Classification and Representation Using Conjoint Data

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Summary: We present new approaches to the analysis of conjoint data. One part of this paper deals with classification, another with representation issues. Both parts start with an overview of available approaches and then introduce new approaches. A real-world application concerning the introduction of a new product in the European air freight market shows advantages of the presented approaches.

1. Introduction

Conjoint analysis is the label attached to a research tool for measuring subjects' tradeoffs among competing objects via rank order or rating scale responses to constructed multiattribute stimuli (see, e.g., Green, Srinivasan (1990)). Surveys on the commercial use of conjoint analysis in the United States (Wittink, Cattin, (1989)) or in Europe (Wittink, Vriens, Burhenne (1994)) indicate that, since the first papers on the applicability of this methodology to marketing problems (see, e.g., Green, Rao, (1971)), conjoint analysis has become a popular research tool within many applications.

Contrary to early definitions of conjoint analysis and contrary to commercial usage reported in earlier surveys where nonmetric procedures like LINMAP or MONANOVA were preferred, more recent surveys show that metric procedures like OLS (Ordinary Least Squares) applied to rank order or rating scale responses are most frequently named. As OLS provides similar results to nonmetric procedures when applied to rank order responses (see, e.g., Green, Srinivasan (1978) for respective references) and the part-worth approach is commonly used for preference modeling (Green, Srinivasan (1990)), the following presentation will be based on part-worth estimation using OLS:

Let be i an index for N respondents, j an index for n stimuli, v an index for V attributes, and w an index for W_v levels of the v-th attribute. With this notation, typical conjoint data are (binary) profile data $B_{111}, \ldots, B_{nVW_V}$ (where B_{jvw} indicates whether stimulus j has level w for attribute v (=1) or not (=0)) and response data $y_{11}, \ldots, y_{nN}$ (where y_{ji} describes the observed preference value for stimulus j obtained from respondent i). Model parameters are the respondents' part-worths $u_{111}, \ldots, u_{NVW_V}$, which are estimated in such a way that the least squares loss function

$$Z = \sum_{i=1}^{N} \sum_{j=1}^{n} (y_{ji} - \hat{y}_{ji})^2 \quad \text{with} \quad \hat{y}_{ji} = \sum_{v=1}^{V} \sum_{w=1}^{W_v} B_{jvw} u_{ivw} \quad \forall j, i \qquad (1)$$

is minimized. Because of

$$\sum_{w=1}^{W_v} B_{jvw} = 1 \quad \forall j, v \tag{2}$$

dummy-variable coding can be used for the design matrix $\dot{\mathbf{B}}$ with elements

$$\dot{B}_{jl} = \begin{cases} 1 & \text{if } l = 1 \\ B_{jv_0w_0} & \text{else, } \begin{array}{l} v_0 = \max\{v|l{>}1 + (W_1\text{-}1) + \cdots + (W_{v\text{-}1}\text{-}1)\}, \\ w_0 = l - (1 + (W_1\text{-}1) + \cdots + (W_{v_0\text{-}1}\text{-}1)) \end{array} \end{cases} \forall j, \tag{3}$$

which we obtain from the profile data by introducing one intercept column and omitting one superfluous level column for each attribute.

Since

$$\hat{y}_{ji} = \underbrace{\sum_{v=1}^{V} u_{ivW_v}}_{=:c_{1i}} + \sum_{v=1}^{V} \sum_{w=1}^{W_v-1} B_{jvw} \underbrace{(u_{ivw} - u_{ivW_v})}_{=:c_{(1+(W_1-1)+\cdots+(W_{v-1}-1)+w)i}} = \sum_{l=1}^{1+(W_1-1)+\cdots+(W_V-1)} \dot{B}_{jl} c_{li}, \quad \forall j, i \tag{4}$$

we get OLS estimates (Note that the existence of $(\dot{\mathbf{B}}'\dot{\mathbf{B}})^{-1}$ is assumed.)

$$\hat{\mathbf{Y}} = ((\hat{y}_{ji})) = \dot{\mathbf{B}}\mathbf{C} \quad \text{with} \quad \mathbf{C} = ((c_{li})) = (\dot{\mathbf{B}}'\dot{\mathbf{B}})^{-1}\dot{\mathbf{B}}'\mathbf{Y} \quad \text{and} \quad \mathbf{Y} = ((y_{ji})) \tag{5}$$

at the disaggregate level from which respondents' part-worths can easily be calculated according to

$$u_{ivw} = \begin{cases} \frac{c_{1i}}{V} + c_{(1+(W_1-1)+\cdots+(W_{v-1}-1)+w)i} & \text{if } w \neq W_v \\ \frac{c_{1i}}{V} & \text{else} \end{cases} \quad \forall i, v, w. \tag{6}$$

Some problems with conjoint analysis applications – even within a so-called average commercial study (n=16 stimuli, V=8 attributes, $W_1=\ldots=W_V=3$ levels (Wittink, Cattin (1989), Green, Srinivasan (1990))) – are as follows:

Firstly, response data is observed and model parameters are estimated, both at the disaggregate level. Due to the usage of reduced designs for stimuli construction, the few degrees of freedom cause a problem. In the average commercial study mentioned, there are 16 observations (one for each stimulus) per respondent and 17 model parameters (the intercept and two coefficients for each attribute) per respondent resulting in overparametrization. Secondly, due to the few degrees of freedom, the response prediction for attribute-level-combinations not included in the data collection step may be insufficient and cause a so-called predictive accuracy problem. Thirdly, whereas tabular and graphical displays of the resulting part-worths may be appropriate for applications with few respondents, information overload problems occur when data from hundreds of respondents has to be analyzed.

In these cases, modified forms of analyses or other graphical display forms – as discussed in the following parts – may be helpful.

2. Classification Using Conjoint Data

2.1 Overview

Various classification approaches have been proposed in order to prevent the above mentioned overparametrization and predictive accuracy problems with conjoint models at the disaggregate level by combining information across respondents. Moreover, these approaches have been used to derive so-called benefit segments (see, e.g., Green, Krieger (1991) for an overview).

At the moment, according to the already mentioned commercial application surveys, so-called sequential approaches seem to be most popular: Segments are formed either with or without usage of cluster analysis based on, e.g., respondents' background characteristics or part-worths estimated at the disaggregate level. Afterwards, segment-specific model parameters are estimated by aggregation or by group level procedures (see, e.g., Moore (1980) for an overview).

In the newer so-called simultaneous approaches, segmentation parameters and segment-specific model parameters are simultaneously estimated. Some of these procedures (e.g., Hagerty (1985), Kamakura (1988), DeSarbo, Oliver, Rangaswamy (1989), Wedel, Kistemaker (1989)) generalize known clusterwise regression procedures (Bock (1969), Späth (1983), DeSarbo, Cron (1988)) to conjoint analysis applications. The new clusterwise regression procedure, which will be presented in the next section, differs only with respect to response data description and parameter estimation from known approaches. Contrary to, e.g., Späth's model for one-mode one-way response data, two-mode two-way response data can be analyzed and the well-known iterative minimum-distance algorithm – instead of some exchange algorithm – is applied for parameter estimation.

2.2 Iterative Minimum-Distance Clusterwise Regression

2.2.1 The Model: We use the same notation as in the introduction, but add an index t for T segments or homogeneous groups of respondents. Input data are again the (binary) profile data $B_{111}, \ldots, B_{nVW_V}$ and the individual response data $y_{11}, \ldots, y_{nN}$.

Model parameters are now the segment membership indicators $h_{11}, \ldots, h_{TN}$, where h_{ti} denotes whether respondent i belongs to segment t (=1) or not (=0), and segment-specific part-worths $u_{111}, \ldots, u_{TVW_V}$. Again, we use a loss function as given in formula (1), but now the individual response estimates are replaced by respective segment-specific response estimates:

$$Z = \sum_{i=1}^{N} \sum_{j=1}^{n} (y_{ji} - \hat{y}_{ji})^2 = \sum_{i=1}^{N} \sum_{t=1}^{T} h_{ti} \sum_{j=1}^{n} (y_{ji} - u_{jt})^2 \rightarrow \min! \qquad (7)$$

with

$$\hat{y}_{ji} = \sum_{t=1}^{T} h_{ti} u_{jt} \quad \forall j, i, \qquad u_{jt} = \sum_{v=1}^{V} \sum_{w=1}^{W_v} B_{jvw} u_{tvw} \quad \forall j, t, \qquad (8)$$

$$h_{ti} \in \{0,1\} \quad \forall t,i, \quad \sum_{t=1}^{T} h_{ti} = 1 \quad \forall i, \quad \sum_{i=1}^{N} h_{ti} > 0 \quad \forall t, \tag{9}$$

where the segmentation schemes are restricted to nonoverlapping.

2.2.2 Parameter Estimation with Given Segmentation Matrix: For the proposed algorithm we use some computational simplifications concerning parameter estimation when response data $\mathbf{Y}$, the already mentioned design matrix $\dot{\mathbf{B}}$, and, additionally, a segmentation matrix $\mathbf{H}=((h_{ti}))$ are given (see also Hagerty (1985), Kamakura (1988)):

We get individual response estimates $\hat{\mathbf{Y}}=\mathbf{UH}$ and segment-specific response estimates $\mathbf{U}=\dot{\mathbf{B}}\mathbf{C}$ by weighting the OLS results obtained from (5):

$$\mathbf{C} = (\dot{\mathbf{B}}'\dot{\mathbf{B}})^{-1}\dot{\mathbf{B}}'\mathbf{Y}\underbrace{\mathbf{H}'(\mathbf{HH}')^{-1}}_{=:\,\mathbf{G}} \tag{10}$$

The elements of matrix $\mathbf{G}$ (the weights) can be easily computed via

$$g_{it} = \begin{cases} \frac{1}{N_t} & \text{if } h_{ti} = 1 \\ 0 & \text{else} \end{cases} \quad \forall t,i \text{ with } N_t = \sum_{i=1}^{N} h_{ti} \quad \forall t. \tag{11}$$

2.2.3 The Algorithm: Our proposed iterative minimum-distance algorithm is given in Tab. 1: In the initialization phase we start with design matrix $\dot{\mathbf{B}}$ and an arbitrary segmentation matrix $\mathbf{H}$. Next, we estimate segment-specific response data $\mathbf{U}$ using OLS estimates based on our dummy-variable coding at the disaggregate level and the corresponding matrix of weights. Additionally, the initial loss function value is computed. In the two-step iteration phase we repeatedly reallocate respondents to segments and estimate segment-specific response data $\mathbf{U}$ in order to minimize the loss function until some stopping criterion is fulfilled. In the final phase, segment-specific part-worths are computed.

Empirical results obtained so far show that typical problems with the iterative minimum-distance algorithm – like, e.g., the reduction of class numbers (see, e.g., Späth (1983)) – are not relevant to this setting.

3. Representation Using Conjoint Data

3.1 Overview

As already mentioned in the introduction, problems sometimes occur with the presentation of conjoint analysis results. Here, the incorporation of MDS (MultiDimensional Scaling), or specifically multidimensional unfolding, to derive joint spaces – with acknowledged display power – may be useful.

Several approaches have already been proposed, incorporating, e.g., constrained multidimensional unfolding (see, e.g., DeSarbo, Rao (1986)) or multiple correspondence analysis (see, e.g., Green, Krieger, Carroll (1987)). The latter uses Green-Carroll-Schaffer-scaling to display results obtained by usage of conjoint analysis and choice simulation. Within other approaches (see, e.g., Carroll, Green, Kim (1989)), first MDS and then conjoint analysis is applied to conjoint data. The methodology discussed in the next section differs from the Carroll, Green, Kim (1989) approach with respect to the concrete models applied and the additional simulation/optimization phase.

{Initialization phase:}

Set $\dot{\mathbf{B}} := \begin{pmatrix} 1 & B_{111} & \cdots & B_{11(W_1-1)} & \cdots & B_{1V1} & \cdots & B_{1V(W_V-1)} \\ \vdots & \vdots & & \vdots & & \vdots & & \vdots \\ 1 & B_{n11} & \cdots & B_{n1(W_1-1)} & \cdots & B_{nV1} & \cdots & B_{nV(W_V-1)} \end{pmatrix}$.

Set $s := 0$. Choose an arbitrary segmentation matrix $\mathbf{H}^{(0)}$ and $\epsilon > 0$.

Set $\mathbf{U}^{(0)} := \dot{\mathbf{B}}(\dot{\mathbf{B}}'\dot{\mathbf{B}})^{-1}\dot{\mathbf{B}}'\mathbf{Y}\mathbf{H}^{(0)\prime}(\mathbf{H}^{(0)}\mathbf{H}^{(0)\prime})^{-1}$.

Set $Z^{(0)} := \sum_{i=1}^{N}\sum_{t=1}^{T} h_{ti}^{(0)} \sum_{j=1}^{n}(y_{ji} - u_{jt}^{(0)})^2$.

{Iteration phase:}

Repeat {Step 1 (Reallocation):}

Set $h_{ti}^{(s+1)} = \begin{cases} 1 & \text{if } \sum_{j=1}^{n}(y_{ji}\text{-}u_{jt}^{(s)})^2 = \min_{t'=1,\dots,T}\{\sum_{j=1}^{n}(y_{ji}\text{-}u_{jt'}^{(s)})^2\} \\ 0 & \text{else} \end{cases} \quad \forall t, i.$

{Step 2 (Estimation):}

Set $\mathbf{U}^{(s+1)} := \dot{\mathbf{B}}(\dot{\mathbf{B}}'\dot{\mathbf{B}})^{-1}\dot{\mathbf{B}}'\mathbf{Y}\mathbf{H}^{(s+1)\prime}(\mathbf{H}^{(s+1)}\mathbf{H}^{(s+1)\prime})^{-1}$.

Set $Z^{(s+1)} := \sum_{i=1}^{N}\sum_{t=1}^{T} h_{ti}^{(s+1)} \sum_{j=1}^{n}(y_{ji} - u_{jt}^{(s+1)})^2$ and $s := s + 1$.

Until $Z^{(s)} - Z^{(s+1)} < \epsilon$.

{Final phase:}

Set $\mathbf{C} := (\dot{\mathbf{B}}'\dot{\mathbf{B}})^{-1}\dot{\mathbf{B}}'\mathbf{Y}\mathbf{H}^{(s)\prime}(\mathbf{H}^{(s)}\mathbf{H}^{(s)\prime})^{-1}$.

Set $u_{tvw} := \begin{cases} \frac{c_{1t}}{V} + c_{(1+(W_1-1)+\cdots+(W_{v'-1}-1)+w)t} & \text{if } w \neq W_v \\ \frac{c_{1t}}{V} & \text{else} \end{cases} \quad \forall t, v, w.$

Tab. 1: Iterative minimum-distance clusterwise regression: The algorithm

3.2 A Combined MDS/Conjoint Analysis Methodology

3.2.1 The Model: Again, the same notation with N respondents, n stimuli, V attributes and $W_1,\dots,W_V$ levels is used. Additionally, we employ $\tilde{j}$ as an index for $\tilde{n}$ competing objects (e.g., brands, products) and p as an index for r space dimensions. Input data are the already mentioned profile data $B_{111},\dots,B_{nVW_V}$ and the response data $y_{11},\dots,y_{nN}$, but now we use, additionally, profile data $\tilde{B}_{111},\dots,\tilde{B}_{\tilde{n}VW_V}$ for the $\tilde{n}$ competing objects.

This time, model parameters are stimulus point coordinates $x_{11},\dots,x_{nr}$, respondents' ideal point coordinates $v_{11},\dots,v_{Nr}$, dimension-specific regression coefficients $\boldsymbol{\beta}_1,\dots,\boldsymbol{\beta}_r$, and object point coordinates $\tilde{x}_{11},\dots,\tilde{x}_{\tilde{n}r}$.

3.2.2 The Algorithm: The algorithm distinguishes three phases, a MDS, a conjoint analysis, and a simulation/optimization phase as shown in Tab. 2.

{MDS phase:}
Set $d_{ijk} := |y_{ji} - y_{ki}| \quad \forall i, j, k$.
Estimate stimulus point coordinates $\mathbf{X}=((x_{jp}))$
using (weighted) MDS based on $d_{111}, \ldots, d_{Nnn}$.
Estimate ideal point coordinates $\mathbf{V}=((v_{ip}))$
using external multidimensional unfolding based on $\mathbf{X}$ and $\mathbf{Y}$.

{Conjoint analysis phase:}
Estimate regression coefficients $\boldsymbol{\beta}_1, \ldots, \boldsymbol{\beta}_r$ (with $\boldsymbol{\beta}_p = ((\beta_{pl}))$)
using OLS via $\mathbf{X} = (\dot{\mathbf{B}}\boldsymbol{\beta}_1 \cdots \dot{\mathbf{B}}\boldsymbol{\beta}_r)$ based on $\mathbf{X}$ and $\dot{\mathbf{B}}$.
Estimate object point coordinates $\tilde{\mathbf{X}}=((\tilde{x}_{\tilde{j}p}))$
using $\tilde{\mathbf{X}} := (\dot{\tilde{\mathbf{B}}}\boldsymbol{\beta}_1 \cdots \dot{\tilde{\mathbf{B}}}\boldsymbol{\beta}_r)$ based on $\boldsymbol{\beta}_1, \ldots, \boldsymbol{\beta}_r$, and $\dot{\tilde{\mathbf{B}}}=((\dot{\tilde{b}}_{\tilde{j}l}))$.

{Simulation/optimization phase:}
Estimate shares of choices or other aggregate response measures
using choice simulators.
Find attribute-level-combinations
maximizing share of choices or other aggregate response measures
using optimal positioning methods.

Tab. 2: A combined MDS/conjoint analysis methodology: The algorithm

In the MDS phase, we estimate a joint space representation of the stimuli and the respondents applying the INDSCAL-model for MDS and the GENFOLD-model for external multidimensional unfolding based on the individual response data $\mathbf{Y}$. In the conjoint analysis phase, we regress the stimulus coordinates $\mathbf{X}$ on the dummy-variables of the design matrix $\dot{\mathbf{B}}$ in a first step. A second step is used to estimate object point coordinates $\tilde{\mathbf{X}}$ based on the estimated regression coefficients $\boldsymbol{\beta}_1, \ldots, \boldsymbol{\beta}_r$ and the objects' design matrix $\dot{\tilde{\mathbf{B}}}$. As a result of this second phase we have a joint space representation of respondents, stimuli, and competing objects. The last phase – the simulation and optimization phase – can now be used to predict shares of choices for the competing objects applying conventional choice simulators or to find suitable attribute-level-combinations for new or modified objects in the competitive context applying optimal positioning methods.

4. Application to the European Air Freight Market

A major European airline company planned the introduction of a new overnight parcel service concerning house-to-airport delivery in the European air freight market. A conjoint analysis application was used in order to analyze the preference structure of potential customers, to derive benefit segments, and to find suitable attribute-level-combinations for the new service. Pretests showed that the attributes 'collection time', 'agency type', 'price' (for a 10 kg parcel with European destination), 'transport control', and 'delivery time' should be considered (see also Baier (1994), Mengen (1993)).

In total, 150 people responsible for parcel delivery within German companies sending more than 25 air freight parcels per month within Europe were personally interviewed. Typical conjoint data was collected with respect to a reduced design with 18 stimuli as given in Tab. 3. Abbreviations of the attribute levels are used as stimulus short names, e.g., the short name '16C160A10' of the first stimulus indicates that attribute 'collection time' has level '16:30', attribute 'agency type' has level 'airline company', attribute 'price' has level '160 DM', attribute 'transport control' has level active, and attribute 'delivery time' has level '10:30'. Additionally, data on company characteristics, on return from attribute-level-combinations and attribute-levels from six competing services ('product A' to 'product F') was collected.

	attributes				
stimulus short name	collection time	agency type	price	transport control	delivery time
16C160A10	16:30	airline company	160DM	active	10:30
16C200P10	16:30	airline company	200DM	passive	10:30
16I200A13	16:30	integrator	200DM	active	13:30
16I240P13	16:30	integrator	240DM	passive	13:30
16S160A12	16:30	forwarding agency	160DM	active	12:00
16S240A12	16:30	forwarding agency	240DM	active	12:00
17C160A13	17:30	airline company	160DM	active	13:30
17C240A13	17:30	airline company	240DM	active	13:30
17I160P12	17:30	integrator	160DM	passive	12:00
17I200A12	17:30	integrator	200DM	active	12:00
17S200A10	17:30	forwarding agency	200DM	active	10:30
17S240P10	17:30	forwarding agency	240DM	passive	10:30
18C200P12	18:30	airline company	200DM	passive	12:00
18C240A12	18:30	airline company	240DM	active	12:00
18I160A10	18:30	integrator	160DM	active	10:30
18I240A10	18:30	integrator	240DM	active	10:30
18S160P13	18:30	forwarding agency	160DM	passive	13:30
18S200A13	18:30	forwarding agency	200DM	active	13:30

Tab. 3: Reduced design with 18 stimuli in the European air freight market

Application of the presented iterative minimum-distance clusterwise regression procedure for simultaneous segmentation and estimation led to the results shown in Tab. 4: For nearly half of the sample, i.e. segments 3 and 4 ('segm.3 (10.0%)', 'segm.4 (38.7%)') the attribute 'collection time' contributes mostly to overall response. Two segments focus on the attributes 'transport control' ('segm.2 (17.3%)') and 'price' ('segm.5 (14.7%)'). The five-segment solution was selected on basis of an elbow criterion with respect to the R^2-measure with values 0.2413, 0.4645, 0.5305, 0.5868, 0.6336, 0.6579, 0.6832 for the one-, two-, ..., seven-segment solutions (see Wedel, Kistemaker (1989) for a similar decision).

Next, the available conjoint data was analyzed by the presented combined MDS/conjoint analysis methodology. For space restrictions, we only discuss the results from the MDS phase and refer to Baier (1994) for results from the remaining two phases: A four-dimensional joint space representation with stimuli's points and respondents' ideal points was derived by application of

INDSCAL for MDS (correlation coefficient R=0.665) and GENFOLD for external multidimensional unfolding (correlation coefficient R=0.760). For comparisons the affiliation of respondents to the above derived five segments ('segm.1' to 'segm.5') is indicated by the corresponding segment numbers ('1' to '5') in Fig. 1. From the stimulus short names we can see that 'dimension1' can be interpreted as collection time dimension, 'dimension2' as price dimension, and 'dimension3' as transport control dimension, whereas 'dimension4' does not allow such an obvious interpretation. From the ideal point positions we recognize two groups of respondents, where the respondents of the larger group are in favour of earlier collection times and the respondents of the smaller group prefer lower prices.

attribute	level	segm.1 (19.3%)	segm.2 (17.3%)	segm.3 (10.0%)	segm.4 (38.7%)	segm.5 (14.7%)
collection time	16:30	0.210	0.000	0.000	0.901	0.100
	17:30	0.316	0.004	0.696	0.237	0.026
	18:30	0.000	0.022	0.717	0.000	0.000
agency type	airline company	0.000	0.118	0.026	0.000	0.128
	integrator	0.002	0.191	0.000	0.000	0.035
	forwarding agency	0.145	0.000	0.006	0.023	0.000
price	160DM	0.148	0.100	0.083	0.033	0.645
	200DM	0.062	0.038	0.049	0.015	0.166
	240DM	0.000	0.000	0.000	0.000	0.000
transport control	active	0.105	0.673	0.053	0.020	0.053
	passive	0.000	0.000	0.000	0.000	0.000
delivery time	10:30	0.286	0.000	0.099	0.022	0.074
	12:00	0.111	0.004	0.121	0.009	0.028
	13:30	0.000	0.022	0.000	0.000	0.000

Tab. 4: (Standardized) part-worths in the European air freight market

As we can see, both approaches try to overcome the three problems with respect to conjoint analysis applications as pointed out in the introduction: Compared to the traditional part-worth estimation at the disaggregate level, the number of model parameters was substantially reduced which leads to more degrees of freedom and – hopefully – to better predictive accuracy. (Note that, e.g., the predictive power of methods at the group level may be lower than that of methods at the disaggregate level, as shown by, e.g., Moore (1980).) Moreover, both approaches provide results in a form that can be easily communicated.

5. Conclusions

New ways of classification and representation using conjoint data offer advantages over traditional approaches with respect to various aspects like overparametrization, predictive power, and communication of results. In this paper, we have only been able to demonstrate some of these advantages within one application example (see Baier (1994) for a more detailed description). Further research on comparisons concerning simultaneous vs. sequential approaches is in preparation.

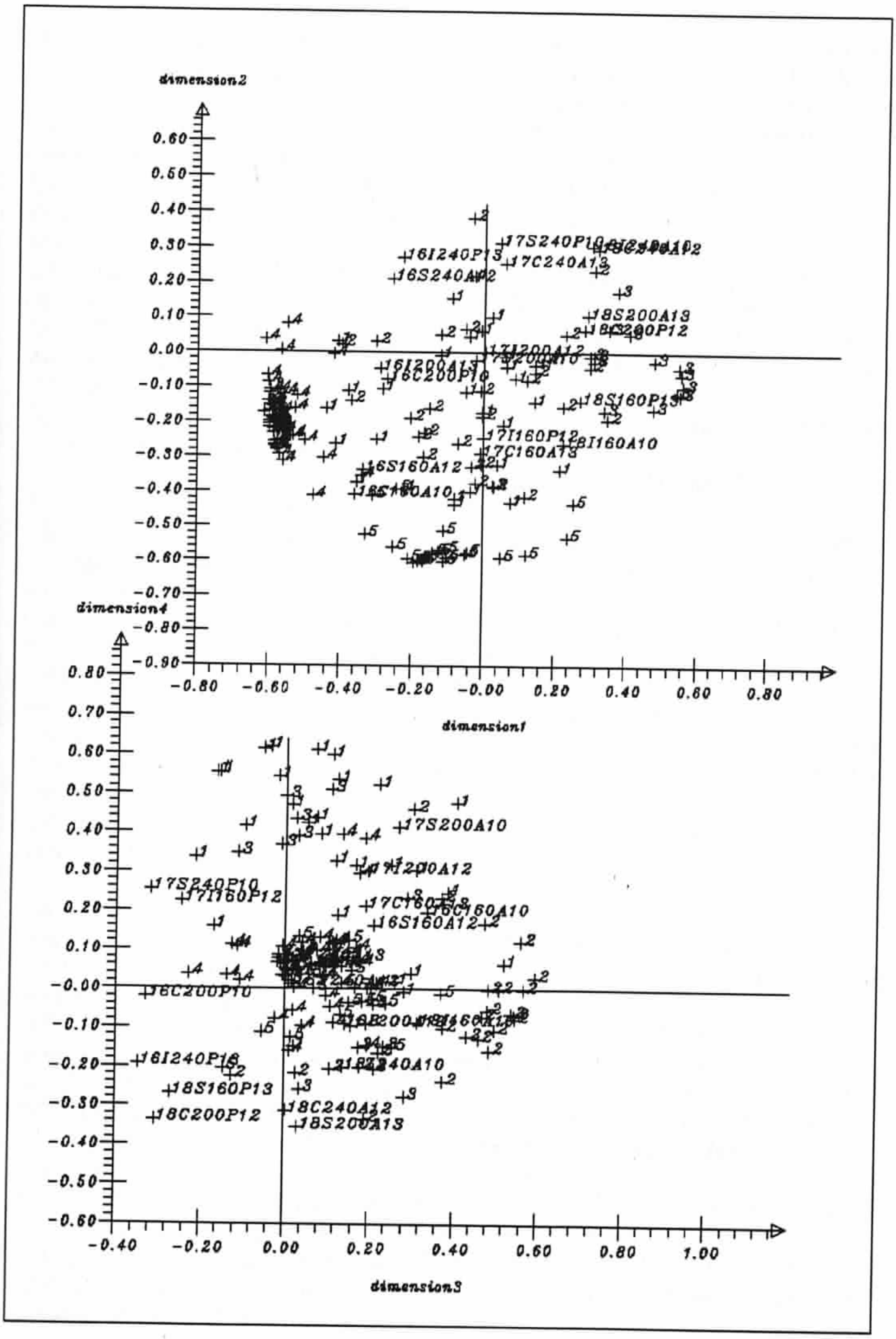

Fig. 1: Joint space representation in the European air freight market

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