Unit - II Datamining



- Similarity and dissimilarity are important because they are used by a number of data mining techniques
 - such as
 - clustering,
 - nearest neighbor classification, and
 - anomaly detection.
- Proximity is used to refer to either similarity or dissimilarity.
 - o proximity between objects having only one simple attribute, and
 - proximity measures for objects with multiple attributes.

- **Similarity** between two objects is a numerical measure of the degree to which the two objects are alike.
 - Similarity high -objects that are more alike.
 - Non-negative
 - between 0 (no similarity) and 1 (complete similarity).
- **Dissimilarity** between two objects is a numerical measure of the degree to which the two objects are different.
 - Dissimilarity low objects are more similar.
 - Distance synonym for dissimilarity

Transformations

- Transformations are often applied to
 - convert a similarity to a dissimilarity,
 - convert a dissimilarity to a similarity
 - \circ to transform a proximity measure to fall within a particular range, such as [0,1].
- Example
 - Similarities between objects range from 1 (not at all similar) to 10 (completely similar)
 - we can make them fall within the range [0, 1] by using the transformation
 - s' = (s-1)/9
 - s Original Similarity
 - s' New similarity values



Table 2.7. Similarity and dissimilarity for simple attributes

Attribute	Dissimilarity	Similarity	
Type			
Nominal	$d = \begin{cases} 0 & \text{if } x = y \\ 1 & \text{if } x \neq y \end{cases}$	$s = \begin{cases} 1 & \text{if } x = y \\ 0 & \text{if } x \neq y \end{cases}$	
Ordinal	d = x - y /(n - 1) (values mapped to integers 0 to $n-1$, where n is the number of values)	s = 1 - d	
Interval or Ratio	d = x - y	$s = -d$, $s = \frac{1}{1+d}$, $s = e^{-d}$, $s = 1 - \frac{d-min_d}{max_d-min_d}$	
		$s = 1 - \frac{d - min_d}{max_d - min_d}$	

Dissimilarities between Data Objects

The Euclidean distance measure given in Equation 2.1 is generalized by the **Minkowski** distance metric shown in Equation 2.2,

$$d(\mathbf{x}, \mathbf{y}) = \left(\sum_{k=1}^{n} |x_k - y_k|^r\right)^{1/r},\tag{2.2}$$

where r is a parameter. The following are the three most common examples of Minkowski distances.

- r = 1. City block (Manhattan, taxicab, L₁ norm) distance. A common example is the **Hamming distance**, which is the number of bits that are different between two objects that have only binary attributes, i.e., between two binary vectors.
- r = 2. Euclidean distance (L₂ norm).
- $r = \infty$. Supremum (L_{max} or L_{\infty} norm) distance. This is the maximum difference between any attribute of the objects. More formally, the L_{\infty} distance is defined by Equation 2.3

$$d(\mathbf{x}, \mathbf{y}) = \lim_{r \to \infty} \left(\sum_{k=1}^{n} |x_k - y_k|^r \right)^{1/r}.$$
 (2.3)

$$d(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{k=1}^{n} (x_k - y_k)^2},$$
(2.1)

Dissimilarities between Data Objects

If d(x, y) is the distance between two points, x and y, then the following **properties** hold.

1. Positivity

(a) $d(x, x) \ge 0$ for all x and y,

(b) d(x, y) = 0 only if x = y.

2. Symmetry

d(x, y) = d(y, x) for all x and y.

3. Triangle Inequality

 $d(x, z) \le d(x, y) + d(y, z)$ for all points x, y, and z.

Note:-Measures that satisfy all three properties are known as **metrics**.



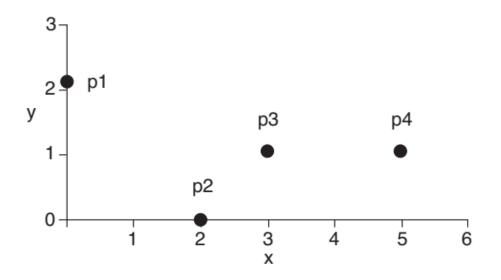


Figure 2.15. Four two-dimensional points.

Table 2.8. x and y coordinates of four points.

point	x coordinate	y coordinate
p1	0	2
p2	2	0
p3	3	1
p4	5	1



Table 2.9. Euclidean distance matrix for Table 2.8.

	p1	p2	p3	p4
p1	0.0	2.8	3.2	5.1
p2	2.8	0.0	1.4	3.2
р3	3.2	1.4	0.0	2.0
p4	5.1	3.2	2.0	0.0



Table 2.10. L_1 distance matrix for Table 2.8.

L_1	p1	p2	р3	p4
p1	0.0	4.0	4.0	6.0
p2	4.0	0.0	2.0	4.0
р3	4.0	2.0	0.0	2.0
p4	6.0	4.0	2.0	0.0



Table 2.11. L_{∞} distance matrix for Table 2.8.

L_{∞}	p1	p2	р3	p4
p1	0.0	2.0	3.0	5.0
p2	2.0	0.0	1.0	3.0
р3	3.0	1.0	0.0	2.0
p4	5.0	3.0	2.0	0.0

Dissimilarities between Data Objects

Non-metric Dissimilarities: Set Differences

A =
$$\{1, 2, 3, 4\}$$
 and B = $\{2, 3, 4\}$,
then A - B = $\{1\}$ and
B - A = \emptyset , the empty set.

If d(A, B) = size(A - B), then it <u>does not satisfy</u> the second part of the positivity property, the symmetry property, or the triangle inequality.

d(A, B) = size(A - B) + size(B - A) (modified which follows all properties)



Dissimilarities between Data Objects

Non-metric Dissimilarities: Time

Dissimilarity measure that is not a metric, but still useful.

$$d(t_1, t_2) = \left\{ \begin{array}{ll} t_2 - t_1 & \text{if } t_1 \le t_2 \\ 24 + (t_2 - t_1) & \text{if } t_1 \ge t_2 \end{array} \right\}. \tag{2.4}$$

$$d(1PM, 2PM) = 1 \text{ hour}$$

 $d(2PM, 1PM) = 23 \text{ hours}$

 Example:- when answering the question: "If an event occurs at 1PM every day, and it is now 2PM, how long do I have to wait for that event to occur again?"

Distance in python

```
>>> from scipy.spatial import distance
>>> p1=(0,2)
>>> p2=(2,0)
>>> print(distance.cityblock(p1,p2))
>>> print(distance.euclidean(p1,p2))
2.8284271247461903
>>> print(distance.minkowski(p1,p2,p=1))
4.0
>>> print(distance.minkowski(p1,p2,p=2))
2.8284271247461903
>>> print(distance.minkowski(p1,p2,p=3))
2.5198420997897464
```

- Typical properties of similarities are the following:
 - 1. s(x, y) = 1 only if x = y. $(0 \le s \le 1)$
 - \circ 2. s(x, y) = s(y, x) for all x and y. (Symmetry)
- A Non-symmetric Similarity Measure
 - Classify a small set of characters which is flashed on a screen.
 - Confusion matrix records how often each character is classified as itself, and how often each is classified as another character.
 - "0" appeared 200 times but classified as
 - "0" 160 times,
 - "o" 40 times.
 - o 'o' appeared 200 times and was classified as
 - "o" 170 times
 - "0" only 30 times.
- similarity measure can be made symmetric by setting
 - \circ S'(x, y) = S'(y, x) = (s(x, y)+s(y, x))/2,
 - S` new similarity measure.

Examples of proximity measures

- Similarity Measures for Binary Data
 - Similarity measures between objects that contain only binary attributes are called similarity coefficients
 - Let x and y be two objects that consist of n binary attributes.
 - The comparison of two objects (or two binary vectors), leads to the following four quantities (frequencies):

```
\mathbf{f_{00}} = the number of attributes where x is 0 and y is 0 \mathbf{f_{01}} = the number of attributes where x is 0 and y is 1
```

 \mathbf{f}_{10} = the number of attributes where x is 1 and y is 0

 \mathbf{f}_{11} = the number of attributes where x is 1 and y is 1

Examples of proximity measures

Similarity Measures for Binary Data
 Simple Matching Coefficient(SMC)

$$SMC = \frac{\text{number of matching attribute values}}{\text{number of attributes}} = \frac{f_{11} + f_{00}}{f_{01} + f_{10} + f_{11} + f_{00}}.$$
 (2.5)

Jaccard Coefficient

$$J = \frac{\text{number of matching presences}}{\text{number of attributes not involved in 00 matches}} = \frac{f_{11}}{f_{01} + f_{10} + f_{11}}.$$
 (2.6)

Examples of proximity measures

Similarity Measures for Binary Data

Example 2.17 (The SMC and Jaccard Similarity Coefficients). To illustrate the difference between these two similarity measures, we calculate SMC and J for the following two binary vectors.

$$\mathbf{x} = (1,0,0,0,0,0,0,0,0,0,0)$$

 $\mathbf{y} = (0,0,0,0,0,0,1,0,0,1)$
 $f_{01} = 2$ the number of attributes where \mathbf{x} was 0 and \mathbf{y} was 1
 $f_{10} = 1$ the number of attributes where \mathbf{x} was 1 and \mathbf{y} was 0
 $f_{00} = 7$ the number of attributes where \mathbf{x} was 0 and \mathbf{y} was 0
 $f_{11} = 0$ the number of attributes where \mathbf{x} was 1 and \mathbf{y} was 1

$$SMC = \frac{f_{11} + f_{00}}{f_{01} + f_{10} + f_{11} + f_{00}} = \frac{0 + 7}{2 + 1 + 0 + 7} = 0.7$$
 $J = \frac{f_{11}}{f_{01} + f_{10} + f_{11}} = \frac{0}{2 + 1 + 0} = 0$

Examples of proximity measures

Cosine similarity (Document similarity)

If x and y are two document vectors, then

$$\cos(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|},\tag{2.7}$$

· indicates the vector dot product, $\mathbf{x} \cdot \mathbf{y} = \sum_{k=1}^{n} x_k y_k$

length of vector
$$\mathbf{x}$$
, $\|\mathbf{x}\| = \sqrt{\sum_{k=1}^{n} x_k^2} = \sqrt{\mathbf{x} \cdot \mathbf{x}}$.

Examples of proximity measures

cosine similarity (Document similarity)

Example 2.18 (Cosine Similarity of Two Document Vectors). This example calculates the cosine similarity for the following two data objects, which might represent document vectors:

$$\mathbf{x} = (3, 2, 0, 5, 0, 0, 0, 2, 0, 0)$$

$$\mathbf{y} = (1, 0, 0, 0, 0, 0, 0, 1, 0, 2)$$

$$\mathbf{x} \cdot \mathbf{y} = 3 * 1 + 2 * 0 + 0 * 0 + 5 * 0 + 0 * 0 + 0 * 0 + 0 * 0 + 2 * 1 + 0 * 0 + 0 * 2 = 5$$

$$\|\mathbf{x}\| = \sqrt{3 * 3 + 2 * 2 + 0 * 0 + 5 * 5 + 0 * 0 + 0 * 0 + 0 * 0 + 2 * 2 + 0 * 0 + 0 * 0} = 6.48$$

$$\|\mathbf{y}\| = \sqrt{1 * 1 + 0 * 0 + 0 * 0 + 0 * 0 + 0 * 0 + 0 * 0 + 0 * 0 + 1 * 1 + 0 * 0 + 2 * 2} = 2.24$$

$$\mathbf{cos}(\mathbf{x}, \mathbf{y}) = \mathbf{0.31}$$

Examples of proximity measures

cosine similarity (Document similarity)

```
# import required libraries
import numpy as np
from numpy.linalg import norm

# define two lists or array
A = np.array([2,1,2,3,2,9])
B = np.array([3,4,2,4,5,5])

print("A:", A)
print("B:", B)

# compute cosine similarity
cosine = np.dot(A,B)/(norm(A)*norm(B))
print("Cosine Similarity:", cosine)
```

Examples of proximity measures

cosine similarity (Document similarity)

- Cosine similarity measure of angle between x and y.
- Cosine similarity = 1 (angle is 0° , and x & y are same (except magnitude or length))
- Cosine similarity = 0 (angle is 90°, and x & y do not share any terms (words))

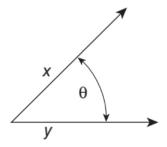


Figure 2.16. Geometric illustration of the cosine measure.

Examples of proximity measures

cosine similarity (Document similarity)

$$\cos(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x}}{\|\mathbf{x}\|} \cdot \frac{\mathbf{y}}{\|\mathbf{y}\|} = \mathbf{x}' \cdot \mathbf{y}', \tag{2.8}$$

$$\mathbf{x}' = \mathbf{x} / \|\mathbf{x}\|$$

$$\mathbf{y}' = \mathbf{y} / \|\mathbf{y}\|.$$

Note:-

Dividing x and y by their lengths **normalizes** them to have a length of 1 (means magnitude is not considered)

Examples of proximity measures

Extended Jaccard Coefficient (Tanimoto Coefficient)

$$EJ(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\|^2 + \|\mathbf{y}\|^2 - \mathbf{x} \cdot \mathbf{y}}.$$
 (2.9)

Examples of proximity measures

Pearson's correlation

$$corr(\mathbf{x}, \mathbf{y}) = \frac{covariance(\mathbf{x}, \mathbf{y})}{standard_deviation(\mathbf{x}) * standard_deviation(\mathbf{y})} = \frac{s_{xy}}{s_x s_y}, \quad (2.10)$$

$$\operatorname{covariance}(\mathbf{x}, \mathbf{y}) = s_{xy} = \frac{1}{n-1} \sum_{k=1}^{n} (x_k - \overline{x})(y_k - \overline{y})$$

$$\operatorname{standard_deviation}(\mathbf{x}) = s_x = \sqrt{\frac{1}{n-1} \sum_{k=1}^{n} (x_k - \overline{x})^2} \qquad \overline{x} = \frac{1}{n} \sum_{k=1}^{n} x_k \text{ is the mean of } \mathbf{x}$$

$$\operatorname{standard_deviation}(\mathbf{y}) = s_y = \sqrt{\frac{1}{n-1} \sum_{k=1}^{n} (y_k - \overline{y})^2} \qquad \overline{y} = \frac{1}{n} \sum_{k=1}^{n} y_k \text{ is the mean of } \mathbf{y}$$

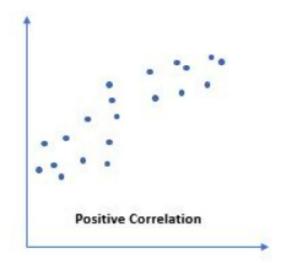
Examples of proximity measures

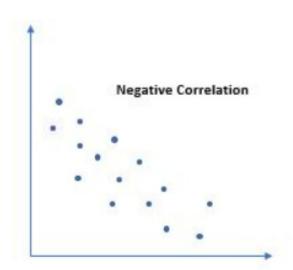
Pearson's correlation

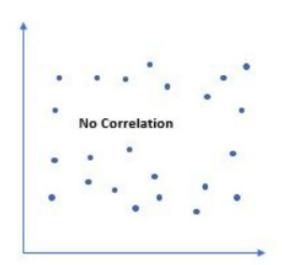
- The more tightly linear two variables X and Y are, the closer Pearson's correlation coefficient(PCC)
 - \circ PCC = -1, if the relationship is negative,
 - PCC=+1, if the relationship is positive.
 - an increase in the value of one variable increases the value of another variable
 - PCC = 0 Perfectly linearly uncorrelated numbers
 - an increase in the value of one decreases the value of another variable.

Examples of proximity measures

Pearson's correlation







Examples of proximity measures

Pearson's correlation (scipy.stats.pearsonr() - automatic)

```
>>> df
                  length
                          width
                                  height
                                          curb-weight
                                                                                     city-mpg
                                                                                                highway-mpg
     wheel-base
                                                              horsepower
                                                                           peak-rpm
                                                                                                              price
                           60.3
           88.4
                   141.1
                                    53.2
                                                  1488
                                                                      48
                                                                               5100
                                                                                            47
                                                                                                          53
                                                                                                               5151
                   144.6
                                    50.8
                                                  1713
                                                                                                          54
                                                                                                               6479
           86.6
                           63.9
                                                                      58
                                                                               4800
                                                                                            49
                   144.6
           86.6
                           63.9
                                    50.8
                                                  1819
                                                                      76
                                                                               6000
                                                                                            31
                                                                                                          38
                                                                                                               6855
                           64.0
           93.7
                   150.0
                                    52.6
                                                  1837
                                                                      60
                                                                               5500
                                                                                            38
                                                                                                          42
                                                                                                               5399
           93.7
                   150.0
                           64.0
                                    52.6
                                                  1940
                                                                               6000
                                                                                            30
                                                                                                          34
                                                                                                               6529
                                                                      76
154
          110.0
                   190.9
                           70.3
                                    58.7
                                                  3750
                                                                     123
                                                                               4350
                                                                                                          25
                                                                                                              28248
                                                  2844
155
          105.8
                   192.7
                           71.4
                                    55.7
                                                                               5500
                                                                                                          25
                                                                     110
                                                                                            19
                                                                                                              17710
156
                                                  3086
          105.8
                   192.7
                           71.4
                                    55.9
                                                                     140
                                                                               5500
                                                                                            17
                                                                                                          20
                                                                                                              23875
157
                   199.6
                                                                               4750
                                                                                                              32250
          113.0
                           69.6
                                    52.8
                                                  4066
                                                                     176
                                                                                            15
                                                                                                          19
158
                                                                                                             31600
          115.6
                   202.6
                           71.7
                                    56.3
                                                  3770
                                                                     123
                                                                               4350
                                                                                            22
[159 rows x 14 columns]
>>> from scipy.stats import pearsonr
>>> import pandas as pd
>>> df=pd.read_csv("Car_price_PLR.csv")
>>> x=df['price']
>>> y=df['city-mpg']
>>> pcc,r=pearsonr(x,y)
>>> print(pcc)
-0.6922730619020598
```

Examples of proximity measures

Pearson's correlation (manual in python)

```
from scipy.stats import pearsonr
import pandas as pd
import numpy as np
def pearson(x,y):
    xbar=np.mean(x)
    ybar=np.mean(y)
    n=2
    sxy=(1/(n-1))*np.sum((x-xbar)*(y-ybar))
    sx=np.sqrt((1/(n-1))*np.sum((x-xbar)**2))
    sy=np.sqrt((1/(n-1))*np.sum((y-ybar)**2))
    pcc=sxy/(sx*sy)
    return pcc
df=pd.read_csv("Car_price_PLR.csv")
x=df['price']
y=df['city-mpg']
pcc=pearson(x,y)
print(pcc)
```

```
$ python3 pearson_m.py
-0.69227306190206
$ ■
```