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Latent Class Models for Marketing: An Application to Pharmaceuticals

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1. Introduction

Since the early 1980s marketing analysts and scholars have applied latent structure and other types of finite mixture models with increasing frequency. One variant of the finite mixture models, the latent class (LC) model, has been perhaps the most popular. Finite mixture models allow to account for respondents' heterogeneity (Dillon & Kumar, 1994), therefore they are a promising instrument especially for market segmentation. It is not surprising then the growing number of papers appearing in the marketing literature that propose special variants of finite mixture models applied to market analysis (see, among many others, Dash, Schiffman & Berenson, 1975; DeSarbo et al., 1992; Dillon & Mulani, 1989;Grover & Srinivasan, 1987; Kamakura & Russel, 1989; Jain et al., 1990).

Recently, latent class models have gained recognition of as a method of segmentation with several advantages over traditional methods (Magidson & Vermunt 2002). LC cluster analysis is a model-based clustering procedure, as such, it is a probabilistic and more flexible alternative to K-means clustering.

In this paper some extensions of the LC class approach are applied to analyse the Italian pharmaceutical market, which is the fourth largest in Europe, behind Germany, France and UK. In 2004, there were 241 producers in Italy employing 73.550 workers (Espiscom, 2006); physicians enrolled in the Italian Physician Roll were 347.759, among these, almost 50.000 were general practitioners (Mariani & Ventre, 2006). The pharmaceutical sector in Italy is characterised by a high level of competitiveness, more limited economic budgets than years ago and, at the same time, expensive sales and promotion activities. In this context, it is very important to understand which factors influence doctors in prescribing medicines, so to design appropriate marketing strategies.

There is recent international literature that tries to understand determinants of doctors', and also patients', demand for drugs; a study with reference to the Italian market can be found, for example, in Coscelli (2000). Pharmaceutical industries, in general, aim at understanding what doctors require from their products and their representatives so to direct investments in order to acquire market share, possibly without wasting resources. Enterprise profits cannot be obtained without considering customer satisfaction, in the case of the pharmaceutical sector, the primary customer is the general practitioner prescribing medicines.

The data at our disposal was collected in a survey on Italian general practitioners. Each doctor was asked to express a judgment on various aspects regarding the promotional activity organised by the pharmaceutical industries he was in contact with and to declare the percentage of drugs, produced by each firm, he usually prescribes.

We apply LC models for multilevel data (Vermunt, 2003) in order to identify segments in the market. Traditional latent class models assume that observations are independent, in our case this assumption is violated since doctors judge more than one pharmaceutical industry; multilevel LC models make it possible to modify this assumption.

A second aim of the paper is to verify which aspects of the firms' promotional activity may be determinant in influencing doctors' prescriptions. LC regression models estimate a linear relation between a dependent variable and a set of explanatory variables accounting for the fact that observations may arise from a number of unknown heterogeneous groups in which regression coefficients differ (Wedel & DeSarbo, 1994). LC regression models can be viewed as random-coefficients models that, similarly to multilevel or hierarchical models, can take into account dependencies between observations. This extends the application of LC regression models to situations with repeated measurements (Magidson & Vermunt 2004).

The paper is organised as follows. Section 2 describes the dataset. In section 3 the Italian pharmaceutical market is segmented applying multilevel LC models. In section 4 the LC regression model is used to identify factors influencing medicines' prescriptions. Section 5 contains some brief concluding remarks.

2. The data

The data used in this paper was collected from 489 Italian general practitioners. On a seven-point scale, doctors expressed how important the following items were in inducing them to prescribe a drug proposed by a pharmaceutical industry: (1) attention of the industry for doctors' updating (ATT), (2) frequency and regularity of visits by pharmaceutical representatives (FRE), (3) assistance on diagnostic and therapeutic problems (ASS), (4) consideration for doctors' experience and suggestions (EXP), (5) quality of training of pharmaceutical representatives (QUA), (6) information on industry activities (INF), and (7) global quality of information and promotion activities (PRO). Few demographic characteristics of doctors were also collected: number of years from university degree - as a proxy of age - area of the country in which working (North, Centre or South of Italy), dimension of the city in which operating (less or more than 400.000 inhabitants), number of patients. Doctors were asked to judge each pharmaceutical industry they were in contact with. Moreover, they were required to supply the percentage of prescriptions, over their total prescriptions of drugs, accorded usually to each brand judged.

Overall, 68 industries have been rated receiving from 1 up to 255 judgments from doctors (a total of 2537 judgments). This result describes quite well the Italian pharmaceutical market in which a group of less than 20 big and well known industries operates together with a larger group of smaller and "local" firms. Doctors differ in the number of responses given, from 1 to 8, as well as in the pharmaceutical industries judged.

Our analysis has two main goals.

1) Identifying groups of doctors homogeneous for attitude towards pharmaceutical representatives' activities. Specifically we want to verify if importance assigned to the various services offered by pharmaceutical industries varies across practitioners in order to possibly devise appropriate marketing strategies for the different segments. We also expect groups to differ for doctors' demographic characteristics.
2) Verify which aspects of the promotional activity may be significant in order to influence prescription quantities taking into account that the market may be composed by segments of doctors showing different attitudes towards medicines' brands.

3. Market segmentation

Segmentation methods can be classified in *a-priori*, when the type and number of segments are determined in advanced by the researcher, and *post-hoc*, when the type and number of segments are determined on the basis of results of data analyses. *A priori* methods include loglinear models, regression, logit and discriminant analysis. Among *post-hoc* methods we can find clustering, AID, mixture models. Clustering methods are the most popular tool for descriptive segmentation; for a review, see, among many others, Arabie and Hubert (1994) and Punj and Stewart (1983).

Latent class (LC) analysis attempts to explain the observed association between the factors that make up a multiway contingency table (Goodman, 1974) by introducing unobservable underlying classes (clusters). Green et al. (1976) first suggested the application of latent class analysis to market segmentation; other interesting applications may be found in Kamakura and Mazzon (1991); Lehman et al. (1982); Paas et al. (2004).

The LC approach to clustering is model-based: the fundamental assumption is that of local independence, which states that objects in the same latent class share a common joint probability distribution among the observed variables (Vermunt, 1997).

3.1. Multilevel LC models

In standard LC models it is assumed that the model parameters are the same for all persons (level-1 units). The basic idea of multilevel LC models is that some of the model parameters are allowed to differ across groups, clusters or level-2 units. Such differences can be modelled by including group dummies in the model, as it is done in multiple-group LC analysis (Clogg & Goodman, 1984), which amounts to using a fixed-effects approach. Alternatively, in a random-effects approach, the group specific coefficients are assumed to come from a particular distribution, whose parameters should be estimated. Depending on whether the form of the mixing distribution is specified or not, either a parametric or non parametric random-effects approach is obtained.
Vermunt (2003) proposes a multilevel LC model as an extension of a random-coefficients logistic regression model (Agresti et al., 2000) in which the dependent variable is not directly observed but rather is a latent variable with several observed indicators.
Let:

Y_{ijk}, *i=1,…,I, j=1,…J, k=1,…K*, denote the response of individual or level-1 unit *i* within group or level-2 unit *j* on indicator or item *k*;

s_k, $s_k = 1,...S_k$, a particular level of item *k*;

X_{ij}, a latent variable with *T* classes;

t, a particular latent class, *t=1,…,T*;

$\underline{Y}_{ij}$, the full vector of responses of case *i* in group *j*;

$\underline{s}$, a possible response pattern.

The probability structure defining a simple LC model can be expressed as follows:

$$P(\underline{Y}_{ij} = \underline{s}) = \sum_{t=1}^{T} P(X_{ij} = t) P(\underline{Y}_{ij} = \underline{s} \mid X_{ij} = t) = \sum_{t=1}^{T} P(X_{ij} = t) \prod_{k=1}^{K} P(Y_{ijk} = s_k \mid X_{ij} = t) \quad (1)$$

As it is specified in equation (1), the probability of observing a particular response pattern is a weighted average of class-specific probability $P(Y_{ijk} = s_k \mid X_{ij} = t)$ with weight the probability that unit *i* in group *j* belongs to latent class *t*. As the local independence assumption implies, indicators Y_{ijk} are assumed independent conditional on latent class membership.

A multilevel latent class model (Vermunt, 2003) consists of a mixture model equation for level-1 units and level-2 units, where a group-level discrete latent variable is introduced so that parameters are allowed to differ across latent classes of groups:

$$P(\underline{Y}_{ij}=\underline{s})=\sum_{m=1}^{M}\left[P(W_j=m)\prod_{i=1}^{n_j}\left[\sum_{t=1}^{T}P(X_{ij}=t\,|\,W_j=m)\prod_{k=1}^{K}P(Y_{ijk}=s_k\,|\,X_{ij}=t)\right]\right] \quad (2)$$

where

W_j denotes the latent variable at the group level, assuming value m, with $m=1,\dots,M$;

n_j is the size of group j.

Equation (2) is obtained with the additional assumption that the n_j members' responses are independent of one another conditional on group class membership.

A natural extension of the multilevel LC model involves including level-1 and level-2 covariates to predict membership, as an extension of the LC model with concomitant variables (Dayton & McReady, 1988).

3.2. Analysis of the Italian pharmaceutical market

Multilevel LC models were estimated in order to identify market segments[1]. Our level-1 units, or situations, are judgments expressed by doctors on the seven aspects of the promotional activity performed by pharmaceutical industries, our level-2 units, or cases, are doctors. We are interested in defining clusters of doctors, called, from now on classes, on the basis of responses given with regard to the various brands. In this respect we may say that we are dealing with a three-way data set since doctors provide multiple ratings for multiple objects (Vermunt, 2006).

Table 1. Model fit (BIC index) for alternative numbers of classes and clusters

M	T	BIC
1	1	57060.757
1	2	57068.596
1	3	57076.435
1	4	57084.273
1	5	57092.112
2	1	52821.245
2	2	52685.205
2	3	52690.608
2	4	52706.235
2	5	52721.893
3	1	51542.040
3	2	51391.486
3	3	51321.967
3	4	51324.478
3	5	51336.165
4	1	51125.633
4	2	50987.352
4	3	50901.910
4	**4**	**50886.077**
4	5	50901.638
5	1	51053.695

[1] The software Latent Gold 4.0 was used (Vermunt & Magidson, 2005).

The model required for our scope is an adaptation of the standard multilevel LC model. The basic assumption is that cases may be in a different latent class depending on the situation or, more specifically, cases are clustered with respect to the probability of being in a particular latent class at a certain situation. The basic idea is to treat the three ways as hierarchically nested levels and assume that there is a mixture distribution at each of the two higher levels; i.e., one at the case and one at the case-in-situation level.

The LC multilevel model which revealed the best fit to the data[2] estimates 4 latent classes of doctors and 4 classes of level-1 units (clusters), its BIC value is lower than the that of models with alternative values of the number classes (M) and the number of clusters (T), as it appears form Table 1.

Table 2. Multilevel LC model – estimation results, standard errors in parentheses

	Size	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**
Size		0.3974(0.0174)	0.3392(0.0180)	0.1526(0.0142)	0.1109(0.0111)
Class 1	0.4567(0.0562)	0.31078(0.0294)	0.5731(0.0325)	0.1044(0.0592)	0.0118(0.1077)
Class 2	0.2519(0.0442)	0.3032(0.0346)	0.2146(0.0373)	0.0868(0.0414)	0.3954(0.0456)
Class 3	0.1826(0.0450)	0.8232(0.0179)	0.0751(0.0180)	0.0825(0.0434)	0.0164(0.1171)
Class 4	0.1089(0.0376)	0.2646(0.0132)	0.0890(0.0402)	0.6200(0.0137)	0.0265(0.0246)
	Mean values				
ATT		6.0508(0.0370)	4.8734(0.0536)	6.7374(0.0352)	3.5998(0.0945)
FRE		6.3415(0.0318)	5.5552(0.0479)	6.7926(0.0306)	4.5093(0.1034)
ASS		5.5921(0.0421)	4.6082(0.0531)	6.5131(0.0458)	3.1826(0.0965)
EXP		5.2615(0.0514)	4.3842(0.0610)	6.4113(0.0524)	2.5688(0.1028)
QUA		6.2912(0.0322)	5.7185(0.0429)	6.8118(0.0273)	4.4104(0.0969)
INF		4.6986(0.0623)	3.9943(0.0717)	6.3291(0.0638)	2.1246(0.0980)
PRO		6.1167(0.0334)	4.8740(0.0496)	6.7726(0.0294)	3.3530(0.0861)

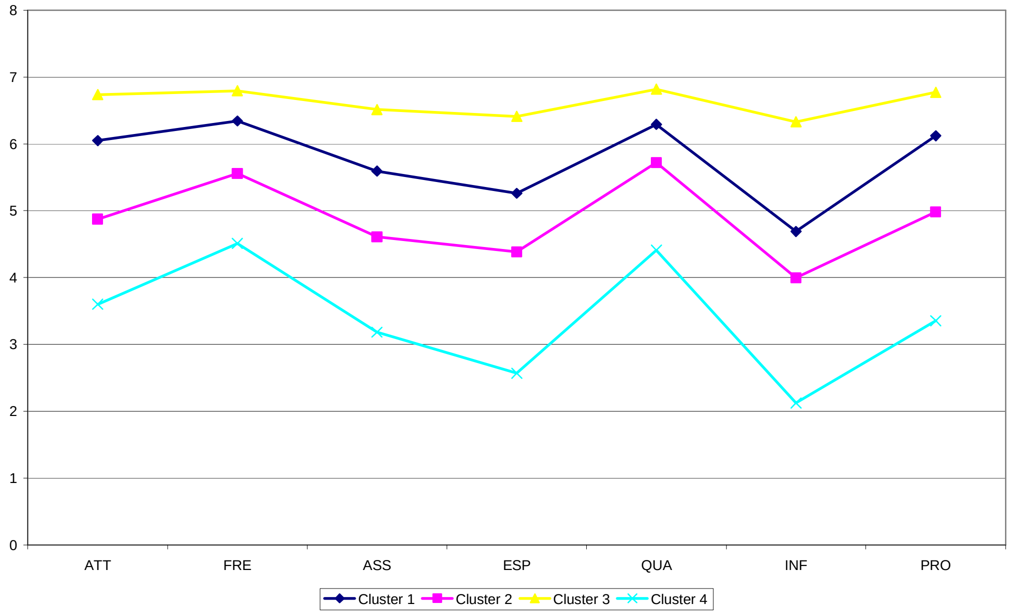
Estimation results with the best fitting model are reported in Table 2. Four clusters of judgments of pharmaceutical representatives' activity and four classes of doctors have been identified. In the lower part of the table average judgments on each aspects of the promotional activity in the four clusters are reported. These same results are used in Figure 1 to describe clusters' profiles in order to aid interpretation. Cluster 3 contains the highest judgments (higher than 6.3), all aspects related to promotional activity are considered very important – differences among aspects judged are negligible. Cluster 1 contains high levels of responses though aspects are differentiated: frequency and regularity of visits, global quality of promotional activity and quality of training representatives are rated as very important, whereas information on industry's activity is considered non relevant at all. Cluster 4 contains the lowest judgments (lower than 4.5), this means that promotional activity is not considered important in any of its features. Cluster 2, finally, contains judgments which are in between the other groups: some aspects such as frequency and regularity of visits and quality of training of pharmaceutical representatives are rated as important (average score higher than 5.5), the other aspects are considered almost negligible.

The upper part of table 2 indicates that the four doctor-level classes have quite different distributions of judgments among clusters. Class 1 is associated with cluster 2, class 3 with cluster 1, class 4 with cluster 3; in class 2 we can find an similar percentage of judgments assigned to cluster 1 and cluster 2. Looking at these results we may try do describe doctors' segments which is the final scope of this analysis.

[2] We carried out the estimation procedure using a few different sets of starting values in order to avoid local maxima. Responses on items have been treated as measured on an ordinal scale.

In class 4 (11%), doctors can be defined as loyal and demanding at the same time; all items are important for them in order to choose among drugs. In class 3 (18%) we find loyal practitioners who are very concerned about the frequency and regularity of visits, the quality of training of representatives, and the global quality of information and promotion activities; information on industry's activity is valued irrelevant. Class 1 (46%) contains practitioners who consider important only frequency and regularity of visits and quality of training for representatives, all other aspects are non considered. Lastly, class 2 is a mixture of doctors totally unconcerned with promotion and information by industries, with a prevalence of this group, and others practitioners only modestly interested in some aspects.

Figure 1. Clusters' profiles



Indications emerging form analyses are important for pharmaceutical industries in order to design appropriate promotional activities for each segment. Industries can concentrate efforts on features of their representatives' activity considered significant in each group, not wasting resources on other aspects that do not have an impact on customers. The most interested segment, although the smallest one, deserves certainly great attention by representatives; on the other hand, industries should meditate if it worth to continue visiting doctors classified in class 2. A parsimonious strategy towards the remaining doctors could be to keep frequency and regularity of visits, emphasize quality of training and do not waste resources on other aspects of promotional activity.

Demographic characteristics of doctors have been inserted in the model as covariates. Unfortunately, they resulted non significant in describing classes, which means that the groups are not significantly different for what concerns doctors' age, area of the country, dimensions of the city where doctors work, average number of patients. Relation with demographic variables usually facilitates segments identification; this is not the case in our market, segments are defined only in terms of attitude towards promotional and information activity.

On the other hand, our segments fulfil a number of the usual criteria required for effectiveness of market segmentation (Wedel & Kamakura, 2000). Segments are large in size (substantiality); since we do not expect that doctors change frequently their opinions on promotion activity by pharmaceutical industries, segments should not change dramatically over time (stability). Segments can be easily reached by industries (accessibility) and their characteristics immediately suggest marketing strategies (actionability), revealing which aspects of the promotional activity are considered most important by doctors. For what concerns responsiveness, in the next section, a method is proposed to evaluate which specific aspects of promotional activity may directly influence the quantity of prescribed medicines.

4. What influences prescriptions?

In order to verify if the various aspects of promotional activity considered in our survey may significantly influence prescriptions, latent class regression models have been estimated. The dependent variable is the percentage of drugs produced by a certain pharmaceutical industry prescribed by the practitioners, predictors are the judgments expressed by the doctors on the seven aspects of the activity of pharmaceutical representatives described in section 2.

In a LC regression model, the latent variable is a predictor that interacts with observed predictors. The LC regression model provides several useful functions. First, it can be used to weaken standard regression assumptions about the nature of the effects and the error term. It makes it possible to identify and corrects for sources of unobserved heterogeneity. It can be used to detect outliers. An important application area for LC regression modelling is clustering or segmentation (Popper et al., 2004; Wedel & Kamakura, 2000).

The most general probability structure for a LC regression takes on the following form:

$$f(y_i \mid z_i^{\mathrm{cov}}, z_i^{pred}) = \sum_{x=1}^{K} P(X \mid z_i^{\mathrm{cov}}) \prod_{t=1}^{T_i} f(y_{it} \mid X, z_{it}^{pred}) \qquad (3)$$

where y_{it} is the value of the dependent variable observed on unit i at occasion t;

T_i is a the number of replications for unit i;

z_i^{cov} is a vector of covariates;

z_i^{pred} is a vector of predictors;

X is single nominal latent variable with K categories, or classes.

Table 3. LC regression model – estimation results.

	Class 1		**Class 2**		**Overall**
Size	0,5532		0,4468		
R^2	0,0082		0,0114		0,1528
		z-values		**z-values**	
Intercept	0,1965	8,9577	0,2870	4,9765	
Predictors					
ATT	0,0006	0,1740	0,0093	1,0600	
FRE	0,0076	2,2224	0,0016	0,1719	
ASS	-0,0059	-1,7539	-0,0098	-1,1719	
ESP	0,0032	1,1385	-0,0014	-0,1711	
QUA	-0,0019	-0,5132	-0,0077	-0,7410	
INF	0,0037	1,5619	0,0081	1,3485	
PRO	-0,0014	-0,3401	0,0128	1,2182	

A two-class solution provided the best fit to the data, with an unsatisfactory R^2 of 0,1528 tough. Table 3 contains estimated parameters and the corresponding value of the z-statistic. As it can be seen in the estimated regression model for class 1, which contains 55% of doctors, only the intercept and importance assigned to the frequency and regularity of visits are significant in explaining percentage of prescription. In the regression model estimated for class 2 (45% of practitioners) only the intercept is statistically significant, no aspects of the promotional activity affect doctors’ prescribing behaviour. Doctors’ characteristics were inserted in the model as active covariates but they resulted non significant.

This results is for sure interesting, tough not very positive, for pharmaceutical industries. It confirms the difficulties in identifying factors influencing doctors’ prescribing behaviour. This result indicates that other factors than those surveyed may be important in affecting prescription of drugs; either other aspects of the promotional activity, or, hopefully, intrinsic characteristics of the products like quality or performance in curing disorders.

5. Conclusive remarks

The results presented above deserve some summarising comments into two directions: regarding the evidences about the Italian pharmaceutical market that emerged and regarding the models estimated.

From our analysis it emerges that the Italian pharmaceutical market, at least looking at general practitioners, is a segmented market. Four distinct segments of doctors emerge with different attitudes towards promotional activity; it is reasonable for industries to contact these four groups with diversified and appropriate strategies. One group appears very interested in all aspects considered, another group is composed by doctors not interested at all, possibly disturbed by promotional activity, other two groups are in between with doctors moderately interested and concerned only with specific aspects of pharmaceutical representatives work.

For what concerns prescription behaviour, two segments in the market are identified. For one group of doctors only the importance assigned to frequency and regularity of the visits of the pharmaceutical representatives is significant, and with a positive effects, in determining the percentage of prescriptions of the various brands; for the other group none of the aspects considered affects prescription behaviour. This topic deserves for sure further attention and research.

From our analysis it emerges also that LC models and their recent extensions deserve attention form researchers involved in market analysis. At is has already been pointed out, the LC approach may help in answering to many questions in marketing analysis, with reference to segmentation but not only.

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