A logical type discriminant model for profiling a segment structure

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Abstract Profiling a segment structure may help to make segments accessible and generally contribute to improving the understanding of the segments, thus helping to support management decisions. Logical type discriminant models yield results that are easy to understand; this makes them particularly useful for profiling. From this point of view, the induction of propositional rules yields better results when compared with hierarchical structures derived from decision tree algorithms. An application in the tourism market illustrates some advantages of the C5 algorithms for the induction of classification trees and sets of propositional rules for profiling a segment structure.

INTRODUCTION

Profiling a segment structure (typically a consumers partition) is meant to provide better understanding of segments, finding the characteristics that discriminate them. Additionally, it may also yield means to classify individuals into the segments.

In 1978, Wind had already identified the problem of determining segment membership (classification) and profiles (discrimination) as a 'major consideration involved in segmentation research studies'.¹ Wedel and Kamakura point out the importance of profiling 'with consumers (firms) descriptors to fulfil the accessibility requirement for effective market segmentation'.² Several authors³⁻⁵ recognise the importance of profiling in the particular context of

tourism applications. Mazanec⁶ underlines the need to search for additional characteristics generating more complete segment profiles, emphasising that a market segmentation strategy is likely to fail unless segments are described objectively, namely with additional geographical, demographic, socio-economic, behavioural and lifestyle criteria. Andereck and Caldwell⁷ emphasise that the segments' characteristics may help marketers to tailor and promote a product or service more effectively. Bargeman *et al.*⁸ point out that managers are interested in the classification of tourists according to socio-economic variables as it allows them to target potential customers better.

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Table 1: Some profiling applications

Alternative profiling methods	Examples of applications
Linear discriminant analysis	Rao and Wang, 1995 ⁹
Logistic regression	Bucklin and Gupta, 1992 ¹⁰
Covariates model	Dillon, Kumar and Borrero, 1993 ¹¹
	Gupta and Chintagunta, 1994 ¹²
Neural networks	Mazanec, 1992 ¹³
Recursive based partitioning (CHAID)	Baron and Worral, 1996 ¹⁴

Several methodologies can be considered for profiling. Table 1 illustrates some of these with examples of applications. In general, profiling a segment structure can be viewed as a discriminant and classification data analysis task. It is a dependence analysis that considers a segment structure as the dependent variable and several relevant variables for profiling as independent. These descriptors should be combined in some way (functional, logical, graphical or other) in order to discriminate better among the segments, yielding a better understanding of the differences between them. Classification can be seen as the conclusion of discriminant analysis, as discriminant rules may be applied to allocate individuals into the segments.

The most commonly used statistical approaches for discriminant analysis are linear discriminant analysis and logistic regression. Linear discriminant analysis is the most frequently used method for profiling.¹⁵ However, the assumptions of this analysis are seldom met as it assumes (for example) that descriptors (discriminant variables) have normal distributions. Logistic regression is an alternative approach for classification when normality assumptions are not met.¹⁶

Bucklin and Gupta developed a nested logit latent segments model to derive households segments that were subsequently characterised by a logistic regression model.¹⁷ Households were

assigned to segments by using their posterior probabilities of segment membership based on their purchase histories. Segments showed different responses concerning choices and purchases of liquid laundry detergents. Profiling of a four segment structure (two choice segments with two nested incidence segments each) was based on demographic and purchase behaviour variables. Four binary logistic regressions were conducted to this end, the emphasis being placed on characterisation and not on classification.

An alternative approach that may be considered for profiling is the inclusion of covariates (or concomitant variables) in a latent segments model. A reparameterisation of posterior probabilities of latent segments is a means to include profiling variables (covariates) in the estimation of the model.¹⁸ Naturally the application of this method implies the use of a mixture model for performing segmentation.

The increase in the availability of large amounts of information supports the use of machine learning techniques to perform discriminant analysis. Using the machine learning terminology, this is a supervised learning task, as segments (dependent variables) are already known (as a result of previous segmentation) and this knowledge supervises learning of discriminant and classification rules based on explanatory variables.

Mazanec compared the performances of a neural network algorithm (a

machine learning methodology) and linear discriminant analysis to predict segment membership. Both approaches provided classification of tourists into benefit segments, derived by a non-hierarchical clustering algorithm. The descriptor variables used concern demographic, socio-economic and behavioural attitudes. Similar hit rates (proportions of individuals correctly allocated to the segments) resulted from the two approaches. The author pointed out, however, some advantages of the neural network approach considering it as 'neither restricted by the number of predictors nor by the number of segments' and 'much more flexible than conventional multivariate techniques with respect to incomplete or missing data'.¹⁹ In fact, these may be considered advantages of machine learning methodologies for classification when compared to traditional multivariate statistical approaches (eg linear discriminant analysis or logistic regression analysis) relying on complete observations and for estimation purposes and having difficulty dealing with large numbers of variables.^{20,21}

Besides the neural network approach other machine learning methods may be considered for profiling, in particular those providing logical type discriminant models. In addition to being able to deal with many and different types of variables and to overcome the difficulties due to the presence of missing values, these algorithms generate interpretable discriminant rules, which is considered relevant for the task of profiling. Several algorithms providing logical type discriminant models, models yielding logical type rules for segments characterisation (eg 'if age > 35 then individual belongs to segment X') may be considered for profiling. Among them the Chi-Square Automatic Interaction Detection (CHAID)²² and Classification

and Regression Trees (CART)²³ are the best known. Baron and Worrall used the CHAID algorithm to profile two binary segment structures. They were particularly interested in profiling a segment of individuals who tended to purchase less healthy foods. They also profiled customers that tended to develop customer-to-customer interactions during purchase (included in the second segment structure). Profiling was based on demographics for the former case and also included behavioural variables in the latter. CHAID provided clear and easy to understand tree diagrams, each terminal node of the trees (subset of individuals) being associated with a propositional condition (specific descriptor values).²⁴

Bargeman *et al.* used CHAID as a means to overcome the problem associated with the existence of many missing values when trying to consider several variables for profiling. Specifically, the authors used CHAID to find a categorisation of profiling (socio-economic) variables and subsequently a loglinear logit analysis was performed to estimate the effects of the socio-economic variables on the probability of belonging to a segment.²⁵ Another author suggested the use of a decision tree to help support the interpretation of logistic regression results. In this approach a CHAID regression tree was adopted to explain probabilities estimated by the logistic model, considering the same descriptors as logistic regression.²⁶

The main goal of this paper is to illustrate the utility of classification trees and sets of propositional rules as alternative methods for profiling a segment structure. The use of the C5 classification tree algorithm²⁷ is suggested, as it provides discriminant logical type models implementing new techniques which may be advantageous when compared with similar approaches (eg

CHAID or CART). Furthermore, the use of C5 specific algorithm for the induction of propositional rules is advocated as it yields results that are very easy to understand.

An application referring to the segmentation of clients of a hotel chain illustrates the proposed approach.

METHODOLOGICAL APPROACH

Measures and tests of association

Measuring the degree of association between candidate profiling variables and the segments may be considered a preliminary step in the task of profiling. For example, the degree of association between the segments and a nominal variable may be measured by the V Cramer Statistic (based on the chi-square statistics). Another measure of association, the uncertainty coefficient U that is based on the measure of entropy, provides additional information about the importance of a certain nominal attribute to explain the segments. Both the V Cramer statistic and the uncertainty coefficient, U, assume a zero value if there is no association and the value one when the degree of association is maximal.²⁸

The use of statistical inference is needed when trying to establish that the association between one specific descriptor and the segments is significant. The Pearson chi-square test, for example, may be used for this end, being able to infer the association between one nominal variable and the segments. For a quantitative variable, the analysis of variance (ANOVA) test may be used to evaluate the significance of the difference of the variable means for the various segments, although certain assumptions must be met (eg normality). If assumptions are not met, nonparametric tests²⁹ like the Kruskal-Wallis test may be

needed to infer the association between ordinal or metric profiling variables and the segments.

As a result of this preliminary analysis, variables yielding a significant association with the segments may be used for the construction of a model that discriminates between the segments. In particular, a logical type discriminant model may be considered to explain the differences between the segments and help to classify new individuals into the segments.

Logical type discriminant models

The C5 algorithm³⁰ provides the induction of logical type discriminant models, namely classification trees and sets of propositional rules.

Classification trees

Classification trees translate a hierarchical partitioning process that starts with a sample of observations concerning descriptors and segment membership (root node) and successively divides nodes based on the descriptors' values. This process attempts to decrease diversity in each new descendent node of the tree, in order to decrease the risk of classification. Thus, in a classification tree each terminal node (leaf) represents a set of relatively homogeneous observations in what concerns segment membership, the class distribution tending to concentrate in one particular segment.

The C5 algorithm grows a classification tree based on the information gain ratio measure, an entropy-based criterion. According to this criterion, the selection of a specific predictor X_j to split a node O is guided by the objective of decreasing diversity (entropy) in the descendent nodes. Diversity in these child nodes should then be inferior to diversity in the parent

node O. As a consequence, the frequency distribution in each child node will thus tend to concentrate in specific segments.

In other words, splitting a node O based on a chosen attribute X_j (and on a particular categorisation of X_j 's levels) translates the capacity of the chosen attribute to add information concerning classification of individuals of node O into the segments.

If X_j is metric or ordinal, binary partitions will be considered as candidates (thresholds will be the sorted values of X_j). If X_j is categorical, its categories will yield a partition of node O. As an option, C5 provides a heuristic procedure that considers possible combinations of attributes' categories in order to optimise the information gain ratio.

To deal with missing observations concerning a chosen attribute (X_j) to split node O, C5 divides these observations among the descendent nodes of O, according to the empirical distribution of frequencies associated with the correspondent categorisation (partition) $a^*_{j\cdot}$.

C5 provides pruning of the initial classification tree to avoid overfitting. A descendent subtree A_0 of node O will be pruned if its pessimistic error of classification is greater than the one corresponding to node O (pessimistic error being the upper bound of a confidence interval associated with the proportion of incorrectly classified observations).

The final classification tree may be translated in a set of propositional rules, each one corresponding to a leaf node. In general, a propositional rule is represented by an 'if condition then class' logical type expression where the condition is a conjunctive proposition that allocates specific values to the descriptors. In particular, in a classification tree, each rule's condition

(descriptors' values) is obtained following the path from the root to each terminal node and the rule's class is the modal segment for this leaf.

Propositional rules

A set of propositional rules may provide means to classify observations that meet the conditions associated with each class. It may be derived directly from a classification tree or a specific algorithm for the induction of propositional rules may be used, yielding discriminant models that cannot be translated into trees. After deriving the classification tree, C5 provides means to simplify, reduce and rank the initial set of propositional rules that corresponds to the leaves of the classification tree, yielding a new model of classification. Simplification of the initial subset of rules obeys the minimum pessimistic error criterion, trying to generalise rules by removing propositions from the rules' conditions (pessimistic error is considered to compare precision of alternative rules).

After simplification, a simulated annealing heuristic is applied to each subset, discarding some rules in order to minimise an estimate of the number of bits necessary to encode each subset (minimum description length criterion).

Finally, rules within each subset are sorted by precision and subsets are sorted according to a minimum of false positives criterion. As such, subsets that incorrectly classify the least number of cases are ranked in first place.

Classification of an observation x_i within a class (segment) is finally provided by the first rule that covers it. If it is covered by multiple rules corresponding to different classes, voting takes place, the weight associated with each vote being the precision associated to each rule. When x_i is not covered by any rule, a default classification is used and x_i is allocated to the segment that

contains the most training cases not covered by any rule.

C5 may also incorporate costs of incorrect classification of an observation that belongs to a class l^* in a class l of the dependent variable ($l, l^* \in \{1 \dots S\}$), in the final classification decision. In this case a minimum cost criterion is adopted (instead of maximum precision).

Finally, in addition to the original software implemented by Quinlan, programs that may be used to run C5 (classification trees and propositional rules) are included in some well-known data mining and statistical packages (eg the SPSS Clementine version was used in the present work).

Model fitting

Measures of precision

Classification trees and propositional rules may be associated with the corresponding measures of precision for classification. In particular, hit rates (the proportion of correctly classified observations) returned by estimated models may illustrate model fitting. Furthermore, these measures may be compared with default measures of classification precision (eg precision that derives from allocating all individuals to the larger segment, according to a majority rule).

Using test samples

When using hit rates corresponding to the training sample there is a tendency to overestimate precision, as the training model tends to overfit this sample's specific set of observations. To overcome this problem, the model derived from the training sample may be applied to a test (or holdout) sample in order to obtain more realistic estimates of classification precision. Furthermore, this procedure will help to test the model's consistency, which

may fail to be proved if estimates derived from the training and test samples are very different.

Increasing the sample size may be a way to improve the precision and consistency of one model because, in general, larger samples tend to be more representative of the population. For this reason, training samples of several hundreds or thousands of cases are commonly found in practical applications, typically accounting for around 60 per cent to 70 per cent of the original sample. In fact, if a good pattern is not discovered (with an associated good level of precision when it refers to classification) or the good pattern may not be replicated (eg using a test sample) it may be that the original sample was not large enough. However, it is also necessary to be aware that even very large samples may not be representative or that, even so, patterns may be difficult to find (eg they may not exist).

Interpretability

Finally, the interpretability of the segment structure profiles yielded by each logical type discriminant model (classification tree or set of propositional rules) is discussed, helping to support model adequacy.

APPLICATION

Introduction

In the present application the segments of clients of a hotel chain are considered for profiling. Segmentation is based on behavioural variables that provide more meaningful segments from the management perspective. Demographic variables are used to profile segments, aiming to identify and access them, the resulting logical type characterisation being expected to support targeting.

Table 2: Segment structure and segmentation base

	First time users	Regular users	Heavy users
Total percentage	442 20.0	1347 60.9	424 19.2
Base variables Mean			
B	0.4	1.4	4.2
C	0.2	1.9	6.4
CSUP	0.1	0.8	2.0
CH	0.2	1.8	5.5
Total (to the nearest whole figure)	1	6	18

Database

The data arose from the answers to a questionnaire directed to the Portuguese clients of Pousadas de Portugal, a high-end small hotel chain. The questionnaires were distributed in all hotels (42 at the time) between November 1996 and October 1997. The distribution was organised following a quarterly plan, each quarter including an equivalent group of heterogeneous *pousadas*. At the time of data collection there were four types of *pousadas* — B, C, CSUP and CH — roughly corresponding to increasing average prices. (Pousadas CH, CSUP, C and B were in number, 13, 4, 14 and 11, respectively).

The sample collected under this project includes over 2,500 respondents (global reply rate was 74 per cent). Information about the respondent's profile and the evaluation of the stay is included in the database.

Segment structure

The segments of Portuguese clients of the *pousadas* are derived through a mixed process. First time users of *pousadas* constitute an *a priori* segment, as the specific characteristics of this segment were *a priori* found interesting to explore. The segmentation of the remaining clients of *pousadas* is performed through a K-means procedure.

Base variables for segmentation (y) express stay frequency and revealed preferences, measured by the number and type of *pousadas* where the respondents had already stayed overnight. $Y_1 = B$) refers to the number of B type *pousadas*; $Y_2 = C$) refers to the number of C type *pousadas*; $Y_3 = CSUP$) refers to the number of CSUP type *pousadas*; $Y_4 = CH$) refers to the number of CH type *pousadas*. As frequency of use is the general base for segmentation, segments are named accordingly as regular users and heavy users of *pousadas* (see Table 2). Regular users stayed in around six *pousadas* and heavy users in about 18 (average totals).

Profiling

Demographic variables are generally more reliable characteristics than alternative segment descriptors such as attitudes or psychographics.³¹

Consequently, these variables in particular, and observable variables in general, are often used for profiling a segment structure, helping to identify and to provide access to the segments.³² When considering a particular application, the selection of variables for profiling is, however, problem and data dependent.

In the present application, the demographics available for profiling the segments of the Portuguese clients of

Table 3: Demographics variables used in profiling

Segments								
Profiling variables		First time users		Regular users		Heavy users		Global sample %
Proportion/index against global sample								
Gender	Female	33%	130	24%	95	20%	81	25
	Male	67%	907	76%	102	80%	106	75
Marital status	Single	16%	200	7%	88	4%	52	8
	Married	81%	93	88%	101	91%	104	87
	Divorced	3%	69	4%	104	4%	92	4
	Widowed	1%	75	1%	107	1%	147	1
Region of residence	Lisbon	47%	83	58%	101	63%	110	57
	Oporto	16%	97	18%	105	17%	100	17
	Other regions	36%	139	25%	94	20%	78	26
Mean/Index against global sample								
Age	(years)	36.7	82	44.2	99	54.4	122	44.8
Median								
Education level	Primary (1)	4		5		5		5
	Basic (2)							
	Secondary (3)							
	Polytechnic (4)							
	Degree (5)							
Income level (per month)	Master/PhD (6)	2		3		3		3
	<1000 Euros (1)							
	1000–2500 Euros (2)							
	2500–5000 Euros (3)							
	>5000 Euros (4)							

pousadas are presented in Table 3 — the table also includes some descriptive measures for each segment.

According to the results of association tests (see Table 4), there are significant differences between the segments and all the demographic descriptors (Kruskal-Wallis tests provide conclusions for the metric descriptors and chi-square tests provide evidence of significant associations between the segment structure and categorical descriptors). Thus, all are considered for the profiling analysis.

In order to profile first time, regular and heavy users the induction of classification trees, as well as sets of propositional rules (based on the C5 algorithms) are used (see Figure 1).

Two random subsamples from the

original sample are generated: one for estimating the discriminant models (the training sample, corresponding to 65 per cent of the global sample) and the other for obtaining hit rates estimates (the test sample). The choice of a larger training than test sample favours the learning phase, hoping to obtain a model that performs better in a test (holdout) sample.

The C5 algorithm is first run to provide a classification tree (C5 CT). The corresponding parameters are indicated in Table 5. The tree is first allowed to grow almost complete (a minimum number of two records per branch is considered) and then pruning is used in order to favour interpretation of results and to prevent overfitting.

According to the results provided by

Table 4: Association test results

Kruskal-Wallis tests			Chi-square tests		
		d.f			d.f
Age	336.44	2	Gender	17.21	2
Education level	47.82	2	Marital status	44.78	6
Income level	125.84	2	Region	29.37	4

Note: All tests return significant associations with the segments ($p < 0.0001$)

Table 5: Algorithms' parameterisations

Recursive based partitioning algorithms				
		Classification tree (C5 CT)	Rules (C5 Ra)	Rules (C5 Rb)
Pruning			75%	
Minimum records per branch			2	
Group symbolic values			Yes	
Costs of incorrect classification	unit		unit	C(Regular Heavy)=2

Figure 1 Profiling methods

this model (C5 CT), 62 per cent (estimate corresponding to the test sample) of the clients are correctly classified. The numbers in the leaves of the classification tree (see Figure 2) illustrate the precision of the corresponding rules, eg 'if Age > 27 and Education level ≤ 4 and Income level ≤ 1 then first time users' is a rule that covers around 15 cases (note that C5 fractionates missing cases) and this rule classifies correctly 77.3 per cent of the cases it covers (cases that match its condition).

The induction of a set of propositional rules is also used to provide means to discriminate among first time, regular and heavy users of *pousadas*. Two alternative

propositional rules models are considered for this purpose (C5 Ra and C5 Rb), its parameters being presented in Table 5.

The first model's results are illustrated in Table 6, its precision being the same as the one obtained for the corresponding classification tree (a 62 per cent hit rate referred to the test sample).

As C5 CT and (consequently) C5 Ra do not provide rules for the heavy users segment, an alternative model (C5 Rb), which associates a higher cost of incorrect classification if heavy users are classified as regular users (see Table 5) is proposed. Although this model favours correct classification of heavy users, its results are more difficult to interpret (see Table 7).

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AGE ≤ 40 [Mode: Regular Users] (636.796)
AGE ≤ 27 [Mode: First Time Users] (111.869)
  AGE ≤ 18 [Mode: Regular Users] (5.378, 0.961) then Regular Users
  AGE > 18 [Mode: First Time Users] (106.491)
    EDUCATION L. ≤ 4 [Mode: First Time Users] (40.043, 0.681) then First Time Users
    EDUCATION L. > 4 [Mode: Regular Users] (66.448)
      FEMALE [Mode: First Time Users] (30.174, 0.567) then First Time Users
      MALE [Mode: Regular Users] (36.274)
        AGE ≤ 24 [Mode: Regular Users] (4.909, 0.973) then Regular Users
        AGE > 24 [Mode: Regular Users] (31.366)
          AGE ≤ 25 [Mode: First Time Users] (5.887, 0.789) then First Time Users
          AGE > 25 [Mode: Regular Users] (25.478, 0.62) then Regular Users
    AGE > 27 [Mode: Regular Users] (524.926)
      EDUCATION L. ≤ 4 [Mode: Regular Users] (184.832)
      INCOME L. ≤ 1 [Mode: First Time Users] (14.759, 0.773) then First Time Users
      INCOME L. > 1 [Mode: Regular Users] (170.073)
        OTHER REGIONS [Mode: Regular Users] (62.302)
        [SINGLE or DIVORCED] [Mode: First Time Users] (7.59, 0.642) then First Time Users
        [MARRIED or WIDOW] [Mode: Regular Users] (54.667, 0.606) then Regular Users
        LISBON [Mode: Regular Users] (81.659, 0.611) then Regular Users
        OPORTO [Mode: Regular Users] (26.112)
        INCOME L. ≤ 2 [Mode: First Time Users] (16.175)
        FEMALE [Mode: First Time Users] (12.467)
          AGE ≤ 34 [Mode: First Time Users] (8.447, 0.848) then First Time Users
          AGE > 34 [Mode: Regular Users] (4.02, 0.959) then Regular Users
          MALE [Mode: First Time Users] (3.708, 0.662) then First Time Users
          INCOME L. > 2 [Mode: Regular Users] (9.937, 0.726) then Regular Users
          EDUCATION L. > 4 [Mode: Regular Users] (340.094, 0.704) then Regular Users

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Note: the terminal nodes (leaves) of the tree are signed in bold and the number and proportion of correctly classified cases are presented between parenthesis.

Figure 2 Classification tree (C5 CT)

In conclusion, model C5 Ra provides some rules having a fairly high precision and adds insights concerning the segments; eg the rules ‘if Age ≤ 40 and Education level ≤ 4 and Income level ≤ 1 then first time users’ and ‘if Other Regions and Age > 67 and Educational level > 2 then heavy users’ may suggest that the individuals that had not yet been in a *pousada* tend to be younger and with lower academic and income levels, and that the individuals living outside Lisbon and Oporto tend to be heavy users if they are older and have higher educational levels.

Regarding the obtained results’ interpretability it may be concluded that the sets of propositional rules are generally easier to interpret, when compared with the original classification trees (see Figure 2 and Table 6), because:

- C5 R rules have no hierarchical structure in opposition to C5 CT rules
- the conditions in the C5 R rules have fewer propositions which makes them simpler
- the number of rules derived from C5 R is lower than the one corresponding to C5 CT.

Classification

Regarding classification precision, similar hit rates are yielded by the three alternative approaches (the model yielded by the classification tree algorithm and the two models yielded by the propositional rules algorithm), all proving to be consistent (see Table 8).

In particular, the discriminant model that includes specific costs of incorrect

Table 6: C5 set of propositional rules (C5 Ra)

Rules for first time users	Rules for regular users
IF OPORTO and AGE>27 and AGE≤34 and FEMALE and EDUCATION L.≤4 and INCOME L.≤2 then first time users (7, 0.889) IF AGE≤40 and EDUCATION L.≤4 and INCOME L.≤1 then first time users (26, 0.786) IF OTHER REGIONS and AGE>27 and AGE≤40 and [SINGLE or DIVORCED] and EDUCATION L.<=4 then first time users (7, 0.778)	IF AGE>24 and AGE≤25 then first time users (14, 0.75) IF AGE>18 and AGE≤27 and EDUCATION L.≤4 then first time users (36, 0.711) IF AGE>18 and AGE≤27 and FEMALE then first time users (52, 0.611) IF AGE≤27 then first time users (104, 0.538)
Default: Regular users	

classification (C5 Rb) shows a better performance for the training sample (specifically, the capacity to classify heavy users correctly is increased). However, for the test sample the results remain similar to the other two models, suggesting that overfitting is the reason for the increase in the classification precision.

The values obtained for global classification precision associated with the demographic profiling variables (see Table 8) should be referred to the original segment distribution which is not uniform (heavy, regular and first time users represent around 20 per cent, 61 per cent and 19 per cent of the *pousadas*' clients). Thus, one may conclude that:

- the difference between the obtained 62 per cent hit rate and the default precision of classification if a random assignment is considered ($45\% = 20\%^2 + 61\%^2 + 19\%^2$) represents a 17 per cent improvement;
- the difference between the obtained 62 per cent hit rate and the default precision of classification if a majority default classification rule is adopted

represents a 1 per cent improvement (regular users account for 61 per cent of the original sample)

These results represent a slight improvement in default classification precision that deserve some additional comments:

- the choice of profiling variables other than the segmentation base variables, decreases the chance of obtaining very good results from a classification precision point of view. (For example, in the present application C5 CT performed very well when based on segmentation variables — B, C, CSUP and CH — yielding hit rates of 99.24 per cent and 97.64 per cent corresponding to the training sample and test sample, respectively.);
- the literature^{33,34} suggests the existence of weak or indirect links between behavioural segments and demographics, which may render profiling based on demographics a difficult task;
- it is reasonable to expect that if alternative discriminant methods

Table 7: C5 set of propositional rules (C5 Rb)

Rules for first time users	Rules for regular users	Rules for heavy users	
IF AGE>24 and AGE≤25 then first time users (14, 0.75) IF AGE>18 and AGE≤27 and EDUCATION L.≤4 then first time users (36, 0.711) IF AGE≤40 and INCOME L.≤1 then first time users (38, 0.675) IF AGE≤53 and EDUCATION L.≤2 then first time users (22, 0.667)	IF AGE≤18 then regular users (5, 0.857) IF AGE>53 and EDUCATION L.≤2 then regular users (18, 0.8) IF OTHER REGIONS and AGE>40 and EDUCATION L.≤2 then regular users (14, 0.75) IF AGE>25 and AGE≤27 and MALE and EDUCATION L.>4 then regular users (24, 0.615) IF EDUCATION L.>2 then regular users (1324, 0.615)	IF OTHER REGIONS and AGE>67 and EDUCATION L.>2 then heavy users (12, 0.786) IF AGE>51 and AGE≤53 and EDUCATION L.≤3 and INCOME L.>3 then heavy users (2, 0.75) IF AGE>40 and AGE≤41 and EDUCATION L.>3 and INCOME L.>3 then heavy users (6, 0.75) IF OPORTO and AGE>53 and EDUCATION L.>4 and INCOME L.>3 then heavy users (5, 0.714) IF AGE>53 and SINGLE and MALE and INCOME L.≤3 then heavy users (4, 0.667)	IF OPORTO and AGE>53 and AGE≤62 and EDUCATION L.≤3 and INCOME L.<= 3 then heavy users (4, 0.667) IF AGE>53 and DIVORCED and MALE and INCOME L.≤3 then heavy users (1, 0.667) IF AGE>53 and AGE≤70 and WIDOW and EDUCATION L.>2 then heavy users (6, 0.625) IF LISBON and AGE>53 and MALE then heavy users (29, 0.548) IF AGE>64 and MARRIED and EDUCATION L.>2 and INCOME L.≤3 then heavy users (81, 0.53)
Default: Regular users			

were used, classification results would be similar.³⁵

Finally, it may be concluded that, although the classification precision improvement was only marginal, useful insights were derived from the discriminant logical type models yielded by C5 (propositional rules model, in particular), helping to profile the segment structure.

DISCUSSION

It has been suggested³⁶ that there is some empirical evidence that similar classification precision may be achieved by different discriminant methods, namely linear discriminant analysis, logistic regression, neural networks and classification trees. When choosing an algorithm for profiling a segment structure, additional criteria must, thus,

be taken into account. In particular, the need for specific parametric assumptions, the capacity to deal with missing observations, the existence of estimation problems and the interpretability of results, should be considered.

As regards interpretability, a set of propositional rules (particularly when derived by the C5 R algorithm) speaks for itself. In fact, the use of natural (logical type) language makes the profiles and the structure of classification easy to interpret, thus proving to be very appealing to practitioners.

In addition, some characteristics of the proposed discriminant logical type models (C5 T and C5 R) may turn out to be an advantage when compared to alternative methods for profiling:

- C5 is a purely nonparametric procedure that requires no assumptions concerning the data, as

Table 8: Classification precision: C5 classification tree and propositional rules

Recursive based partitioning models									
C5 CT			C5 Ra			C5 Rb			
Hit rate (training s.)			63.3%			63.2%			64.0%
Predicted \ Actual	First time users	Regular users	Heavy users	First time users	Regular users	Heavy users	First time users	Regular users	Heavy users
First time users	71	225		67	229		52	44	0
Regular users	29	847		26	850		19	854	3
Heavy users	0	278		0	278		1	255	22
Hit rate (test s.)			62.0%			62.1%			61.9%
First time users	25	121		25	121		26	120	0
Regular users	23	448		22	449		20	441	10
Heavy users	4	142		4	142		1	140	5

Note: The numbers in the diagonals correspond to the number of correctly classified cases

- opposed to other discriminant methods that may be restricted to obey some assumptions (eg normality in linear discriminant analysis)
- C5 has a specific procedure (summarised in this text) to deal with missing values, as opposed to general statistical discriminant approaches that rely on complete observations for allowing estimation of parameters
- the induction of logical type discriminant models has no estimation problems while some estimation problems may occur when trying to derive statistical models (eg when trying to maximise complex likelihood functions as those that may be associated with mixture models).

Thus, it would be interesting to compare further the proposed approach with alternative discriminant methodologies concerning the above points. Additionally, the following limitations should also be considered:

- C5 results do not include measures of the descriptors' relative importance for discrimination (typically provided by statistical approaches)
- as the C5 results consistency must be based on cross-validation procedures, the quantity of available data may be a critical issue for the proposed approach.

Finally, further research may also be conducted to compare the performance of the C5 R algorithm with alternative induction of propositional rules algorithms,³⁷ for the task of profiling a segment structure.

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GLOSSARY

Classification	Refers to the decision of allocating individuals into classes (eg market segments)
Classification tree	An hierarchical structure that is meant to support the decision of classification. In the root of the tree there are all the observations that base its construction. The leaves represent sub-groups of observations where diversity associated with classes is intended to be minimal
Discriminant analysis	It builds rules (quantitative, logical type or other) that are meant to help differentiating classes. These rules may also be used for classification
Machine learning	It refers to computational algorithms that learn models based on data. Learning with observations is expected to improve with experience (training) in order to yield a better accomplishment of the proposed tasks (eg prediction or classification)
Propositional rule	An if <i>condition</i> then <i>class</i> logical type expression where the condition is a conjunctive proposition that allocates specific values to predictors. (Note that a rule may incorrectly classify some observations meeting its <i>condition</i>)
Segment structure	The result from a segmentation process (typically a partition of consumers)
Test set	The set of observations that helps to test a model's adequacy
Training set	The set of observations that base a model's construction

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