Fakultät für Wirtschaftswissenschaften
Facoltà di Economia
Faculty of Economics and Management

Workshop:
Clustering methods and their applications
28 November 2014, Free University of Bolzano

Fuzzy segmentation in the postmodern era

Marta Disegna

Free University of Bozen-Bolzano, Faculty of Economics and Management, Italy

- D'Urso P., Disegna M., Massari R., Osti L. (2014) "Fuzzy segmentation in postmodern consumers" (Settembre 2014). Available on REPEC: http://pro1.unibz.it/projects/economics/repec/bemps20.pdf
- D'Urso P., Disegna M., Massari R., Prayag G. (2015), "Bagged fuzzy clustering for fuzzy data: An application to a tourism market", *Knowledge Based Systems*, 75, 335-346

Research objectives

Aim:

to propose a clustering procedure that embraces the fuzzy theory from the beginning to the end of the process:

1. transforming the segmentation variables into fuzzy numbers
2. adopting a fuzzy clustering algorithm
3. profiling the clusters using the fuzzy membership degrees

Why?

How does it work?

Two empirical studies in the field of tourism are presented.

Postmodern era

1960-1970: the "absolute reality" and "universality" concepts that characterize the modern era are put into discussion by postmodern philosophers –Lyotard, Foucault, Derrida, Baudrillard among the most eminent– who introduced concepts like de-realisation, subjectivation, deconstruction, and hyperreality:

In the postmodern era the complexity of the world is **not captured only through an absolute perspective** but **different perspectives are accepted**. Therefore, the postmodern era is characterized by the absence of an ultimate reality, an absolute truth, and, consequently, a universal perspective.

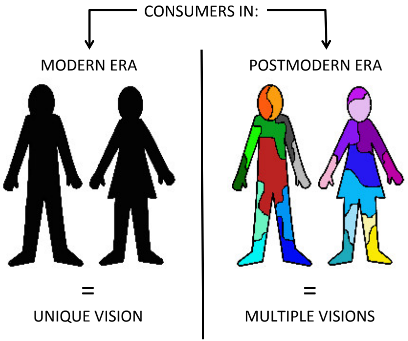
1990: the marketing literature has started to debate and investigate the new postmodern consumer. Nowadays, postmodernism is considered to shape today's world society in preferences, choices, and behaviour (Goneos-Malka et al, 2014; Napoli et al., 2014; Avery, 2012; Dunn & Castro, 2012; Riefler, 2012).

Who is the postmodern consumer?

Main characteristics of postmodernism in marketing (Brown, 2006; Firat & Venkatesh, 1995):

• blurring of the distinction between real and non-real, multiple and disjointed consumption experiences;

• lack of commitment to any (central) theme, language as the basis for subjectivity, experiences that allow the coexistence of differences and paradoxes, postmodernism as a culture of consumption.



How to segment postmodern consumers?

Among *a posteriori* segmentation approaches, cluster analysis remains the most popular method and the most frequently used in the literature (Jain, 2010; Dolnicar, 2002; Wedel & Kamakura, 2000).

Clustering algorithms are generally split into three groups:

- **non-overlapping** (hard) algorithm, which allows each observation to belong to a single segment only (Tuma et al., 2011),
- **overlapping** algorithm, which allows each observation to belong to more than one cluster (Wedel & Kamakura, 2000),
- **fuzzy** (or soft) algorithm, which assigns each observation to each cluster with a certain degree of membership that assumes value between 0 and 1 (Tuma et al., 2011).

How to cluster postmodern consumers?

Operationally, researchers can choose from a great number of clustering methods and each of them may conduct to a peculiar description of the data.

What is the correct clustering method?

Different clustering algorithms produce **different solutions** (Grekousis & Thomas, 2012) and present **different aspects** of the data (Leisch, 2006).

Unfortunately, no single clustering algorithm achieves satisfactory clustering solutions for all types of data sets (Ghaemi et al, 2009). Therefore, **no absolutely** "correct" or commonly shared **way to segment a market exists** in the literature (Brida et al., 2012; Tkaczynski & Rudle-Thiele, 2011; Kotler, Bowen, & Makens, 2010; Dolnicar et al., 2008).

Why use Fuzzy clustering? (1)

Fuzzy procedures allow the assignment of units to each cluster with a membership degree, **relaxing the assumption of exclusiveness**.

Suggestion:

The **fuzzy algorithm** seems to be the most suitable way to cluster postmodern consumers since it is able to capture the "**undefined**" consumers' behaviour, preferences, emotions, or other feelings, allowing an observation to belong to **more than one cluster** simultaneously (Russell & Lodwick, 1999).

The membership degree represents the uncertainty (vagueness) by which each unit is assigned to each cluster $\longrightarrow$ **the greater the membership degree, the greater the confidence in assigning the unit to that cluster**.

Why use Fuzzy clustering? (2)

The **fuzzy algorithm** not only allows **to capture the imprecision/vagueness** with which units are assigned to each cluster, but has also many other advantages over more traditional cluster algorithms (D'Urso, 2014):

1. computationally more efficient (Coppi et al., 2012)
2. less affected by local optima problems (D'Urso, 2007)
3. more stable when compared to hard methods (Wang et al., 2008).

Profiling phase of Fuzzy clustering

The membership degrees are the final result of a fuzzy algorithm. The greater the membership degree, the greater the confidence in assigning the unit to that cluster, but this **does not necessarily mean that the consumer only belongs to the cluster with which s/he has the higher membership degree** (Chaturvedi et al., 1997).
A common practice (Lim, Kim, & Runyan, 2013; Chiang, 2011; Malinverni & Fangi, 2009) in the profiling phase is to assign **each unit to a cluster in a crisp (or hard) way**, adopting a "defuzzification" procedure and/or specifying a cut-off point for membership degree (Malinverni & Fangi, 2009).

This procedure is in itself contradictory since **the segmentation phase is fuzzy**, of "soft", **but the profiling phase is hard** and this is in contrast with the very essence of both fuzzy clustering and the postmodern consumer.

Suggestion:

to use the membership degree in the profiling phase.

How to measure the “undefined” consumers’ behaviour?

Oftentimes, information regarding opinions, satisfaction, emotions, and other aspects that involve a personal judgement are (1) **vaguely defined** and captured through (2) **imprecise measurements** (D’Urso, 2007).

1. **Uncertain judgements:** individual judgements regarding an attribute depend on prior expectations or beliefs of the respondents, and on the weight or importance that the attribute has for the respondent (Engel, Blackwell, & Miniard, 1995), thus these judgements are vague, or, in a word, “fuzzy”, by definition.

2. **Uncertain measurements:** qualitative scales, such as Likert–type scales, are often used to capture human feelings in general (Li et al. 2013; Coppi, D’Urso, & Giordani, 2012; Benítez et al., 2007). The widespread use of Likert–type scales is related to the ease of developing and administering them but they entail **two sources of uncertainty...**

Uncertainty of empirical information

1. Linguistic expressions, such as Likert–type scales, are used to capture **subjective opinions, preferences, judgments, knowledge** of the respondent (Benítez et al., 2007; Coppi & D'Urso, 2002).

2. The interpretation of the **meaning of each linguistic expression is subjective, vague and uncertain**, since it depends on the characteristics and personal knowledge of the respondent. Furthermore, respondents are forced to automatically convert their opinions to scores and **these conversions can be inaccurate**, thus causing loss of information, imprecision, and uncertainty (D'Urso, 2007; Benítez et al., 2007).

The concept to be evaluated is unique but the mind of the consumer is fuzzy and vague (Lin & Yeh, 2013).

How to manage uncertain data?

Fuzzy sets, firstly proposed by Zadeh (1965), are commonly used to capture the imprecision or vagueness that characterize real-life (Wong et al., 2014) and provide a useful tool to make decisions based on imprecise and/or incomplete information (Pèrez-Gladish et al., 2010).

A **fuzzy set** is defined by a function that assigns to each unit a membership degree that indicates how close, similar, or compatible with the concept expressed by the fuzzy set the unit is.

Fuzzy number is a fuzzy set characterized by a membership function that is: continuous; that maps an interval $[a, b]$ to $[0, 1]$; and that is monotonically increases (Zimmermann, 1996).

Why use fuzzy sets and fuzzy numbers?

1. are able to capture and measure the uncertainty of individual evaluations (Coppi, & D'Urso, 2002; Benítez et al., 2007; Sinova et al., 2012).
2. have a very intuitive meaning, which can be easily grasped by potential users, and it is more comprehensive than other methods
3. can better describe complex processes of real-life which are often difficult or ambiguous to model with traditional statistical methods (Sohrabi et al., 2012).
4. can be adapted to a wide range of imprecise data, due to the richness of the scale of fuzzy sets and fuzzy numbers, including real and interval fuzzy numbers (Sinova et al., 2012; Sohrabi et al., 2012, Wong et al., 2014).

Suggestion:

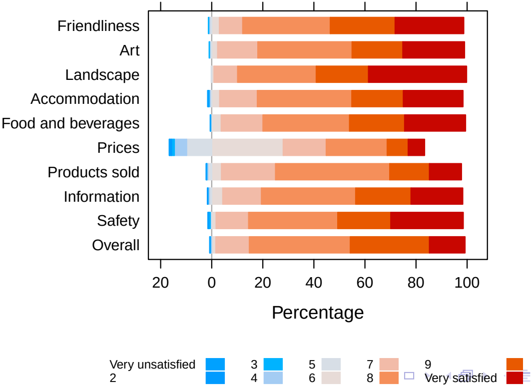
It is useful to formalize the linguistic variables in terms of fuzzy numbers **before** the adoption of a segmentation method, in order to **reduce** (not eliminate!) the imprecision/vagueness of the observed data.

Empirical study: 1

Survey: annual inbound survey “International Tourism in Italy” (*Banca d’Italia*).

Dataset: 997 international visitors who spent their holidays in any municipality located in the SouthTyrol region (Northern Italy) in 2010 and 2011.

Segmentation variables: level of satisfaction (measured through a 10–point Likert scale) of visitors with 10 different aspects of the destination.



Fuzzy numbers

A general class of fuzzy data, called *triangular* LR fuzzy data (LR1), can be defined in a metric form following Dubois and Prade (1988):

$$\widetilde{\mathbf{X}} \equiv \{\tilde{x}_{ik} = (m_{ik}, l_{ik}, r_{ik})_{LR} : i = 1, \ldots, N; k = 1, \ldots, K\}, \tag{1}$$

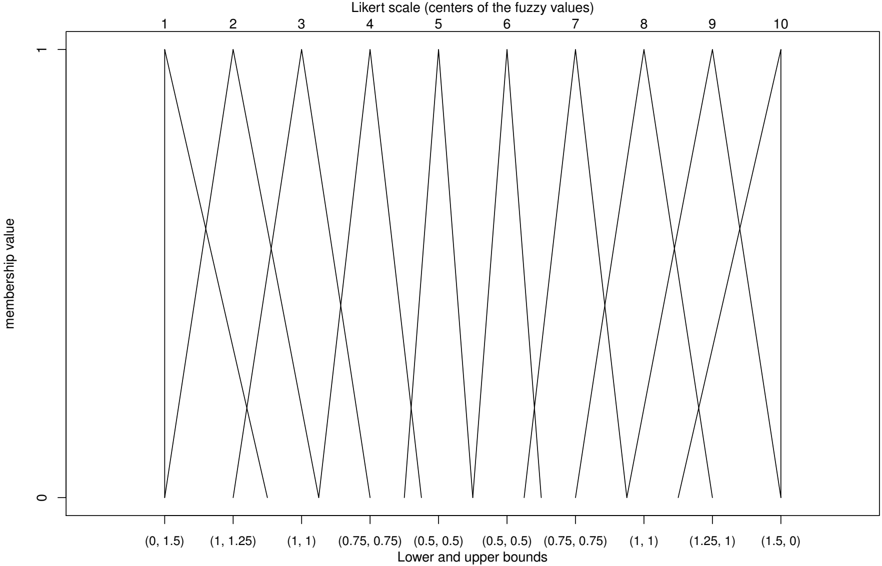
where:

- $\tilde{x}_{ik} = (m_{ik}, l_{ik}, r_{ik})_{LR}$ denotes the LR fuzzy variable k observed on the ith unit;
- m_{ik} indicates the center, i.e. the "core" of the fuzzy number;
- l_{ik} and r_{ik} represent the left and right spreads, i.e. the vagueness of the observation.

The choice of the fuzzy coding of Likert-type scales and the analysis of the robustness and stability of the results obtained from a fuzzy data analysis are two important research topics widely discussed in the literature (De la Rosa de Sàa, 2014).

Moreover, the *elicitation* and *specification* of the membership functions are two critical issues in the conversion of Likert-type scales into fuzzy data (Coppi et al, 2006).

Fuzzy recoding: from Likert scale to fuzzy numbers



Distance for fuzzy data

Since fuzzy segmentation variables are used, the following squared (Euclidean) distance measure for fuzzy data proposed by Coppi et al. (2012) is adopted:

$$d_F^2(\tilde{\mathbf{x}}_i, \tilde{\mathbf{x}}_{i'}) = w_M^2 \left(\|\mathbf{m}_i - \mathbf{m}_{i'}\|^2 \right) + w_S^2 \left(\|\mathbf{l}_i - \mathbf{l}_{i'}\|^2 + \|\mathbf{r}_i - \mathbf{r}_{i'}\|^2 \right),$$

where:

- $\tilde{\mathbf{x}}_i \equiv \{\tilde{x}_{ik} = (m_{ik}, l_{ik}, r_{ik})_{LR} : k = 1, \ldots, K\}$ denotes the fuzzy data vector for the ith unit;
- $\mathbf{m}_i$, $\mathbf{l}_i$ and $\mathbf{r}_i$ are the vectors of the centers and of the left and right spreads, respectively;
- $\|\mathbf{m}_i - \mathbf{m}_{i'}\|^2$ is the squared Euclidean distances between the centers;
- $\|\mathbf{l}_i - \mathbf{l}_{i'}\|^2$ and $\|\mathbf{r}_i - \mathbf{r}_{i'}\|^2$ are the squared Euclidean distances between the left and right spread, respectively;
- w_M, $w_S \geq 0$ are suitable weights for the center component and the spread component, constrained by the following conditions:

  $w_M + w_S = 1$ (*normalization condition*) and

  $w_M \geq w_S \geq 0$ (*coherence condition*) (Coppi et al., 2012).

Fuzzy clustering for fuzzy data

Fuzzy C-Means (FCM) clustering algorithm (Bezdek, 1981) was adopted. Using the distance measure propose by Coppi et al. (2012), the FCM algorithm for fuzzy data (FCM-FD) become:

$$\begin{cases} \min : \sum_{i=1}^{N} \sum_{c=1}^{C} u_{ic}^{m} d_F^2(\tilde{\mathbf{x}}_i, \tilde{\mathbf{h}}_c) \\ \sum_{c=1}^{C} u_{ic} = 1, \qquad u_{ic} \geq 0, \\ w_M \geq w_S \geq 0; \; w_M + w_S = 1 \end{cases} \tag{2}$$

where:

- u_{ic} indicates the membership degree of the ith unit in the cth cluster;
- $d_F^2(\tilde{x}_i, \tilde{h}_c)$ represents the suggested dissimilarity measure between the ith unit and the prototype of the cth cluster;
- $m > 1$ is a weighting exponent that controls the fuzziness of the obtained partition;
- the fuzzy vector $\tilde{\mathbf{h}}_c \equiv \{\tilde{h}_{ck} = (h_{ck}^M, h_{ck}^L, h_{ck}^R)\}$ represents the fuzzy prototype of the cth cluster.

Note that the prototypes obtained with the FCM-FD are of LR1 type, inheriting their typology from the observed data (Coppi et al., 2012).

▸ Algorithm

Cluster validity

As regards the identification of the optimal number of clusters, the following modified Xie and Beni (1991) index (S) was adopted:

$$S = \frac{\sum_{i=1}^{N}\sum_{c=1}^{C} u_{ic}^{m} d_F^2(\tilde{\mathbf{x}}_i, \tilde{\mathbf{h}}_c)}{N \cdot (d_{min})^2} \tag{3}$$

where:

- N is the total number of data;
- $(d_{min})^2$ is called the separation of the fuzzy c-partition.
  d_{min} is the minimum Euclidean Norm between two fuzzy prototypes:

A smaller S indicates that all the clusters are overall compact and separate from each other $\Longrightarrow$ **The goal is to find the partition with the smallest S.**

Profiling

In order to profile the identified clusters, the matrix of other information ($\mathbf{Y} = \{(y_{i1}, \ldots, y_{ik}, \ldots, y_{iK}) : i = 1, \ldots, N; k = 1, \ldots, K\}$), such as the socio–demographic and traveling characteristics, collected through the survey can be used.

When the profiling variables were **categorical**, the weighed percentage frequency ($\tilde{f}_{kjc}$), referring to the jth ($j = 1, \ldots, J$) modality of the kth original variable ($\mathbf{y}_k$) for the cth ($c = 1, \ldots, C$) cluster, was calculated as follows:

$$\tilde{f}_{kjc} = \frac{\sum_{i=1}^{N} y_{ikj} u_{ic}}{\sum_{c=1}^{C} \sum_{i=1}^{N} y_{ikj} u_{ic}} \cdot 100 \tag{4}$$

where u_{ic} was the membership degree of unit i to each final cluster c.

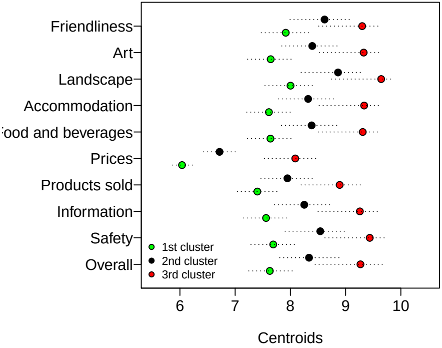
When the profiling variables were **quantitative**, the usual weighed mean ($\tilde{y}_{kc}$) was calculated as follows:

$$\tilde{y}_{kc} = \frac{\sum_{i=1}^{N} y_{ik} u_{ic}}{\sum_{i=1}^{N} u_{ic}} \tag{5}$$

The cluster solution

The Xie-Beni index calculated for the partitions with 2 and 3 clusters suggests that the two cluster solutions are very similar, taking values respectively equal to 0.42 and 0.84

$\Longrightarrow$ we have decided to choose the 3 cluster solution since it enables us to obtain a more precise and detailed clustering of the market.



Cluster 1 (34%) and **2** (31%) group, respectively, people less and more satisfied with the investigated aspects in comparison to the third cluster $\longrightarrow$ were labelled respectively "Unfulfilled" and "Enthusiasts". **Cluster 3** (35%) groups visitors who are neither very nor little satisfied $\longrightarrow$ was named "With reservations".

- All clusters are less satisfied with "Prices", "Products sold", and "Information".
- All clusters rank "Landscape" first.

Profiling: Socio–demographic characteristics of the visitors

Description

Variables	Sample	Cluster 1	Cluster 2	Cluster 3	*p*-value
Socio–demographic characteristics					
Male	68.91	70.74	66.13	69.60	
Age					
Less than 35 years old	21.16	22.39	19.74	21.25	
35-44 years old	28.59	26.57	31.07	28.33	
45-64 years old	36.41	35.52	37.22	36.54	
More than 64 years old	13.84	15.52	11.97	13.88	
Employment status					
Self–employed	11.57	11.38	11.61	11.68	
Clerk	16.20	14.67	17.74	16.52	
Other employee	53.72	53.89	52.58	54.42	
Retired	12.47	14.07	11.29	11.97	
Other	6.04	5.99	6.78	5.41	
Country of origin					***
Austria	21.06	**29.85**	14.84	18.13	
Germany	50.85	42.99	**56.45**	53.26	
Other EU countries	21.46	20.59	**22.58**	21.25	
Outside EU	6.63	6.57	6.13	**7.36**	

Notes: Percentage composition of the whole sample (first column) and the weighed relative frequencies per each profiling variable and cluster are presented. Significance of the Chi-square test was reported. All test results are not significant unless indicated otherwise: ***Significant at $p \leq 0.01$, **Significant at $p \leq 0.05$, *Significant at $p \leq 0.1$.

Profiling: Traveling characteristics

Variables	Sample	Cluster 1	Cluster 2	Cluster 3	*p*-value
Trip characteristics					
Visit alone	23.97	**31.14**	18.71	21.81	***
Only one cities visited	84.05	86.97	81.61	83.57	
Number of times in Italy before					***
Zero	23.97	**31.14**	17.10	23.23	
Up to 5 times	24.87	22.15	**27.10**	25.50	
More than 5 times	51.15	46.71	**55.80**	51.27	
Main purpose of travel					***
Montain holiday	46.14	39.70	**50.48**	48.43	
Cultural holiday	18.86	19.40	**19.29**	17.95	
Other kind of holiday	11.03	9.55	**12.86**	10.83	
Other personal motivations	13.44	**17.92**	9.97	12.25	
Business	10.53	**13.43**	7.40	10.54	
Expenditure behavior					
Accommodation	84.25	73.05	**93.55**	86.67	***
Transportation	71.51	58.98	**83.97**	72.52	***
Food & Beverages	83.35	77.91	**87.70**	84.70	***
Shopping	72.52	68.66	**76.77**	72.44	*
Other services	35.31	31.94	**37.10**	36.93	

Notes: Percentage composition of the whole sample (first column) and the weighed relative frequencies per each profiling variable and cluster are presented. Significance of the Chi-square test was reported. All test results are not significant unless indicated otherwise: ***Significant at $p \leq 0.01$, **Significant at $p \leq 0.05$, *Significant at $p \leq 0.1$.

Implications

Theoretical implications

The FCM-FD represents an innovative approach for the treatment of data derived from linguistic (qualitative) variables. This method is able to capture uncertainty resulting from:

- the assignment of an observation to a certain cluster;
- the subjective evaluation of the linguistic expression from respondents.

Managerial implications

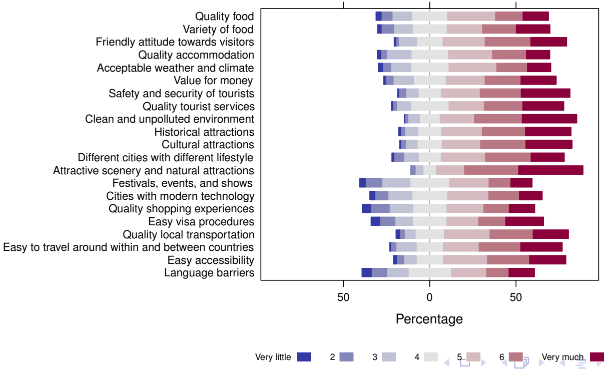
- all visitors perceive prices to be too high and inadequate $\longrightarrow$ Destination managers and planners should therefore encourage tourism operators to justify prices through quality of the products
- the "Unfulfilled" travel alone, visit Italy for the first time and for business or personal reasons, spend less frequently than other visitors in all shopping categories and are mainly from Austria;
- the "Enthusiasts" rank friendliness of local residents as 5th, are mainly from Germany, and have visited Italy 5 or more times.

Empirical study: 2

Survey: survey in Beijing as part of a larger study on Chinese perceptions of Western Europe

Dataset: 328 respondents of 18-44 years old who intend to travel to Western Europe.

Segmentation variables: 21 image attributes measured tourism products generally offered to Chinese travellers. The items were measured on a 7–point Likert scale where [1] *Offers very little* and [7] *Offers very much*.



Fuzzy numbers

A class of *trapezoidal* LR fuzzy data (LR2) can be defined as follow:

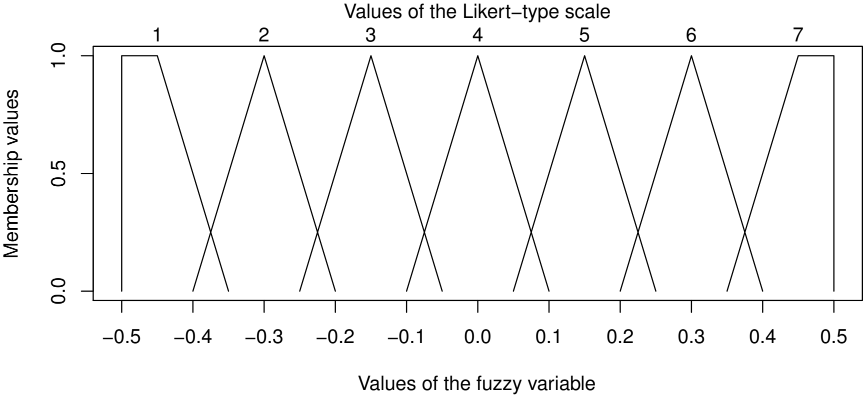
$$\widetilde{\mathbf{X}} \equiv \{\tilde{x}_{ij} = (m_{1ij}, m_{2ij}, l_{ij}, r_{ij})_{LR} : i = 1, \ldots, N; \, j = 1, \ldots, J\}, \qquad (6)$$

where:

- $\tilde{x}_{ij} = (m_{1ij}, m_{2ij}, l_{ij}, r_{ij})_{LR}$ denotes the LR fuzzy variable j observed on the ith unit;
- m_{1ij} and m_{2ij} indicate the left and right centers;
- l_{ij} and r_{ij} represent the left and right spreads.

The fuzzy coding proposed by Kazemifard et al. (2011) was used in this study.

Fuzzy recoding: from the Likert scale to the fuzzy numbers



Distance for fuzzy data

By considering the ith and the i'th units, the following squared (Euclidean) distance measure proposed by Coppi et al. (2012) is adopted:

$$\begin{aligned} d_F^2(\tilde{\mathbf{x}}_i, \tilde{\mathbf{x}}_{i'}) &= w_M^2 \left(\left\| \mathbf{m}_{1i} - \mathbf{m}_{1i'} \right\|^2 + \left\| \mathbf{m}_{2i} - \mathbf{m}_{2i'} \right\|^2 \right) \\ &+ w_S^2 \left(\left\| \mathbf{l}_i - \mathbf{l}_{i'} \right\|^2 + \left\| \mathbf{r}_i - \mathbf{r}_{i'} \right\|^2 \right), \end{aligned}$$

where:

- $\tilde{\mathbf{x}}_i \equiv \{\tilde{x}_{ij} = (m_{1ij}, m_{2ij}, l_{ij}, r_{ij})_{LR} : j = 1, \dots, J\}$ denotes the fuzzy data vector for the ith unit;
- $\mathbf{m}_{1i}\, \mathbf{m}_{2i}$, $\mathbf{l}_i$ and $\mathbf{r}_i$ are the vectors of the left and right centers and of the left and right spreads, respectively;
- $\left\| \mathbf{m}_{1i} - \mathbf{m}_{1i'} \right\|^2$ and $\left\| \mathbf{m}_{2i} - \mathbf{m}_{2i'} \right\|^2$ are the squared Euclidean distances between the the left and right centers;
- $\left\| \mathbf{l}_i - \mathbf{l}_{i'} \right\|^2$ and $\left\| \mathbf{r}_i - \mathbf{r}_{i'} \right\|^2$ are the squared Euclidean distances between the left and right spread, respectively;
- w_M, $w_S \geq 0$ are suitable weights for the center component and the spread component, constrained by the following conditions:

  $w_M + w_S = 1$ (*normalization condition*) and

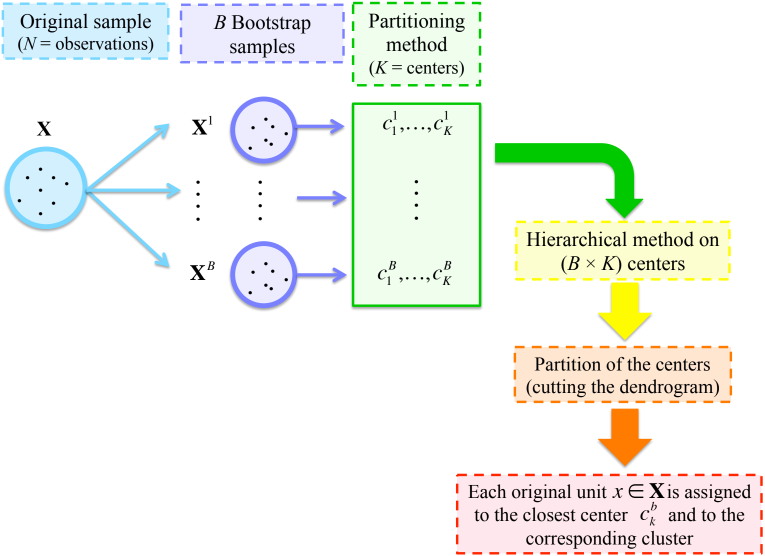
  $w_M \geq w_S \geq 0$ (*coherence condition*) (Coppi et al., 2012).

Fuzzy clustering algorithm

The Bugged fuzzy C-Means algorithm of fuzzy data (BFCM-FD)

A novel segmentation method that combine the Bagged Clustering (BC) procedure (Leisch, 1999) with the fuzzy C-Means algorithm for fuzzy data (FCM-FD) inheriting the advantages of both BC and FCM-FD.

The BC (Leisch, 1999)



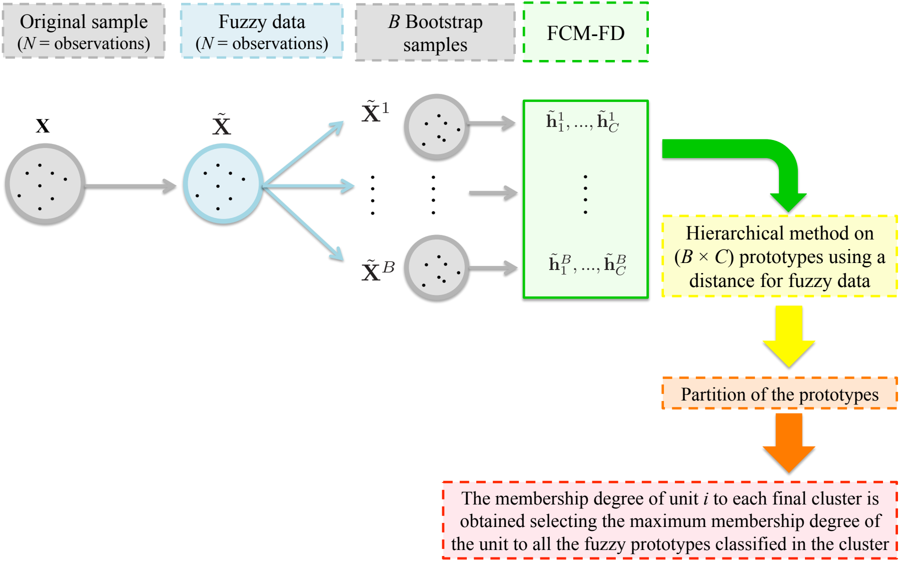
Advantages of the Bagged Clustering (BC)

BC combines a **partitioning clustering** method with a **hierarchical clustering** method avoiding many of the limitations of both methods.

In general:

- Less dependence on the starting solution.
- Greater stability of solutions.
- Possibility to identify niches.
- A priori decision on the number of clusters is not necessary.
- Performs better than several standard partitioning methods from both binary and continuous data.

The BFCM-FD



Original sample
(N = observations)
Fuzzy data
(N = observations)
B Bootstrap samples
FCM-FD
X
X̃
X̃¹
X̃ᴮ
h̃₁¹, ..., h̃_C¹
h̃₁ᴮ, ..., h̃_Cᴮ
Hierarchical method on (B × C) prototypes using a distance for fuzzy data
Partition of the prototypes
The membership degree of unit i to each final cluster is obtained selecting the maximum membership degree of the unit to all the fuzzy prototypes classified in the cluster

Detection of the best partition

As regards the identification of the final best partition, the Average Silhouette width (I_S) criterion proposed by Rousseeuw (1987) was adopted:

$$I_S = \frac{1}{B \cdot C} \sum_{c=1}^{B \cdot C} S_c \quad \text{where} \quad S_c = \frac{b_{cp} - a_{cp}}{\max\{a_{cp}, b_{cp}\}}$$

where:

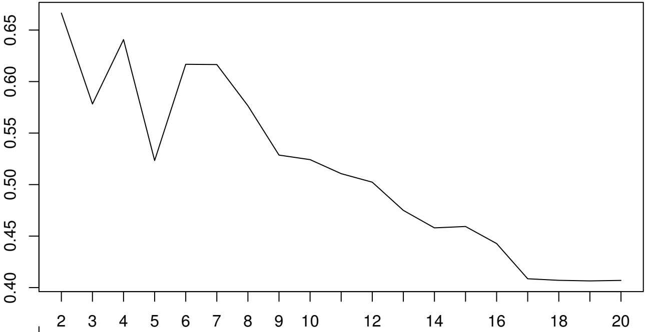
- a_{cp} is the average distance of the c-th prototype from all other prototypes belonging to cluster p;
- b_{cp} is the minimum average distance of the c-th prototype belonging to cluster p from all prototypes belonging to another cluster $p'(p' \neq p)$. $\longrightarrow b_{cp}$ represents the dissimilarity of the c-th prototype belonging to the generic cluster p to its closest neighbouring cluster;

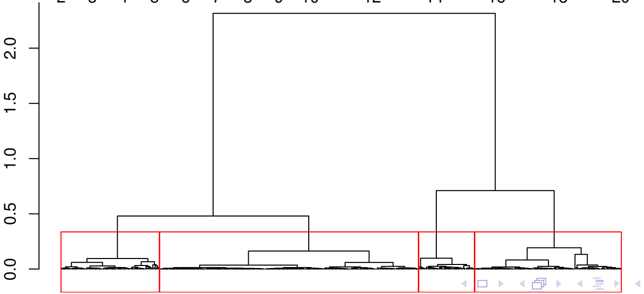
The higher S_c, the better the assignment of the cth prototype to the pth cluster $\longrightarrow$ The best partition is achieved when the S_c is maximized, which implies minimizing the intra-cluster distance (a_{cp}) while maximizing the inter-cluster distance (b_{cp}).

Profiling

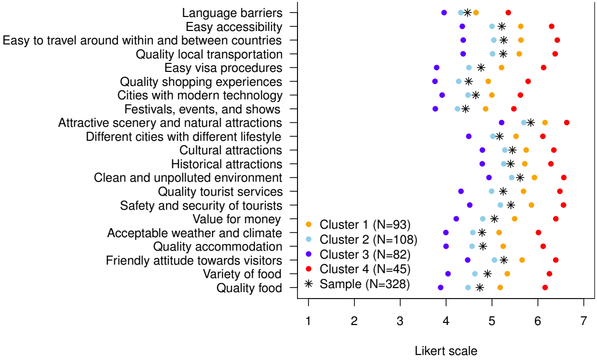
...as proposed in the first empirical study

The cluster solution (1)





The cluster solution (2)



Cluster 1 (29%), generally has positive perceptions of most attributes ⟶ was labelled "Enthusiasts".

Cluster 2 (33%), grouped travellers who rated most of the image attributes as neither offering much nor offering little ⟶ was labelled "Moderates".

Cluster 3 (25%) groups travellers who perceive more than other travellers that Western Europe has little to offer on image attributes such as "easy visa procedures", "quality shopping experiences", "cities with modern technology", "festival, events and shows", and "quality food" ⟶ was labelled "Apathetics".

Cluster 4 (13%) groups travellers who believe more than other travellers that Western Europe offers all the image attributes considered. However, they rated "festivals, events and shows" and "language barriers" lower and "attractive scenery and natural attractions" higher than the other attributes ⟶ was labelled "Admirers".

Profiling (1)

▸ Description

Variables	Sample	CL1	CL2	CL3	CL4	*p*-value
Socio–demographic and economic characteristics						
Female	57.32	**63.44**	54.63	43.90	**75.56**	***
Individual Monthly Income	67.08	64.13	65.42	68.29	75.00	
Single	61.06	66.30	62.75	60.98	46.67	
Educational Level	62.46	69.57	58.49	56.10	68.89	
Age	51.53	56.52	51.40	52.44	40.00	
Employment Status	54.29	50.00	51.85	58.02	62.22	
Trip characteristics						
Preferred type of accommodation	42.64	44.57	35.19	41.46	**59.09**	*
Visitation status to WE	76.95	83.70	72.90	75.64	75.00	
Estimated duration of the next trip to WE	62.58	58.70	64.81	62.96	64.44	
Party group of the next trip to WE	60.37	50.00	64.49	63.29	66.67	
Main Purpose of travel						
VFR	3.96	2.15	4.63	3.66	6.67	
Study	19.21	21.51	20.37	19.51	11.11	
Work	5.18	4.30	9.26	2.44	2.22	
Holiday	83.54	84.95	82.41	78.05	93.33	

Notes: Percentage composition of the whole sample (first column) and the weighed relative frequencies per each profiling variable and cluster are presented. Significance of the Chi-square test was reported. All test results are not significant unless indicated otherwise: ***Significant at $p \leq 0.01$, **Significant at $p \leq 0.05$, *Significant at $p \leq 0.1$.

Profiling (2)

Variables	Sample	CL1	CL2	CL3	CL4	*p*-value
What destinations are you most likely to visit?						
UK	55.49	**64.52**	51.85	**46.34**	62.22	*
Italy	54.57	54.84	51.85	58.54	53.33	
Belgium	13.41	8.60	12.96	15.85	20.00	
Portugal	9.45	7.53	12.96	4.88	13.33	
France	72.56	74.19	**65.74**	70.73	**88.89**	**
Switzerland	53.05	51.61	52.78	46.34	68.89	
Ireland	17.99	16.13	20.37	14.63	22.22	
Netherlands	30.79	29.03	33.33	30.49	28.89	
Germany	39.63	41.94	39.81	**29.27**	**53.33**	*
Spain	39.33	37.63	45.37	32.93	40.00	
Austria	22.87	25.81	25.00	14.63	26.67	
Greece	50.30	56.99	47.22	**37.80**	**66.67**	***
What information source are you likely to use to plan your trip to Western Europe?						
TV or radio advertising	15.85	13.98	17.59	19.51	8.89	
Guidebook	33.84	29.03	**44.44**	24.39	35.56	**
Internet search engine	77.13	**84.95**	75.93	**76.83**	64.44	*
Travel agency	44.51	51.61	38.89	42.68	46.67	
Travel forums & blogs	47.56	53.76	50.00	**35.37**	51.11	*
Specialised magazine	29.88	31.18	32.41	26.83	26.67	

Notes: Percentage composition of the whole sample (first column) and the weighed relative frequencies per each profiling variable and cluster are presented. Significance of the Chi-square test was reported. All test results are not significant unless indicated otherwise: ***Significant at $p \leq 0.01$, **Significant at $p < 0.05$, *Significant at $p < 0.1$.

Implications

Theoretical implications

BFCM-FD offers a rigorous, visually simple, and alternative way of segmenting consumers and allows for the identification of niche markets.

Managerial implications

- Western Europe offering much in terms of attractive sceneries and natural attractions, clean and unpolluted environment, safety and security, and cultural attractions $\longrightarrow$ these attributes should feature prominently in future marketing campaigns;
- the Chinese outbound market values safety and security. Individual countries within Western Europe should ensure that tourists feel safe;
- Chinese tourists are attracted by the perceived "cleanliness" of Europe compared to China and the region's perceived pristine environment can be effectively used for destination advertising and promotion in China;
- the least favourably assessed attribute by all segments is "festivals, events and shows". The new generation of Chinese travellers will not necessarily follow the classic cultural-historical itineraries currently offered in Europe $\longrightarrow$ marketing to the young generations of Chinese tourists will require the promotion of festivals, events and shows that are relevant to this generation.

Conclusions

- A **fuzzy clustering procedure** seems to be a good way to segment postmodern consumers.
- The results are **comprehensible and easy to read** since they appear similar to that obtained through more traditional clustering techniques $\longrightarrow$ Practitioners can use the results to create future management and marketing strategies to develop and maintain a competitive advantage in the postmodern era.
- It is necessary to find **suitable instruments** able to handle and capture the imprecision associated with the use of Likert-type scales.
- It is necessary to investigate the applicability of **fuzzy rating scales** in real settings.

Thank you for your attention!

Marta Disegna: marta.disegna@unibz.it

Description of the variables empirical study 1

Independent variables	Descriptions
Socio–demographic and economic characteristics	
Male	1= Male; 0= Female
Age	
Less than 35 years old	1 = ticked; 0 = otherwise
35-44 years old	1 = ticked; 0 = otherwise
45-64 years old	1 = ticked; 0 = otherwise
More than 65 years old	1 = ticked; 0 = otherwise
Employment status	
Self-employed	1 = ticked; 0 = otherwise
Clerk	1 = ticked; 0 = otherwise
Other employee	1 = the respondent is an executive, worker, and other; 0 = otherwise
Retired	1 = ticked; 0 = otherwise
Other employment status	1 = ticked; 0 = otherwise
Country of origin	
Austria	1 = ticked; 0 = otherwise
Germany	1 = ticked; 0 = otherwise
Other EU countries	1 = ticked; 0 = otherwise
Outside EU	1 = ticked; 0 = otherwise
Trip characteristics	
Visit alone	1 = the respondent makes the trip alone; 0 = otherwise
Only one cities visited	1 = only one city visited in the South-Tyrol during the trip; 0 = otherwise
Number of times in Italy before	
Zero	1 = the interviewee visits any city in Italy for the first time; 0 = otherwise
Up to 5 times	1 = been in Italy from 1 to 5 times before the interview; 0 = otherwise
More than 5 times	1 = been in Italy more than 5 times before the interview; 0 = otherwise
Main purpose of travel	
Montain holiday	1 = ticked; 0 = otherwise
Cultural holiday	1 = ticked; 0 = otherwise
Other kind of holiday	1 = the respondent makes the trip for other holiday purposes (sea, lake, sport, wine & food, etc.); 0 = otherwise
Other personal motivations	1 = The respondent makes the trip for a personal motivations (visiting friends & relatives, study, shopping, etc.) ; 0 = otherwise
Business	1 = ticked; 0 = otherwise
Expenditure behavior	
Accommodation	1 = The expenditure on accommodation is positive; 0 = otherwise
Transportation	1 = The expenditure on transportation is positive; 0 = otherwise
Food & Beverages	1 = The expenditure on food and beverages is positive; 0 = otherwise
Shopping	1 = The expenditure on shopping is positive; 0 = otherwise
Other services	1 = The expenditure on other services is positive; 0 = otherwise

FCM for fuzzy data algorithm

Fix C and $max.iter$;
Set $iter = 0$;
Generate the initial membership degree matrix $\mathbf{U}^{(0)}$, subject to:
$$\sum_{c=1}^{C} u_{ic} = 1, \qquad u_{ic} \geq 0$$
Compute the prototypes $\tilde{\mathbf{h}}_c^{(0)} \equiv \{\tilde{h}_{ck}^{(0)} = (h_{ck}^{M(0)}, h_{ck}^{L(0)}, h_{ck}^{R(0)})\}$, $c = 1, \dots, C$ using $\mathbf{U}^{(0)}$;
repeat
    Update the weights $w_M^{(t)}$ and $w_S^{(t)}$, keeping fixed $\mathbf{U}^{(t-1)}$ and $\tilde{\mathbf{h}}_c^{(t-1)}$, $c = 1, \dots, C$, where $t \geq 1$ denotes the iteration number, and set $w_M^{(t)} = w_S^{(t)} = 0.5$ if $w_S^{(t)} > 0.5$;
    Update the prototypes $\tilde{\mathbf{h}}_c^{(t)}$, $c = 1, \dots, C$, keeping fixed $\mathbf{U}^{(t-1)}$;
    Update the membership degree matrix $\mathbf{U}^{(t)}$ keeping fixed $\tilde{\mathbf{h}}_c^{(t)}$, $c = 1, \dots, C$ and $w_M^{(t)}$ and $w_S^{(t)}$.
    $iter \leftarrow iter + 1$;
until $\|\mathbf{U}^{(t)} - \mathbf{U}^{(t-1)}\| < \varepsilon$, $\varepsilon > 0$, or $iter = max.iter$

Description of the variables empirical study 2

Independent variables	Descriptions
Socio–demographic and economic characteristics	
Female	1= ticked; 0= not ticked
Individual monthly income	1= Individual monthly income equal to 7,000 RMB or less; 0 = otherwise
Single	1= ticked; 0= not ticked
Educational level	1 = University degree and less; 0 = Post-graduate degree
Age	1 = 18 and 25 years old; 0 = 26 years old and over
Employment Status	1 = Full-time employee; 0 = student or not employed
Trip characteristics	
Preferred Type of Accommodation	1= 3–5 star hotel; 0= otherwise (e.g. hostel, guest house)
Visitation Status to WE	1= First–timer in Western Europe; 0= otherwise
Estimated Duration of the Next Trip to WE	1= Less than 2 weeks in Western Europe; 0= otherwise
Party Group of the Next Trip to WE	1= Family or partner on the next trip to Western Europe; 0= otherwise
Main Purpose of travel	
VFR	1= visiting friends & relatives; 0= otherwise
Study	1= ticked; 0= not ticked
Work	1= ticked; 0= not ticked
Holiday	1= ticked; 0= not ticked
What destinations are you most likely to visit?	
UK	1= ticked; 0= not ticked
Italy	1= ticked; 0= not ticked
Belgium	1= ticked; 0= not ticked
Portugal	1= ticked; 0= not ticked
France	1= ticked; 0= not ticked
Switzerland	1= ticked; 0= not ticked
Ireland	1= ticked; 0= not ticked
Netherlands	1= ticked; 0= not ticked
Germany	1= ticked; 0= not ticked
Spain	1= ticked; 0= not ticked
Austria	1= ticked; 0= not ticked
Greece	1= ticked; 0= not ticked
What information source are you likely to use to plan your trip to Western Europe?	
TV or radio advertising	1= ticked; 0= not ticked
Guidebook	1= ticked; 0= not ticked
Internet search engine	1= ticked; 0= not ticked
Travel agency	1= ticked; 0= not ticked
Travel forums & blogs	1= ticked; 0= not ticked
Special magazine	1= ticked; 0= not ticked