Binary Correspondence Analysis (B.C.A.) and Multiple Correspondence Analysis (M.C.A) are largely applied in social studies to identify and visualize structural relationships existing in survey data sets by means of two-dimensional graphical displays and simple geometrical interpretative tools. The knowledge from such results is usually enriched by the informative contribute due to the application of Clustering algorithms on factorial coordinates. In such a way two-step procedures allow to perform a strategic aggregation of typologies of individuals with homogeneous structural characteristics. However, a sole model for factor analysis hardly synthetises collective behaviours, beliefs or attitudes when data sets include several and heterogeneous sub-structures. The aim of this paper is to introduce an innovative approach, we denote Typological Non Symmetrical Correspondence Analysis (T-NSCA), to contextually identify and describe local structural relationships able to explain different aspects of the dependence of a set of categorical variables on one or more sets. Such iterative procedure is based on the local maximisation of the numerator of predictability index $\tau$ by Goodman and Kruskal. An example is presented from a social research to remark the advantages of the proposed technique.

Key words: Non Symmetrical Data Analysis, Typological Analysis, Non hierarchical Cluster Analysis, Tau predictability index, Gini’s heterogeneity index.

1 INTRODUCTION

Correspondence Analysis (Benzecri, 1973) has became commonly used in social studies to synthetize and visualize the association structure among the modalities of two or more qualitative variables, such as behaviours, beliefs or attitudes. The possibility to consider Binary and Multiple Correspondence Analysis as special cases of Principal Component Analysis on dummy variables (Greenacre, 1984) allows to apply clustering algorithms on the factorial coordinates to identify groups of individuals characterized by homogeneous social typologies (two step procedures).

If it is available a priori information about the asymmetrical role played by the different qualitative variables, Simple or Multiple Non Symmetrical Correspondence Analysis (Lauro, D’Ambra, 1984) can be used. In particular, very often in social studies, the two way of a contingency table present a logical dependence relationship (i.e. the social status may be influenced by the economic position).

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Non Symmetrical Correspondence Analysis (NSCA) aims at discovering and displaying the dependence structure among the row and the column categories of two variables I and J in a suitable subspace by decomposing on the principal axes of inertia the numerator of predictability index $\tau$ by Goodman and Kruskal (Goodman & Kruskal, 1954):

$$\tau = \frac{\sum_i \sum_j [(f_{ij} - f_i f_j) / f_{ij}]}{1 - \sum_i f_i^2}$$

(1)

where $f_{ij}$ denotes the relative joint frequency of $i$-th modality of I and $j$-th modality of J while $f_i$ and $f_j$ are respectively the rows and columns marginals.

From a geometrical viewpoint NSCA looks for an orthonormal basis which allows to account for the largest part of inertia (in the sense of predictability) in order to visualize the dependence relationships between I and J in a lower dimension subspace $R^{m*}$, with $m < m = [\min (I, J) - 1]$. NSCA geometry implies that a strong dispersion of modalities’ coordinates from the origin is interpretable as a condition of good predictability of I given knowledge about J. On the contrary, the representation refers to an independence hypothesis of I on J and NSCA application is useless.

Furthermore it can be difficult to explain the results on the factorial maps when the method is applied to data sets from questionnaires submitted to numerous groups of individuals which deeply differ one another with respect to the dependence functional relationships among the analysed variables.

In fact, the presence of more and opposite sub-structures in the data makes a synthesis of collective behaviours by means of a unique model constrictive and less informative. In such situations relevant information doesn’t emerge from the analysis (the points are nearest to the origin, also if the variability is concentrated on the first axes) and the global analysis appears unable to model the dependence specifically related to the different typologies of individuals.

The factorial maps can became more useful when they are obtained from local models by means of a suitable criterion reflecting several and heterogeneous dependence functional patterns.

2 THE TYPOLOGICAL APPROACH FOR IDENTIFYING LOCAL MODELS BASED ON DIFFERENT DEPENDENCE SUB-STRUCTURES

The aim of this work is introducing a methodology, Typological Non Symmetrical Correspondence Analysis (T-NSCA), to contextually separate and visualize local structural relationships among I and J modalities which are able to give “typologies” description and characterization.

The classification of individuals in the different groups is carried out by maximizing the informative power of each local analysis with respect to the global one.

The specification of several optimal sub-analysis represents the basic idea of the approach of the so-called Typological Analysis introduced by Diday (Diday, 1980) and proposed for Canonical Correlation Analysis, Correspondence Analysis and Discriminant Analysis.

We adopted such approach and performed an original algorithm which works to
identify $T$ local models able to improve, according with NSCA criterion, the predictability of $I$ modalities by means of $J$ modalities in each of the sub-factor models.

3 TYPELOGICAL NON SYMMETRICAL CORRESPONDENCE ANALYSIS: OUTLINE OF THE METHOD

Let us consider $X_{[N, I]}$ and $Y_{[N, J]}$ two matrices reporting the dummy variables respectively related to the modalities of $I$ and $J$, observed on $N$ individuals, and $F$ the contingency table obtained from $Y'X$ as follows in Figure 1.

Figure 1. Data matrices

$$
\begin{align*}
1 & \quad \ldots \quad \ldots \quad I \\
\vdots & \quad \ldots \quad \ldots \quad \vdots \\
N & \quad \begin{pmatrix} 
Y \\
y_1,\ldots,y_i,\ldots,y_I \\
\end{pmatrix} \\
& \quad \begin{pmatrix} 
1 \\
\vdots \\
N \\
\end{pmatrix}
& \quad \begin{pmatrix} 
1 \\
\vdots \\
N \\
\end{pmatrix}
& \quad \begin{pmatrix} 
X \\
(x_1,\ldots,x_i,\ldots,x_J) \\
\end{pmatrix}
\end{align*}
$$

Let us define $\tilde{F}$ the matrix of relative frequencies centered with respect to the independence hypothesis (whose general element is $\tilde{f}_{ij} = f_{ij} - f_i f_j / f_{..}$), $D$ the diagonal matrix of column marginal frequencies $f_i$, and $\tilde{F}D_j$ the centered column profile matrix (with general element $(f_{ij} / f_i) - f_i / f_{..}$).

The NSCA factorial axes are obtained by maximizing:

$$
\max \ u_\alpha' \tilde{F}D_j \tilde{F}'u_\alpha = \lambda_\alpha \quad \forall \alpha = 1,\ldots,\text{rank}(\tilde{F}D_j \tilde{F}') \text{, with ortho-normality constraints } \quad (2)
$$

with $u_\alpha$ eigenvector of $\tilde{F}D_j \tilde{F}'$, associated to the largest eigenvalue $\lambda_\alpha$, which represents the variability of conditional distribution of the $I$ modalities with respect to the $J$ modalities explained by the axis. The total inertia explained by the model is equal to the quantity $C_{(\text{NSCA})}$ (NSCA target):
$$C_{(\text{NSCA})} = \sum_{n=1}^{\text{rank}[^{\text{FD}^{-1}}_{\text{F}}]} \lambda_n = \text{trace}(^{\text{FD}^{-1}}_{\text{F}}^{*})$$  \hspace{1cm} (3)$$

and corresponds to numerator of $\tau$, that is Gini heterogeneity index (Gini, 1912) for conditional distributions. Geometrically it is a measure of the spread of the I row points around their centroid in the space $R^J$ spanned by the columns of $^{\text{FD}^{-1}}_{\text{F}}^{*}$.

Let now consider the generic partition $P = (P_1, P_2, ..., P_T)$ of the $N$ individuals that identifies $T$ groups such as to determine $T$ sub-matrices of $X$ and $Y$, as shown in Figure 2.

**Figure 2. Sub-matrices of $Y$ and $X$ defined by the partition $P$ on the $N$ individuals**

$$1 \begin{bmatrix} 1 & \cdots & I \\ \vdots & \ddots & \vdots \\ N & & \vdots \\ \vdots & \ddots & \vdots \\ 1 & \cdots & I \\ \vdots & \ddots & \vdots \\ N & & \vdots \\ \vdots & \ddots & \vdots \\ 1 & \cdots & I \\ \vdots & \ddots & \vdots \\ N & & \vdots \end{bmatrix} = 1 \begin{bmatrix} y_1 \\ \vdots \\ y_I \\ \vdots \\ y_c \\ \vdots \\ y_{c+1} \\ \vdots \\ y_N \\ \vdots \\ y_{c+1} \\ \vdots \\ y_{N-c+1} \\ \vdots \\ y_{N-1} \\ \vdots \\ y_N \end{bmatrix}$$

For each of those $T$ couples of sub-matrices $(Y_c, X_c)$, with $c = 1, ..., T$, it is possible to perform a sub-NSCA which allows to explore the structural dependence relationships with reference to the relative group of individuals. The global inertia (predictability) explained by the $T$ separate NSCA is given by the quantity $C_{(T-\text{NSCA})}$:

$$C_{(T-\text{NSCA})} = \sum_{c=1}^{T} \text{rank}[^{\text{FD}_{j\epsilon}^{1}}_{\text{F}_{c}}^{*}] \sum_{a=1}^{T} \lambda_a \text{trace}(^{\text{FD}_{j\epsilon}^{1}}_{\text{F}_{c}}^{*}) \equiv \sum_{c=1}^{T} \text{numerators of local } \tau$$  \hspace{1cm} (4)$$

where and $^{\text{FD}_{j\epsilon}^{1}}_{\text{F}_{c}}$, named $C_{(C-\text{NSCA})}$, is maximized.
The purpose of Typological Non Symmetrical Correspondence Analysis (T-NSCA) is to identify the partition of individuals which permits to obtain the \( T \) sub-models that better explicate the dependence sub-structures in the data and maximize \( C_{(T\text{-NSCA})} \).

The advantages in terms of informative gain are manifold. It is expectable that the sum of information given from the \( T \) separate analysis is major than the one coming from the global \( NSCA \). However, the real potentiality of the procedure is verified when the mean predictability power of the sub-analysis, \( \overline{C}_{(c\text{-NSCA})} \), is major than \( C_{(NSCA)} \) and, first of all, when is all the single numerators of the local \( \tau \), \( C_{(c\text{-NSCA})} \) are major than \( C_{(NSCA)} \).

Furthermore, \( T\text{-NSCA} \) jointly presents the properties of a factorial technique and a Clustering algorithm because aims at separating the homogeneous sub-groups of individuals by maximizing the target function of \( NSCA \).

4 THE ALGORITHM

The optimal partition \( P^* \) of individuals is obtained by applying an iterative algorithm, whose steps are schematically presented in this paragraph.

The algorithm requires the preliminar choice of the number \( T \) of groups (“typologies”) and the assegnation of the individuals to the initial partition (in the first step is preferable that groups present the same number of individuals).

- **Step 1**
  \[ n = 0 \]
  The initial partition: \( P^{(0)} = \left( P_1^{(0)}, P_2^{(0)}, ..., P_c^{(0)}, ..., P_T^{(0)} \right) \) is defined to obtain the sub-matrices \( Y_c \) and \( X_c \), with \( c = 1, ..., T \).

- **Step 2**
  \( T \) sub-matrices \( \tilde{F}_c D_{jc}^{-1} \) of columns profiles centered with respect to the independence hypothesis are computed and \( T \) numerators of Goodman and Kruskal’s \( \tau \) are obtained as traces of the matrices \( \tilde{F}_c D_{jc}^{-1} \).

- **Step 3**
  Let \( u_i \) be the generic unit originally assigned to the group \( c \).
  \( T - 1 \) indicators of incremental advantage in reallocation are computed for all the possible transitions of \( u_i \) from \( c \) to \( c' \), with \( c' \neq c \).
  The major positive indicator identifies the group to which \( u_i \) has to be assigned in order to improve the predictability power of the \( T \) sub-analysis.

- **Step 4**
  \[ n = n + 1 \]
  The partition \( P^{(n+1)} = \left( P_1^{(n+1)}, P_2^{(n+1)}, ..., P_c^{(n+1)}, ..., P_T^{(n+1)} \right) \) is updated taking into account the performed transition of \( u_i \).

- **Step 2, 3 and 4** are iterated.
  The iteration goes on until algorithm converges: when no reallocation else is able to improve the variability explained by the so-defined sub-models of \( NSCA \).
The indicator of incremental advantage in reallocation we refer at step 3 is obtained as follows. For the potential transition of a unit $u_i$ from the origin group $o$ to the destination group $d$ (at the iterative step $n$) it is equal to:

$$W(u_i, o^{(n)}, d^{(n)}) = \left[ (R_{o-NSCA}^-- R_{o-NSCA}^+) + (R_{d-NSCA}^+ - R_{d-NSCA}^-) \right]$$

(5)

where $R_{o-NSCA}^-$ and $R_{o-NSCA}^+$ are the traces of the matrices $\tilde{P}_c D_{jc}^{-1} \tilde{P}_c^{-t}$ and $\tilde{P}_c D_{jc}^{-1} \tilde{P}_c^{-t}$ (with $c = o$) obtained from the couples of sub-matrices $(Y^c_-, X^c_-)$ and $(Y^c_+, X^c_+)$ respectively not including and including the individual $u_i$, and $R_{d-NSCA}^+$ and $R_{d-NSCA}^-$ are the trace of the matrices $\tilde{P}_c^+ D_{jc}^{-1} \tilde{P}_c^+ t$ and $\tilde{P}_c^+ D_{jc}^{-1} \tilde{P}_c^+ t$ (with $c = d$) obtained from the couples of sub-matrices $(Y^c_+, X^c_+)$ and $(Y^c_-, X^c_-)$ respectively including and not including $u_i$.

The value of $W$ depends thence on the sum of informative improvements (according to NSCA criterion) due to the removal of the unit from the origin group and to its assignation to the considered destination group.

The criterion of reallocation adopted by the algorithm is the following in the Table 1.

**Table 1. Criterion of reallocation**

$CRIT(n)$: $u_i$ is moved from origin class $o$ to the destination class $d$ if simultaneously:

1) $W(u_i, o^{(n)}, d^{(n)}) > 0$;
2) $W(u_i, o^{(n)}, d^{(n)}) = \max(W(u_i, o^{(n)}, d^{(n)}), d^{(n)}) = 1, ..., T; d^{(n)} \neq o^{(n)}$.

$W$ is positive if it is convenient to remove the unit from the origin class and assumes the maximum value if the assignation to considered destination group gives the major predictability power improvement to NSCA so-defined sub-analysis.

Once obtained the final partition it is possible to carry out $T$ NSCA and describe the dependence “typical” substructures which characterises different classes of units and could not be readable on global factorial planes. To increase the robustness of proposed procedure other well known algorithms can be used.

5 A SOCIAL RESEARCH BY BANK OF ITALY

The data set used is taken from a large survay realized by the Bank of Italy during 2003. It refers to a sub-sample of 3500 families an intends verify the structure of the influence of economic position on social status. The contingency matrix we refer is the one proposed in Table 2.

**Table 2. Matrix F**

<table>
<thead>
<tr>
<th></th>
<th>Worker</th>
<th>Employee</th>
<th>Manager</th>
<th>Entrepren.</th>
<th>Freelance</th>
<th>Pensioner</th>
<th>Unemployed</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Married</td>
<td>486</td>
<td>262</td>
<td>97</td>
<td>104</td>
<td>205</td>
<td>563</td>
<td>67</td>
<td>1784</td>
</tr>
<tr>
<td>Unmarried</td>
<td>106</td>
<td>190</td>
<td>30</td>
<td>29</td>
<td>41</td>
<td>185</td>
<td>52</td>
<td>552</td>
</tr>
<tr>
<td>$F =$</td>
<td>Divorcee</td>
<td>46</td>
<td>72</td>
<td>15</td>
<td>28</td>
<td>14</td>
<td>70</td>
<td>275</td>
</tr>
<tr>
<td>Widower /Widow</td>
<td>10</td>
<td>15</td>
<td>2</td>
<td>9</td>
<td>4</td>
<td>817</td>
<td>72</td>
<td>929</td>
</tr>
<tr>
<td>Total</td>
<td>648</td>
<td>458</td>
<td>144</td>
<td>170</td>
<td>264</td>
<td>1635</td>
<td>221</td>
<td>3540</td>
</tr>
</tbody>
</table>
6 APPLICATION OF T-NSCA

NSCA has been performed on above-mentioned data set. The first factorial plane is reported in Figure 3.

Figure 3. The NSCA global model results

The matrix in Table 2 does not present a strong dependence structure. The value of $\tau=0.1406$ means that, being known the employment position, it is possible to predict the civil status only in the 14.06% of cases.

Most of such low predictability is synthetised on one dimension: the first factorial axis of NSCA explains over the 93% of inertia. It opposes essentially the old people pensioners which are more characterised by a status of "widower/widow" to the younger active employees and, principally, to workers which seem to be the category more disposed to get married. The modalities "divorcee" and "unmarried" seem not to be explained by means of a dependence relationship on the work profile instead. On the second axis (explaining about 6% of inertia) the modalities of the dependent variable present very low coordinates: it implies that the weak opposition of people "married or widows/widowers" with positive coordinates and "not married or voluntary not more married" with negative coordinates, cannot be explained by considering the employment position because of the poor dependence strength.

In such situation the dependence structure synthetised by NSCA is not very informative and we can conclude by observing the model results that there is not an evident relationship between the two analysed variables.

We applied the Typological Non Simmetrical Correspondence Analysis on the same data-set. In Table 3 are reported the results, in terms of $\tau$ and Gini's heterogeneity index for the three sub-models obtained by the application of the algorithm compared to the results computed on the global analysis.
Table 3. Predictability results for global NSCA and T-NSCA on 3 sub-models

<table>
<thead>
<tr>
<th>NSCA on the global model</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>τ:</td>
<td>0.1406</td>
<td>0.7049</td>
<td>0.6299</td>
</tr>
<tr>
<td>τ numerator:</td>
<td>0.0909</td>
<td>0.3789</td>
<td>0.4015</td>
</tr>
<tr>
<td>Gini index:</td>
<td>0.6468</td>
<td>0.5376</td>
<td>0.6995</td>
</tr>
</tbody>
</table>

Local NSCA on groups selected by the T-NSCA algorithm

It is evident the relevant improvement in τ numerator we get by performing three sub-analysis instead of one, while the heterogeneity measure for the categories of the dependent variable (civil status) appears quite similar for the three groups and with respect to the global model. In particular, we can note that both the mean τ and the single three τ derived from the sub-analysis are greater than the one from the original model.

After the application of the algorithm the knowledge of employment position allows to correctly predict the civil status in about the 74% of the cases (mean τ = 0.7437)

By carrying out the sub-analysis we can explain the dependence structures which characterize the three “typologies” of individuals identified by the algorithm. The following Figures 4, 5 and 6 report the first factorial plane for each one of the three NSCA and the histograms of predictability explained on the factorial axis. Furthermore, for each model a table is given with the description of the peculiar features of the members of the cluster by means of categories of illustrative qualitative variables (not directly considered in the analysis).

Figure 4. NSCA on the group 1: first factorial plane, histogram of explained predictability and description of group characterizing features
Figure 5. NSCA on the group 2: first factorial plane, histogram of explained predictability and description of group characterizing features

<table>
<thead>
<tr>
<th>Category</th>
<th>Male</th>
<th>North Italy</th>
<th>Over 500,000 residents</th>
<th>Centre Italy</th>
<th>20,000-40,000 residents</th>
<th>South Italy and Islands</th>
<th>0-20,000 residents</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FC</td>
<td>FRC</td>
<td>FT</td>
<td>FRT</td>
<td>FRC/FRT</td>
<td>FC</td>
<td>FRC</td>
</tr>
<tr>
<td>Male</td>
<td>1049</td>
<td>0.784</td>
<td>2326</td>
<td>0.657</td>
<td>1.193</td>
<td>565</td>
<td>0.422</td>
</tr>
<tr>
<td>North Italy</td>
<td>565</td>
<td>0.422</td>
<td>1375</td>
<td>0.388</td>
<td>1.087</td>
<td>221</td>
<td>0.165</td>
</tr>
<tr>
<td>Over 500,000 residents</td>
<td>705</td>
<td>0.527</td>
<td>1725</td>
<td>0.487</td>
<td>1.081</td>
<td>239</td>
<td>0.179</td>
</tr>
<tr>
<td>Centre Italy</td>
<td>143</td>
<td>0.107</td>
<td>367</td>
<td>0.104</td>
<td>1.031</td>
<td>565</td>
<td>0.422</td>
</tr>
<tr>
<td>20,000-40,000 residents</td>
<td>239</td>
<td>0.179</td>
<td>619</td>
<td>0.175</td>
<td>1.022</td>
<td>221</td>
<td>0.165</td>
</tr>
<tr>
<td>South Italy and Islands</td>
<td>269</td>
<td>0.201</td>
<td>825</td>
<td>0.233</td>
<td>0.863</td>
<td>269</td>
<td>0.201</td>
</tr>
<tr>
<td>0-20,000 residents</td>
<td>221</td>
<td>0.165</td>
<td>623</td>
<td>0.176</td>
<td>0.939</td>
<td>534</td>
<td>0.399</td>
</tr>
</tbody>
</table>

- Over 500,000 residents
- Female
- Male
- North Italy
- 40,000-500,000 residents
- Centre Italy
- 20,000-40,000 residents
- South Italy and Islands
- 0-20,000 residents
We consider Sex (Male, Female), Residence (North Italy, Centre Italy, South Italy and Islands), and City dimension (0-20,000 residents, 20,000-40,000 residents, 40,000-500,000 residents, over 500,000) as illustrative variables. In the descriptive table for each of those modalities are given the FC (absolute frequency in the class), FRC (relative frequency in the class), FT (absolute frequency in the total sample), FRT (relative frequency in the total sample), and a measure of characterization due to the index FRC/FRT.

The three sub-analysis clearly evidence the presence of structural dependence relationships which better describe three different clusters of individuals.

The first one is characterized by the opposition on the first dimension (which explains the 81% of inertia) of factors which impact on marriage/celibate. In detail, we can observe that employment position (and indirectly the economic status) seems to have a great impact in determine personal life choices. For such cluster is evident that the more stable and economically satisfying are the working positions (such as freelance or manager) the more the positive influence on marriage. On the contrary, the precariousness which in Italy characterizes a relevant fraction of workers and employees (first of all young people), impacts on the frequencies of unmarried or divorcees. In the same direction it is possible to read the impact of
unemployment. If we look at the features of that cluster we can note that it is composed principally by males, prevalently of northern or central Italy and resident in medium-great cities.

For this class the economic stability appears a concrete impact factor on personal life decisions.

A peculiar category is represented by entrepreneurs and professionals, that are more present among divorced people.

A different dependence structure is presented by the second group of individuals. On the first axis of the second model (which explains 52% of inertia) is clearly shown the linkage between the choice of very time-intensive and deeply involving activities (i.e. manager, freelance, entrepreneur, professional) and the condition of less structured and stable family life (i.e. unmarried or divorcees). This model synthesizes the dependence relationship of civil status on economic position which is typical of women (principally from North Italy and great cities).

The third model represents typical dependence relationships which characterize Italian people from south and islands (principally women and residents in medium-little cities). Its peculiarity is due to the quite unidimensional relationship that opposite married young and ripe employed people to pensioners and widowers. It is not relevant the predictability for the modalities divorcee and unmarried that present in this cluster very low frequencies.

7 CONCLUDING REMARKS

In this paper we proposed an iterative procedure, Typological Non Symmetrical Analysis (T-NSCA), useful in social studies to synthetise and describe sub-structures characterizing typologies of individuals strongly homogeneous with reference to the dependence relationships (among the modalities of two qualitative variables) and very different one another. The proposed method allows to identify local models in order to maximize the predictability power explained by means of each sub-analysis. It also allows to deeply explore dependence sub-structures the global model is unable to identify. The application on a real data-set showed the concrete informative improvements given by that approach. The principles of T-NSCA can be also applied to Multiple and Partial Non Symmetrical Correspondence Analysis (Lauro & D’Ambra, 1984) for dealing with the description of typologies with reference to dependence relationships among categories or more sets of variables. Further extensions may be given by its application to three-way non symmetrical correspondence analysis.

Finally, when the sub-analysis identifies the presence of well-defined sub-structures very heterogeneous (the numerators of local $\tau$ have an average very greater than the global model one) it can be very useful to perform Multiple Factor Analysis (MFA) on the $T$ sub-model to obtain a compromise NSCA factorial analysis. Such approach was just applied by Lauro and Fucili (Fucili, 2003; Lauro, Fucili, 2004) for Non Symmetrical Analysis of quantitative data.

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