf{p} and \mathbf{q} and $d(\mathbf{p}, \mathbf{q}) = 0$ iff $\mathbf{p} = \mathbf{q}$
 - 2. Symmetry: $d(\mathbf{p}, \mathbf{q}) = d(\mathbf{q}, \mathbf{p})$ for all \mathbf{p} and \mathbf{q}
 - 3. Triangle inequality: $d(\mathbf{p}, \mathbf{r}) \le d(\mathbf{p}, \mathbf{q}) + d(\mathbf{q}, \mathbf{r})$ for all \mathbf{p}, \mathbf{q} and \mathbf{r}
- A distance that satisfies these properties is called a metric

Similarity Between Binary Vectors

p

•	M_{00} = number of attributes
	with $p_k = 0$ and $q_k = 0$, etc.

		0	1
n	0	M_{00}	M_{10}
1	1	M_{01}	M_{11}

Simple matching coefficient (SMC):

$$s(\mathbf{p}, \mathbf{q}) = \frac{\text{# matches}}{\text{# attributes}} = \frac{M_{00} + M_{11}}{M_{00} + M_{01} + M_{10} + M_{11}}$$

Jaccard coefficient:

$$s(\mathbf{p}, \mathbf{q}) = \frac{\text{# 11 matches}}{\text{# not-both-zero}} = \frac{M_{11}}{M_{01} + M_{10} + M_{11}}$$

SMC versus Jaccard

P

• p =	[1 (0 (0 0	0	0 0	0	0]	
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•
$$\mathbf{q} = [0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 1]$$

	0	1
0	7	1
1	2	0

q

Simple matching coefficient (SMC):

$$s(\mathbf{p}, \mathbf{q}) = \frac{\text{# matches}}{\text{# attributes}} = \frac{7}{10} = 0.7$$

Jaccard coefficient:

$$s(\mathbf{p}, \mathbf{q}) = \frac{\text{# 11 matches}}{\text{# not-both-zero}} = \frac{0}{3} = 0$$

Cosine Similarity

Specifically for documents vectors

$$S(\mathbf{p}, \mathbf{q}) = \frac{\mathbf{p} \cdot \mathbf{q}}{\|\mathbf{p}\| \|\mathbf{q}\|}$$

With inner product

$$\mathbf{p} \cdot \mathbf{q} = \sum_{k=1}^{n} p_k q_k$$

And vector length

$$\|\mathbf{p}\| = \sqrt{\mathbf{p} \cdot \mathbf{p}}$$



Cosine Similarity Example

• $\mathbf{p} = [3\ 2\ 0\ 5\ 0\ 0\ 0\ 2\ 0\ 0$]
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•
$$\mathbf{q} = [1\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 2]$$

	Document	team	coach	play	ball	score	game	Win	lost	timeout	season	
p	1	3	2	0	5	0	0	0	2	0	0	
	2	0	7	0	2	1	0	0	3	0	0	
q	3	1	0	0	0	0	0	0	1	0	2	
	4	1	4	0	2	3	0	1	6	2	1	
	5	2	3	3	1	6	1	3	0	0	4	

• Inner product:

$$\mathbf{p} \cdot \mathbf{q} = 3 \times 1 + 2 \times 0 + 0 \times 0 + 5 \times 0 + 0 \times 0 + 0 \times 0 + 0 \times 0 + 2 \times 1 + 0 \times 0 + 0 \times 2 = 5$$

- Vector lengths: $\|\mathbf{p}\| = \sqrt{3^2 + 2^2 + 5^2 + 2^2} = \sqrt{42}$ and $\|\mathbf{q}\| = \sqrt{1^2 + 1^2 + 2^2} = \sqrt{6}$
- Cosine similarity:

$$s(\mathbf{p}, \mathbf{q}) = \frac{\mathbf{p} \cdot \mathbf{q}}{\|\mathbf{p}\| \|\mathbf{q}\|} = \frac{5}{\sqrt{252}}$$

