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COMPONENTIAL SEGMENTATION BASED CONJOINT ANALYSIS *vs* CLUSTER ANALYSIS

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Abstract. *In Componential Segmentation interest focuses on the interaction effect of person and product attribute levels to produce a response (overall evaluation) for various product descriptions. A person's reaction to a product is broken into the sum of two components: 1) the average part-worth utilities due to the attribute levels of the product and 2) the interactions between the person's background variables and the attribute levels. In this paper we adopt the dummy-coded parametrization of the model, which provides two baselines.*
Two segmented methods of performing conjoint analysis, clustered and componential segmentation, are compared with each other. The predictive power of the clustered segmentation model is higher than that of componential segmentation.

Keywords: *Componential segmentation, Clustered segmentation, Metric Conjoint Analysis, Predictive power.*

1. INTRODUCTION

Conjoint Analysis (COA) is used to investigate the joint effect of a set of independent variables on a dependent variable.

COA deals with preference data (ratings, ranks or choices) expressed by individuals (consumers, service users, potential buyers, etc.), in a consumer research, on a set of stimuli (products or services) described by attributes assuming different value (attribute-levels). Each stimulus is a combination of attribute levels.

Aim of the COA is to evaluate the relative importance of levels-attributes using only the global preference (*overall*) – known – on the product: the preference model is additive and decompositive.

The early applications of COA (Green and Rao, 1969, 1971) indicated that a separate utility function was estimated for each individual (*Individual level models*). Though individual models have demonstrated good predictive power, the output of the estimation procedure – a separate set of utility weights for

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each individual – makes managerial analysis and understanding difficult when the number of respondents is large.

At the other extreme of aggregation *continuum* is the case in which the preference ratings are pooled across all respondents and one overall utility function is estimated (*Aggregate model*). A potential problem with pooled analysis is termed the “majority fallacy” by Kuehn and Day (1962). It occurs when the item chosen by the “average” customer is not chosen most often.

Optimally, then, one would like a model that combines (*Segmented model*) the most desirable properties of the two extreme levels of aggregation and avoids the problems of each.

In this area, Green, Carroll, and Carmone have proposed (1977) the *Componential Segmentation* (CS) procedure.

In a review of market segmentation, Wind (1978) refers to two traditional methods of segmentation, a priori and clustering, and two methods, flexible and componential.

The clustering and componential segmentation methods, which are also mentioned by Green and Srinivasan (1978), are discussed further on.

Paragraph 2 refers to the two main lines of study of the CS (based *Metric* COA and *Factorial* COA); the section 3 explains the relative methodology adopted in this paper (based *metric* COA); the section 4 describes algebraic formulation of the model. Its application is illustrated in section 5, together with an interpretation of the model parameters. In the paragraph 6 we lead an empirical comparison between componential and clustered segmentation models and their predictive validity.

2. THE MAIN APPROACHES TO COMPONENTIAL SEGMENTATION

In CS interest focuses on the joint effect of judges and product attribute levels to produce a response on a set of stimuli, i.e. various product descriptions.

The primary objective of CS is to predict how a consumer, described in terms of a multiattribute profile, would choose among a set of alternative products (or services), also described as multiattribute profiles.

Each component of each individual profile, considered jointly with each component of product profile, is assumed, potentially, to contribute to the total evaluation of the product (overall evaluation).

Therefore, an individual’s reaction to a product is broken into the sum of two components: 1) the average part-worth utilities due to the attribute levels of the product, pooled across all respondents in a consumer research and 2) the interactions between the person’s background variables and the attribute levels.

For the estimation of the part-worth utilities and interactions, Green and De Sarbo (1979) have proposed an approach – a stagewise fitting procedure – so structured (Coseg-II model):

a) first, a pooled multiple regressions was run, with preference (assumed to be interval-scaled) as the dependent variable and the effects coding of attributes as the independent variables, to estimate the aggregate part-worth utilities;
b) then a separate regression was run for each of the background variables, with the residuals from the pooled regressions as the dependent variable and interactions between the object profiles and the particular bachground variable – of time to time – as the independent variables (*stagwise regression*).

   This approach involves burdensome iterations of calculation, as it does not estimate the interaction parameters simultaneously .

Later, Lauro, Scepi, Giordano (2002) have proposed a CS model (based *metric approach* to COA) to estimate the parameters wich differs from the previous in the second step, since it estimates the interaction effects simultaneously and it uses – in order to identify the solution of the model – the Moore-Penrose generalized inverse for the experimental design of the attributes of the product ($\mathbf{G}_1^- = (\mathbf{X}'\mathbf{X})^-$) and for the background characteristics matrix of respondents ($\mathbf{G}_2^- = (\mathbf{Z}'\mathbf{Z})^-$), with heavy passage of matrix calculation (see Schott, 1977, p. 174).

Still in Lauro Scepi, Giordano (2002) it is proposed an alternative approach (based *Factorial conjoint analysis*) in the context of Multidimensional Data Analysis (MDA), in order to obtain suitable synthesis of part-worth coefficients ($\widehat{\mathbf{B}}$) in a lower dimensional space in terms of principal components, performing a PCA on the matrix $\widehat{\mathbf{B}}$.

The two informative structures (see Takane, Shibayama, 1991; Giordano, Scepi, 1999) has been put in the context of COA (see Giordano, Lauro, Scepi, 2010), combining the estimation method with its geometrical representation.

In this paper, following the *metric approach* to COA, for the estimation of the part-worth utilities and interactions in CS we propose the simple dummy variable coding of the product attributes and of the background characteristics.

This method allows an operational solution easier than the one proposed by Lauro *et alii* (2002) – in terms of matrix calculation (De Luca, 2014) – to estimate the parameters and in terms of (more direct) interpretation of the results.

In order to identify the solution of the model we drop, in the experimental design matrix (**X**) and in the characteristics matrix of respondents (**Z**), the first column of the dummy variables for each factor.

Thus we come to two baseline joined (constant of the equation).

This circumstance is new in the context of the identification of the solution of attitude models, which normally involve a single baseline (see, e.g., De Luca, Ciapparelli, 2011).

This parametrization of the model, by means of two baselines joint, requires an original interpretation of the interaction effects.

This paper also aims to provide a unified description of the CS methodology, by linking and integrating the two treatments: *a)* Green and De Sarbo (1979) and *b)* Lauro *et alii* (2002), which taken individually are fragmented.

3. COMPONENTIAL SEGMENTATION: ESTIMATION METHOD

In the *metric approach* to conjoint analysis the objects are described in terms of K_j +1 (j = 1, 2, …, J) *levels* of J attributes; the i-th object can be represented by a vector of dummy variables variables $\tilde{\mathbf{x}}_i = (\tilde{x}_{i1}, \tilde{x}_{i2}, \dots, \tilde{x}_{iK})$.

The individual regression model for metric COA is:

$$Y_i = \sum_{l=1}^{K} \hat{\beta}_l \tilde{x}_{il} + e \qquad (1)$$

where:

- Y_i is the preference for the i-th object (i = 1, 2, …, Q). The objects are described in terms of K_j +1 (j = 1, 2, …, J) *levels* of J *attributes*; the i-th object can be represented by a vector of dummy variables $\tilde{\mathbf{x}}_i = (\tilde{x}_{i1}, \tilde{x}_{i2}, \dots, \tilde{x}_{iK})$ corresponding to the i-th product and the level j-th of the generic attribute of the product;
- $K = \sum_{j=1}^{J} K_j$;
- $\hat{\beta}_l$ is the part-worth utility estimate of the l-th attribute level;
- e is the error term.

In CS each component of each consumer profile, considered jointly with each component of the product profile, is supposed to contribute to the *overall evaluation* of the product.

The CS focuses on the *effect of interactions* between the *product* profile, **x** (a vector of dummy variables that describes the object) and the *person* profile **z** (a vector of dummy variables that describes the person in terms of a certain set of *background characteristics*) on preference for the product.

Through this mechanism one is able to predict how a person with a certain set of background characteristics will react to a particular product.

Thus, a consumer’s reaction onto a product is split into two components:

1) the average *part-worth utilities* due to the attribute levels of the product (pooled across all persons);

2) the interactions between the consumer's *background variables* and the *attribute levels*.

The part-worth utilities and interactions are estimated by the following equation (Moore, 1980):

$$Y_i = \sum_{j=1}^{K} \hat{\beta}_j \cdot \tilde{x}_{ij} + \sum_{h=1}^{S} \sum_{j=1}^{K} \hat{\gamma}_{jh} \cdot \tilde{x}_{ij} \cdot \tilde{z}_h + e \tag{2}$$

were:

Y_i, $\hat{\beta}_j$, $\tilde{x}_{ij}$ and e have been afore explained;

$\tilde{\mathbf{z}} = (\tilde{z}_1, \tilde{z}_2, \dots, \tilde{z}_S)$ is a vector of dummy variables that is used to describe the person's background variables, were $S = \sum_{h=1}^{H} M_h$ (M_h +1 is the number of levels of external variable h-th; $h = 1, 2, \dots, H$);

$\hat{\gamma}_{jh}$ is the interaction between the attribute level of the i-th product represented by $\tilde{x}_{ij}$ and the background variable level represented by $\tilde{z}_h$. The person's background variables can be represented by a vector of dummy variables $\tilde{\mathbf{z}} = (\tilde{z}_1, \tilde{z}_2, \dots, \tilde{z}_S)$, were $S = \sum_{h=1}^{H} M_h$ (M_h is the number of levels of the external variable h-th: $h = 1, 2, \dots, H$).

4. ALGEBRAIC FORMULATION OF THE CS MODEL

The multivariate regression model corresponding to (2) is estimated by the metric approach to COA and in two steps (see Green, 1977; Moore, 1980):

- first step: *modelization* of the preference and estimation of part-worths;
- second step: *explanation* of the part-worths estimated by background variables.

4.1 COMPUTATIONAL ASPECTS

Due to the peculiar structure of the design matrix **X** (in which the objects are described in terms of K_j +1 levels of J attributes), it can be seen that it is rank deficient.

In order to **identify** the solution we use the inverse of $\tilde{\mathbf{X}}'\tilde{\mathbf{X}}$, where $\tilde{\mathbf{X}}$ is a full-rank matrix obtained by dropping one column (the first) for each factor (the first *baseline*).

Similarly, from matrix **Z**' of background characteristics in dummy variable coding, we pass to matrix $\tilde{\mathbf{Z}}'$ (full-rank matrix), obtained by dropping one column (the first) for each socio-demographic variable; the dropped columns compose the *second baseline*.

We hence come to two joined baselines (constant of the equation).

Using a two-stage approach, the part-worth utilities and interactions of the COA model are estimated according the following model (Giordano, Scepi, 1999):

$$\begin{cases} \widetilde{\mathbf{Y}}_{Q\times G} = \widetilde{\mathbf{X}}_{Q\times K}\widehat{\mathbf{B}}_{K\times G} + \mathbf{E}_{Q\times G} \\ \widehat{\mathbf{B}}'_{G\times K} = \widetilde{\mathbf{Z}}'_{G\times S}\widehat{\mathbf{\Theta}}_{S\times K} + \mathbf{F}_{G\times K} \end{cases} \tag{3}$$

were:

$\widetilde{\mathbf{Y}}_{Q\times G}$ = overall evaluation matrix for Q products described in terms of K_j levels of J factors ($K = \sum_{j=1}^{J} K_j$);

$\widetilde{\mathbf{X}}_{Q\times K}$ = full-rank design matrix, in which we report the dummy variables x_{ij} corresponding to each product i (i = 1, 2, ..., Q), obtained by dropping on column for each factor (reference categories);

$\widehat{\mathbf{B}}_{K\times G}$= matrix of part-worth utilities – for each *level* of each *factor* for each *respondent* – estimates of the jth factor level ($\hat{\beta}_j$);

$\widehat{\mathbf{B}}'_{G\times K}$ = transposed matrix of $\widehat{\mathbf{B}}_{K\times G}$;

$\widetilde{\mathbf{Z}}'_{G\times S}$= full-rank matrix of background variables in dummy variable coding, in which the person's variables are represented by a vector of dummy variables $\tilde{\mathbf{z}} = (\tilde{z}_1, \tilde{z}_2, \dots, \tilde{z}_S)$, were s = number of socio-demographic groups obtained by dropping one column (the first) for each background variables (reference categories);

Q = number stimuli;

K = number attribute levels of the product;

G = number judges;

$\widehat{\mathbf{\Theta}}_{S\times K}$ = matrix of the interaction effects ($\hat{\gamma}_{jh}$) between product factor levels and background variable levels, i.e., between the factor level of the i-th product represented by x_{ij} and the background variable level represented by z_h;

$\mathbf{E}_{Q\times G}$ and $\mathbf{F}_{G\times K}$ are the error matrix.

In (3) each value $\hat{\theta}_{k,s}$ the generic term of $\widehat{\mathbf{\Theta}}_{k,s}$ is interpreted as a measure of preference of the s-th socio-demographic group (market segment), s = 1, 2, ..., S, for the k-th factor level of the product.

5. APPLICATION OF THE CS MODEL: DATA AND RESULTS

We consider an application of the dummy-coded parametrization of the CS model.

In this study we are interested in how subjects evaluate various kinds of smartphones. 192 people took part in the COA study.

The full factorial design of product profile is composed of 512 stimuli (ie: 4×2×2×2×2×2×2×2).

From this factorial plan was extracted a set of 16 stimulus card description (1/32 fractional full factorial design), with statistical randomness, and a set of 5 stimulus card for *validation.*

They were asked to rate their preferences on a 1 to 10 equal interval scale for each of the 21 hypothetical smartphone (16 *calibration* and 5 *validation*).

The respondents background variables and the attributes used to describe the mobile phone are given in Table 1.

Each person's ratings were normalized (by dividing the score expressed by a respondent on the total of their ratings; Bass and Wilkie, 1973) to eliminate main effects due to subjects, thus we pass from the matrices $\mathbf{Y}_{18,192}$ to matrix $\mathbf{Y}_{11,192}$.

We apply the two-step approach (3), as described below, in Microsoft Excel 2010 Programming Language environment.

In the *first* step of the (1) the subjects' overall evaluative responses (assumed to be interval scaled and *normalized* as noted before) are first regressed – on all respondents – on the dummy variable predictors representing the product attributes ($\tilde{\mathbf{X}}_{16,11}$).

Tab.1: Background variables and levels, product attributes and levels

Background variables and levels

Age	Sex	Qualification	Occupation
1. *18-25 years old*	1. *Male*	1. *Up licentiate*	1. *Student*
2. *26-35 years old*	2. *Female*	2. *Graduate*	2. *Officer worker*
3. *over 35 years old*			3. *Other*[a]

Product attributes and levels

Brand	Display	Battery run-time	Camera
1. *Apple*	1. *4"*	1. *8 hours*	1. *10 Mp*
2. *Samsung*	2. *5"*	2. *12 hours*	2. *13Mp*
3. *BlackBerry*			
4. *Nokia*			
Connection to Social networks	Payment features	Map features	Price
1. *Yes*	1. *Yes*	1. *Yes*	1. € 599
2. *No*	2. *No*	2. *No*	2. € 699

a - This category includes the "corporate officer " and "other" categories. These two categories were combined in subsequent analysis because of the small number of people in "other".

The average part-worth utilities ($\widehat{\mathbf{B}}_{11,192}$) due to the attribute levels of the product are obtained by applying the classical principle of ordinary least squares (OLS).

In the *second* step of the (3) a multivariate regression is run, with the estimated part-worth utilities (in the first step) as the dependent variable ($\widehat{\mathbf{B}}'_{192,11}$) and dummy variable of socio-demographic characteristics ($\tilde{\mathbf{Z}}'_{192,7}$) as the independent variables, to estimate the socio-demographic group part-worth utilities ($\widetilde{\mathbf{\Theta}}_{7,11}$).

Each value $\hat{\theta}_{h,k}$, generic term of $\widehat{\mathbf{\theta}}_{7,11}$ in (3), is interpreted as a preference measure of the *s-th* (s = 2, 3, …, 7) socio-demographic group (market segment) for the *k-th* (k = 2, 3, …, 11) attribute level of the product; in correspondence to s =1 and k = 1 we have the two baselines.

The results model, which is the interaction effects (as regards to the *baselines*) between the product attributes and person's background (measured effects as regards a *reference categories*), are given in Table 2.

Tab. 2: Estimation results for CS model in relation to various profiles of smartphone and socio-demographic characteristics of the evaluators

Background variables ↓	*Product attribute* →	*Base-line1*	Brand *Samsung*	*Black-berry*	*Nokia*	Display *5"*	Battery *12 h.*	Camera *13 Mp*	Con-necting *No*	Payment *No*	Map *No*	Price *$ 699*
Background	*Baseline 2*	**0,0630**	**-0,0049**	**-0,0133**	**-0,0108**	**0,0020**	**0,0020**	**0,0039**	**-0,0058**	**-0,0085**	**-0,0066**	**-0,0044**
Age	26-35yea.	**-0,0049**	0,0018	**0,0080**	0,0064	0,0002	0,0017	-0,0030	-0,0007	0,0022	0,0014	-0,0005
	> 35 yea.	**-0,0018**	0,0051	0,0078	**0,0103**	0,0020	0,0037	-0,0015	-0,0012	-0,0030	-0,0043	-0,0022
Sex	Female	**0,0029**	**0,0008**	-0,0021	0,0002	0,0011	0,0003	0,0009	-0,0029	-0,0036	-0,0008	-0,0013
Qualif.tion	Graduate	**-0,0002**	0,0015	**0,0026**	0,00003	-0,0004	-0,0014	0,0009	0,0008	-0,0019	-0,0008	**0,0019**
Occupation	Office w.	**0,0007**	-0,0028	-0,0050	-0,0082	-0,0016	-0,0009	-0,0006	0,0040	0,0014	0,0025	**0,0011**
	Other	**-0,0002**	-0,0031	-0,0031	-0,0054	-0,0009	0,0005	0,0002	0,0024	0,0015	0,0001	**0,0012**

Baseline 1: **Apple** for *Brand*, **4"** for *Display*, **8 hours** for *Battery run-time*, **10Mp** for *Camera*, **Yes** for *Connection Social Networks*, **Yes** for *Payment features*, **Yes** for *Map features*, **€ 599** for *Price*.
Baseline 2: **18-25 years old** for *Age*, **Male** for *Sex*, **Up licentiate** for *Qualification*, **Student** for *Occupation*.

In the first row of numerical values in Table 2 we read the relative effects with respect to constant term (values of deviations from 0,063).

We observe that the presence of category *5"* of the *Display* factor has a positive relative effect (0,002) on the overall evaluation, as are the categories *12 hours* (0,002) of *Battery run-time* factor and *13 Mp* (0,0039) of the *Camera* factor.

By Table 2 we observe that: the *18-25* year old *judges* prefer *Apple* brand (0,0063); the respondents of *26-35* years old prefer the *Blackberry* brand (0,008), most preferred level; people over 35 prefer *Nokia* brand (0,0103), most preferred level; etc.

Also all other values in Table 2 indicate the *interaction effects* (deviations from the constant term).

In Table 3 we report significant interactions at the 0,05 level, established by the *multivariate* analysis of variance- *Manova* (IBM Spss 22.0).

The interaction between background variables (e.g. sex) and product attributes (e.g. price) indicate that people with different background variables have different utilities for levels of an attribute (*women* wanted *less expensive* mobile phone (-0,013) than *men*, reference category).

The increase in explanatory power achieved through the addition of the interaction variables gives some very useful indications about the segmentability of the market.

Tab. 3: Interaction in Compenential Segmentation[a]

Age/Brand		*Apple*	*Samsung*	*BlackBerry*	*Nokia*
	18-25 years old	**0,0630**	-0,0049	-0,0133	-0,0108
	26-35 years old	-0,0049	0,0018	**0,0080**	0,0064
	over 35 years old	-0,0018	**0,0051**	0,0078	**0,0103**
Occupation/Brand		*Apple*	*Samsung*	*BlackBerry*	*Nokia*
	Student	0,0630	-0,0049	--0,0133	-0,0108
	Officer worker	0,0007	-0,0028	-0,0050	**-0,0082**
	Other	-0,0002	-0,0031	-0,0003	-0,0054
Sex/Connection to Social Networks		*Yes*	*No*		
	Male	0,0630	-0,0058		
	Female	0,0029	**-0,0029**		
Sex/Payment features		*Yes*	*No*		
	Male	0,0630	-0,0085		
	Female	0,0029	**-0,0036**		

[a]Significant interaction coefficients, at the 0,05 level, between background variables and product attributes are underlined

6. COMPONENTIAL AND CLUSTERED SEGMENTATION MODELS: AN EMPIRICAL COMPARISON

The 16 calibration objects were analysed by using two models: *componential segmentation* and *clustered segmentation* model.

"Benefit segments" were formed by clustering respondents into groups that were *homogeneous* with respect to the *individual* part-worth utilities, estimated in the previous subsection.

The clustering was done by using the *k-means* algorithm in Spss environment in a *non-hierarchical* routine that minimizes the Euclidean distance between each data point and the centre of the cluster.

The part-worth utilities for the clusters are listed in columns 2, 3, 4 and 5 of Table 4.

A four-cluster solution was chosen as most appropriate on the base of the increase – in the passage from a number of groups g to $(g + 1)$ – of the R^2

(index of global validity; Zani, 2007), exploiting the Anova table and the relative size of the clusters.

Tab. 4: Estimation results by two levels of aggregation

	Clustered segmentation clusters				*Componential segmentation*[b]
Attributes	*First*[a]	*Second*[a]	*Third*[a]	*Fourth*[a]	
Brand					
Apple	0,000	0,000	0,000	0,000	0,000
Samsung	-0,016	0,004	-0,004	-0,003	-0,004
BlackBerry	-0,036	0,004	-0,012	-0,008	-0,011
Nokia	-0,037	-0,014	0,001	-0,009	-0,010
Display					
4”	0,000	0,000	0,000	0,000	0,000
5”	0,003	-0,001	0,005	0,001	0,002
Battery run-time					
8 hours	0,000	0,000	0,000	0,000	0,000
12 hours	0,001	0,019	-0,005	0,004	0,003
Camera					
10 Mp	0,000	0,000	0,000	0,000	0,000
13Mp	0,002	0,004	0,006	0,002	0,003
Connection to Social Networks					
Yes	0,000	0,000	0,000	0,000	0,000
No	-0,006	0,003	-0,014	-0,003	-0,005
Payment features					
Yes	0,000	0,000	0,000	0,000	0,000
No	-0,016	-0,001	-0,020	-0,007	-0,011
Map features					
Yes	0,000	0,000	0,000	0,000	0,000
No	-0,008	0,005	-0,016	-0,005	-0,007
Price					
€ 599	0,000	0,000	0,000	0,000	0,000
€ 699	-0,008	0,001	-0,006	-0,003	-0,004

[a]Part-worth utilities for each level of each attribute. Most preferred levels are underlined.
[b]Part-worth utilities-main effects coefficients have been transformed (as the zero point is arbitrary) to allow easy comparison with other columns.

A *discriminant analysis* was run (IBM Spss 22.0) to determine whether there were any differences among the four groups in terms of background variables (see Moore, 1980). These differences were significant at the 0,05 level and the relationships between background variables and utility functions made sense. The picture of the group's heterogeneity is similar to that found in column 5 of Table 4.

There is substantial accordance across segments on the preferred levels of *Camera* and *Payment features*, but there are differences with respect to *Brand, Display*, *Battery run-time*, *Connection to Social Networks*, *Map features* and *Price*.

Group 1 contains a higher than average proportion of women, of respondents aged 18-25, of up-licentiate qualification – this segment prefers the *Apple* brand, wishes *low price* and connection to *Social networks*. Group 2 contains about one half of women, a higher proportion of *Graduate* qualification: this group is more interested in *Samsung* and *BlackBerry* brands and not interested in a connection to *Social networks*. Group 3 also contains more women than average with a larger proportion of graduates and students – this group was most interested in a *5" display, 13 Mp Camera*, wanted a *low price* and connection to *Social networks*. Group 4 contains more men than average and a larger proportion of up-licentiates, of respondents aged 26-35 – this group is most interested in *Apple* brand, *Battery run-time* and *low price*.

6.1 PREDICTIVE VALIDITY

The two models are compared on their ability to predict each person's preference for five validation objects. The average correlations between each person's predicted and stated preference are given in Table 5.

The predictive power of the *clustered segmentation* model is higher than that of *componential segmentation*.

Tab. 5: Comparison of predictive powers of two models

		Average correlations between predicted and stated preferences
Componential segmentation		0,511
Cluster 1	0,967	
Cluster 2	0,987	
Cluster 3	0,582	
Cluster 4	0,979	
Clustered segmentation		0,873

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