# ON SOME PROPERTIES ON CHI-SQUARE DISTANCE

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#### ABSTRACT

In this paper we have described the properties of the distance between two multi dimensional points, which is called Chi-square distance. It is a weighted Euclidean distance.

#### INTRODUCTION

A large number of multivariate problem can be viewed in terms of "distances" between two observations, or between samples of observations, or between populations of observations. Many distance measures have been proposed and used in multivariate analysis. Here we introduce the distance used in factor analysis of correspondence (method of a multivariate analysis proposed by J.P. Benzercri in (1962)).

This distance has many properties which deserves our attention.

Let  $K_{IJ}$  be a contingency table of positive numbers k (i,j) with I rows and J columns:

$$K_{IJ} = \{k (i,j) \mid i \in I, j \in J\}$$

We define the marginals  $k_I$ ,  $k_J$  and the total K over  $K_{IJ}$ ; also the profiles  $f_j^i$  and  $f_i^j$  of the rows and the columns of  $K_{IJ}$ . The definitions are given below:

$$\forall i \in I, k(i) = \sum_{j} k(i,j), K_I = \{k(i) | i \in I\}$$

$$\forall j \varepsilon J, k(i) = \sum_{i} k(i,j), K_{J} = \{k(j) | j \varepsilon J\}$$

$$K = \sum_{i} \sum_{j} k(i,j).$$

$$f_{ij} = \frac{k(i,j)}{K}, f_{IJ} = \{f_{ij} \mid i \in I, j \in J\}$$

$$f_i = \frac{k(i)}{K}, f_I = \{f_i | i \in I\}$$

$$f_j = \frac{k(j)}{K}, f_J = \{f_j \mid j \in J\}$$

$$f_j^i = \frac{k(i,j)}{K(i)} = \frac{f_{ij}}{f_i}, f_i^j = \{f_i^j \mid j \in J\}$$

$$f_j^i = \frac{k(i,j)}{K(j)} = \frac{f_{ij}}{f_i}, f_i^j = \{f_I^j | i \in J\}$$

The class of the profiles of the rows is defined as:

$$N_I = \{ (f_I^i, f_i) \mid i \in I \}$$

and similarly for the columns we define

$$N_J = \{ (f_I^j, f_j) \mid j \in j \}$$

we can say that the profile  $f_J^i$  of the rows i is weighted by the marginal probabilities  $f_i$  of i.

**Definition**: The chi-square distance  $d^2(i,i')$  between the profiles of two rows i' and i is given by

$$d^{2}(i,i') = \sum_{j} \left\{ \frac{1}{f_{j}} \left( f_{j}^{i} - f_{j}^{i'} \right)^{2} \right\}$$

$$= \sum_{j} \{ \frac{1}{f_{i}} (\frac{f_{ij}}{f_{i}} - \frac{f_{i'j}}{f_{i'}})^{2} \}$$

Similarly the chi-square distance  $d^2(j,j')$  between the conditional probabilities  $f_j^i$  and  $f_j^{i'}$  profiles of the columns j and j' is given by

$$d^{2}(j,j') = \sum_{i} \{ \frac{1}{f_{i}} (f_{i}^{j} - f_{i}^{j'})^{2} \}$$

we can say that the chi-square distance is a weighted Euclidean distance.

This chi-square has the following properties:

### Lemma (1):

If the two discrete random variables x and y are both independent of another discrete random variable z then the chi-square distance between their conditional probabilities is zero.

Proof: Consider

$$d^{2}(x,y) = \sum_{z} \left\{ \frac{1}{f_{z}} (f_{z}^{x} - f_{z}^{y})^{2} | z \varepsilon Z \right\}$$

$$= \sum_{z} \left\{ \frac{1}{f_{z}} (\frac{f_{xz}}{f_{x}} - \frac{f_{yz}}{f_{y}})^{2} | z \varepsilon Z \right\}$$

$$= \sum_{z} \left\{ \frac{1}{f_{z}} (\frac{f_{x} f_{z}}{f_{x}} - \frac{f_{y} f_{z}}{f_{y}})^{2} | z \varepsilon Z \right\}$$

$$= \sum_{z} \left\{ \frac{1}{f_{z}} (f_{z} - f_{z})^{2} | z \varepsilon Z \right\} = 0$$

If we have a contingency table with two rows i and i' such that  $\forall$  j  $\epsilon$  k (i',j) =  $\alpha$  k(i,j) for some  $\alpha \in \mathbb{R}^+$  (proportional rows) then it follows that K(i')=  $\alpha$ k(i). Therefore adding io is such that  $\forall$  j  $\epsilon$  J: we have

$$k(i_o,j) = k(i,j) + k(i',j)$$
$$= k(i,j) + \alpha k(i,j)$$

$$= (1 + \alpha) k (i,j).$$

Furthermore.

$$f_{i_o}j = \frac{(k(i_o, j))}{K} = \frac{(1+\alpha)k(i, j)}{K} = \frac{k(i, j)}{K} + \frac{\alpha k(i, j)}{K}$$
i.e.,
$$f_{i_o} = f_{ij} + f_i'j$$

### Lemma (2):

(preservation of the addition). The chi-square distance between two columns j and j', is not changed by the addition of the two rows which become one row.

Proof: Let

$$S = \frac{1}{f_{i}} (f_{j}^{i} - f_{j}^{i'})^{2} + \frac{1}{f_{i'}} (f_{j}^{i'} - f_{i}^{i'})^{2}$$

$$= \frac{1}{f_{i}} \left( \frac{f_{ij}}{f_{j}} - \frac{f_{ij'}}{f_{j'}} \right)^{2} + \frac{1}{f_{i'}} \left( \frac{f_{i'j}}{f_{j}} - \frac{f_{i'j'}}{f_{j'}} \right)^{2}$$

$$= f_{i} \left( \frac{f_{ij}}{f_{i}f_{j}} - \frac{f_{ij'}}{f_{i}f_{j'}} \right)^{2} + f_{i'} \left( \frac{f_{i'j}}{f_{i'}f_{j}} - \frac{f_{i'j'}}{f_{i}f_{j'}} \right)^{2}$$

$$= f_{i} \left( \frac{f_{j}^{i}}{f_{j}} - \frac{f_{j}^{i'}}{f_{j'}} \right)^{2} + f_{i'} \left( \frac{f_{j}^{i'}}{f_{j}} - \frac{f_{j}^{i'j}}{f_{j'}} \right)^{2}$$

$$= \left( f_{i} + f_{i'} \right) \left( \frac{f_{j}^{io}}{f_{j}} - \frac{f_{j}^{io}}{f_{j'}} \right)^{2}$$

$$= f_{io} \left( \frac{f_{j}^{io}}{f_{j}} - \frac{f_{j}^{io}}{f_{j'}} \right)^{2}$$

Since

$$f_j^i = f_j^i = f_j^{io} \text{ and } f_j^i = f_j^{i'} = f_j^{io}$$

$$= \frac{1}{f_{io}} \left( f_{io}^{j} - f_{io}^{j} \right)^{2}$$

Therefore,

$$d^{2}(j,j') = \sum_{i} \left\{ \frac{1}{f_{i}} \left( f_{i}^{j} - f_{i}^{j'} \right)^{2} | i \varepsilon I \right\}$$
$$= \sum_{i} \left\{ \frac{1}{f_{i}} \left( f_{i}^{j} - f_{i}^{j'} \right)^{2} | i \varepsilon I^{*} \right\}$$

Note that Card I = Card I-1

## Lemma (3):

Let (X,Y) be the bivariate random variable and A be a vector whose elements are the conditional probability of x with respect to y then  $|A|^2 \le$ 

$$\frac{1}{f_X(x)}$$
 with  $f_X$  is the marginal probability of x

Proof:

| A | 2 = | 
$$f_Y^X$$
 | 2 =  $\sum_{y} \{ \frac{1}{f_y} (f_y^x)^2 | y \varepsilon Y \}$ 

$$\sum_{y} \left\{ \frac{1}{f_{y}} \left( \frac{k(x,y)}{k(x)} \right)^{2} \mid y \, \epsilon \, Y \right\}$$

$$\sum_{y} \left\{ \frac{1}{f_{y}} \frac{k(x,y)}{k(x)} \cdot \frac{k(x,y)}{k(x)} | y \varepsilon Y \right\}$$

$$\sum_{y} \left\{ \frac{K}{k(y)} \frac{k(x,y)}{k(x)} \cdot \frac{k(x,y)}{k(x)} | y \varepsilon Y \right\}$$

$$= \frac{K}{k(x)} \sum_{y} \frac{k(x,y)}{k(y)} \cdot \frac{k(x,y)}{k(x)} | y \varepsilon Y \right\}$$
we know that  $\forall y \varepsilon Y : \left| \frac{k(x,y)}{k(y)} \right| \le 1$ 

$$\|\mathbf{a}\|^{2} \le \frac{K}{k(x)} \sum_{\mathbf{y}} \left\{ \frac{k(\mathbf{x}, \mathbf{y})}{k(\mathbf{x})} \right\}$$

$$= \frac{K}{k(\mathbf{x})} \frac{k(\mathbf{x})}{k(\mathbf{x})}$$

$$= \frac{K}{k(\mathbf{x})} = \frac{1}{f_{\mathbf{x}}(\mathbf{x})}$$

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