Original Article

Reducing the optimal to a useful number of clusters for model-based clustering

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Pascal van Hattum

studied Business Mathematics and Computer Science at the Free University Amsterdam. After his study in 2000, he has started as a statistical consultant at The SmartAgent Company, where he is currently responsible for all the statistical processes and research & development. In 2004, he started a PhD project in the Faculty of Social and Behavioural Sciences of Utrecht University under the supervision of Professor Herbert Hoijtink. In 2009, he got his PhD with his thesis 'Market Segmentation Using Bayesian Model Based Clustering'. The knowledge of his PhD project is successfully used in the day-to-day business of The SmartAgent Company.

Herbert Hoijtink

is Professor in Applied Bayesian Statistics at the Department of Methodology and Statistics in the Faculty of Social and Behavioural Sciences of Utrecht University. Besides Bayesian Statistics his areas of expertise are, among others, model-based clustering for large data sets, regression, (repeated) measures, analysis of variance, multiple hypotheses testing and structural equation modeling.

ABSTRACT Market segmentation is the process in marketing of grouping customers into smaller subgroups, according to a certain segmentation basis. Market segmentation is only practically useful if the effectiveness and profitability of marketing activities are influenced substantially by discerning separate homogeneous groups of customers. Using six criteria, described by Wedel and Kamakura, the effectiveness and profitability of market segmentation can be determined. However, using model-based clustering techniques to group customers, the statistically optimal solution often contains too many clusters for the intended marketing purposes. Using the six criteria of good market segmentation, an information criterion and two conjectures, describing the geometry of model-based clustering models, presented by Hoijtink and Notenboom, a procedure to reduce the statistically optimal number of clusters to a smaller number, suited for the intended marketing purposes, is presented.

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INTRODUCTION

Many people today believe that market segmentation, that is *the grouping of customers who share common aspects*, is the key strategic concept in marketing.^{1–3} Marketeers perform market

segmentation, expecting to find some segments or clusters in a particular market, responding differently than others to (relevant) marketing items. These marketing clusters can be used for several (differentiated) marketing actions, like for example, differentiated mail packages, differentiated catalogues, prevention against churn in specific clusters, cross/up-selling strategies and so on.

Correspondence: Pascal van Hattum
Department of Methodology and Statistics, Faculty of Social Sciences,
Utrecht University, PO Box 80140, NL-3508 TC Utrecht, the Netherlands
E-mail: p.vanhattum@uu.nl

From a market segmentation study in the domain housing it is known, that the (statistically) optimal number of market segments (or clusters) in the Dutch housing market is 35.⁴ Of course, it is nice to know that in the Netherlands the total housing market can be divided into 35 clusters, but as money and time is limited in most marketing companies, it is undesirable to interpret, describe or make differentiated marketing plans for these 35 market segments. In marketing there is a wish of dividing a market as effectively as possible. Resulting in a market segmentation with as few clusters as possible to fully describe the total market and, finally, to solve the marketing decision problem at hand. From this point of view it is clear, that it is possible that there may be a difference between the statistically optimal solution and the solution suited for the intended marketing purposes. This article describes an algorithm to reduce the (statistically) optimal number of clusters to a smaller number suited for marketing purposes. The effectiveness and profitability of these market segments or clusters are determined using six criteria, described by Wedel and Kamakura.⁵

The structure of this article is as follows. Section 'Market segmentation' briefly describes market segmentation. Section 'Model-based clustering techniques' introduces the clustering algorithm that is used for market segmentation in this article. In Section 'Using information criteria in a decision tree', the procedure to reduce the (statistically) optimal number of clusters to a smaller number, suited for marketing purposes, is described. Sections 'Market segmentation', 'Model-based clustering techniques' and 'Using information criteria in a decision tree' are illustrated using a market segmentation study in the domain housing. This article concludes with a discussion in Section 'Discussion'.

MARKET SEGMENTATION

Introduction

Market segmentation is an essential element of marketing in industrialized countries. Goods can

no longer be produced and sold without considering customer needs and recognizing the heterogeneity of those needs.⁵ Research in the private sector¹ has shown conclusively, that if you can find segments or clusters that, (1) you can identify and differentiate, (2) will remain effectively stable, and (3) can effectively be reached, a company can increase sales and profits by marketing to these segments or clusters, beyond profits possible from treating the market as homogeneous. The concept of market segmentation is further described in Section 'Using segmentation in marketing'. Section 'Application: The Dutch housing market' introduces a market segmentation study in the domain housing.

Using segmentation in marketing

The basic problem of market segmentation is *the grouping of customers who share common aspects*. In his article, Smith⁶ stated that it was better to recognize several customer demand schedules. As Wedel and Kamakura⁵ mention in their book, Smith recognized the existence of heterogeneity in the demand of goods and services. Smith stated: *Market segmentation involves viewing a heterogeneous market as a number of smaller homogeneous markets, in response to differing preferences, attributable to the desires of customers for more precise satisfaction of their varying wants*. The idea of market homogeneity in marketing theory is also rejected by Alderson,⁷ whose theory of marketing was also based on the concept of heterogeneity. Heterogeneity in its most extreme case, also called complete market heterogeneity,⁸ means that each customer is unique in at least one important aspect (or, in Smith's terminology demand schedule) and in this aspect is like no other person. In other aspects customers may be more or less similar. The concept of complete market heterogeneity overstates the reality of practical marketing. Pockets of similarity, known as market segments or clusters, do exist. Thus, in spite of the fact that each customer differs from every other, it is still true that each customer tends to be more like some customers than like others.¹

Marketeers do not attribute these similarities to chance. They know that there are basic differences among market segments. Marketing practice requires that a marketer knows how market segments differ in their attitudes and susceptibilities to marketing efforts. From this knowledge, separated or differentiated marketing strategies can be made.⁸ For example, differentiated mail packages, differentiated catalogues, prevention against churn in specific clusters, cross/up-selling strategies and so on.

However, market segmentation is only practically useful if the effectiveness and profitability of such marketing activities are influenced substantially by discerning separate homogeneous groups of customers. Using six criteria, described by Wedel and Kamakura,⁵ the effectiveness and profitability of market segmentation can be determined. Below, brief descriptions of these six criteria are given:

1. *Identifiability*: a cluster must be clearly defined. It must be clear who is in the cluster.
2. *Substantiality*: A cluster must be large enough to ensure the profitability of developing a differentiated marketing strategy.
3. *Accessibility*: a cluster must be reachable through promotional or distributional marketing activities.
4. *Responsiveness*: A cluster must respond uniquely to marketing activities.
5. *Stability*: A cluster must be stable in time, at least for a period long enough for identification of the clusters, implementation of a differentiated marketing strategy and to produce profitable results.
6. *Actionability*: A cluster and the differentiated marketing strategy must be consistent with the goals and core competencies of the company.

Application: The Dutch housing market

Competition in the Dutch housing market is fierce. Owing to growing working mobility, electronic access possibilities and a growing (inter)national orientation, the customer is not only focused on the local housing market. More

than ever, project developers, investors, real estate consultants and governmental housing institutions must be aware of their target group. Who are they? What drives them? What do they want? How can I reach them? Or, like the philosopher Heidegger⁹ mentioned: *only when we know how to live, we can build*; it is important to understand what the key drivers of customers are on the housing market. In order to find out what kind of housing customers there are in the Netherlands, a market segmentation study is conducted. In this segmentation study, the framework of Brand Strategy Research (BSR)¹⁰ is used.

The data that are used in this article are collected by The SmartAgent Company, the Netherlands (www.smartagent.nl) through a questionnaire on the Internet in 2000. The process behind BSR is the following: a respondent is asked to characterize a person, resembling himself, who looks or feels the same as the respondent towards housing. The whole BSR questionnaire consists of five questions, each containing multiple psychographic items. The first question contains items that describe a person's character. The second question tells something about a person's type of household. The third gives a person's occupations, the fourth question tells something about a person's hobbies and interests and the last question tells which values a person can have in life. Appendix displays the BSR questions. In total, there are 149 psychographic items answered by 2294 respondents. For each question, a respondent has to pick the items which describe the person he has in mind the best. As each question contains a broad range of items, it is unlikely that a respondent cannot pick an item from the item list.

Using a model-based clustering algorithm, which is described in the next section, the 2294 respondents are clustered according to the 149 psychographic items. Resulting in groups of customers who have (more or less) the same view, motivations and attitude with respect to housing. In order to further describe these motivational clusters found, the online questionnaire also contains observable items,

like for example, demographical items (that is, gender, age, education, marital status and so on), economical items (that is, working position, social economic status, prosperity, income and so on), housing-specific items (that is, preferred house, preferred neighborhood, preferred price and so on) and so on. What the different types of customers are in the Dutch housing market and how they can be described using the observable items, is shown in Section 'Application'. The results of the segmentation study are described in the research report Woonbeleving 2000¹¹ and has been used by several housing corporations and real estate managers.

MODEL-BASED CLUSTERING TECHNIQUES

Introduction

Much of the literature about market segmentation has evolved around the technique of identifying clusters from data; see Wedel and Kamakura⁵ for an extensive overview of these techniques. A substantial part of this literature are comparative papers, that contrast the most widely used clustering techniques; see MacLachlan and Mulhern² for an overview of these papers. More recent papers^{2,12,13} compare mixture models (mixture models, model-based clustering algorithms and latent class models are all models coming from the generalized latent variable model framework) with more traditional cluster techniques such as K-means and so on. Within the context of market segmentation a number of papers do suggest better market segments, when using mixture models; see MacLachlan and Mulhern for an overview of these papers.² An important advantage of mixture modeling over traditional clustering techniques is the statistical framework mixture models are based on. A disadvantage is, that mixture models are less available in popular statistical software than the traditional clustering models. This often results in researchers making their own software^{5,4,14,15} and commercial packages, like for example: Glimmix⁵ and LatentGold.¹⁶ For other advantages and disadvantages of mixture modeling, see MacLachlan and Mulhern.²

Model-based clustering algorithm

This article uses a model-based clustering approach, that is proposed in Van Hattum and Hoijtink.⁴ The reason for choosing this clustering technique is, that it can be applied to the large (in terms of number of items and customers) data sets, that are often encountered in marketing and can handle missing values. The proposed clustering technique has incorporated a missing value mechanism that can deal with missing values.

The core of the model-based clustering algorithm is the estimation of a set unknown parameters, which are:

- for all J items assuming within cluster independence of the item responses: within each cluster $q = 1, \dots, Q$, a vector π_q , containing the cluster-specific probabilities of picking the items, is estimated. Note that $\pi_q = \{\pi_{1|q}, \dots, \pi_{j|q}, \dots, \pi_{J|q}\}$ and $\pi_{j|q}$ is the probability of picking item j in cluster q ;
- a vector $\omega = \{\omega_1, \dots, \omega_q, \dots, \omega_Q\}$, containing the cluster weights, that is the proportion of customers allocated to each cluster, is estimated;
- a vector $\tau = \{\tau_1, \dots, \tau_i, \dots, \tau_N\}$, containing the unobserved cluster memberships for each of the N customers, is estimated. Note that for customer $i = 1, \dots, N$, $\tau_i \in \{1, \dots, Q\}$.

The interested reader is referred to Van Hattum and Hoijtink⁴ for the technical details of the proposed model-based clustering algorithm. In this article, the framework of the model-based clustering algorithm is illustrated using a simple data set (for simplification, only $J = 1, \dots, 4$ BSR items and $N = 1, \dots, 7$ customers are used) in Table 1 and cluster weights and cluster-specific item probabilities in Table 2. From the data set in Table 1 it is clear that the data set can be divided into two groups of customers, with (more or less) the same answer pattern on the four items. As a result of the division each customer is allocated to one of the two clusters, that is cluster 1 or cluster 2. This is shown in column τ in Table 1, which are the unobserved cluster memberships. As can be seen from the unobserved cluster memberships, the proportion of customers allocated to cluster 1 is four out of

Table 1: Example: Data set and unobserved cluster memberships

Customer	Gentle	Honest	Capable	Leader	τ
1	1	1	0	0	1
2	1	0	0	0	1
3	1	1	1	0	1
4	1	1	0	1	1
5	0	0	1	1	2
6	0	1	1	1	2
7	0	0	1	1	2

Table 2: Example: Cluster weights and cluster-specific item probabilities

Item	Cluster 1	Cluster 2
ω	0.57	0.43
Gentle	$\pi_{1 1}=1.00$	$\pi_{1 2}=0.00$
Honest	$\pi_{2 1}=0.75$	$\pi_{2 2}=0.33$
Capable	$\pi_{3 1}=0.25$	$\pi_{3 2}=1.00$
Leader	$\pi_{4 1}=0.25$	$\pi_{4 2}=1.00$

seven customers, and to cluster 2 is three out of seven customers. These proportions are shown in row ω in Table 2, which are the cluster weights. Furthermore, the cluster-specific probabilities of picking the items are calculated using the unobserved cluster memberships. The cluster-specific item probabilities for this example are shown in Table 2. For example, three out of four customers, allocated to cluster 1, picked item 'Honest', resulting in $\pi_{2|1}=0.75$, that is the probability of picking item 'Honest' ($j=2$) in cluster 1. Likewise, the probability of picking item 'Honest' ($j=2$) in cluster 2 is 0.33 and so on.

According to two conjectures,¹⁴ the model-based clustering algorithm renders the globally optimal solution. The main implication of these two conjectures is that the globally optimal solution has Q_{max} latent clusters and all solutions with $Q < Q_{max}$ latent clusters are known to be locally optimal solutions, that are non-overlapping combinations of the Q_{max} clusters.

Running the model-based clustering algorithm with the data set concerning the Dutch housing market, as described in Section 'Application: The Dutch housing market', renders a globally optimal solution with $Q_{max}=35$ latent clusters. Or, in other words, the total Dutch housing

market can be divided into 35 groups of customers who have (more or less) the same view, motivations and attitude with respect to housing.⁴ Of course, it is nice to know that in the Netherlands the total housing market can be divided into 35 clusters, but as time and money is limited in most marketing companies, it is undesirable to interpret, describe or make differentiated marketing plans for these 35 market segments, taking the six criteria of good market segmentation into account. In marketing, there is a wish of dividing a market as effectively as possible. Resulting in a market segmentation with as few clusters as possible to fully describe the market and, finally, to solve the marketing decision at hand. Section 'Application' describes how these 35 clusters are reduced to a smaller number, suited for the intended marketing purposes. Point of departure for the reduction algorithm is the main implication of the two conjectures, that is the globally optimal solution has Q_{max} latent clusters and all solutions with $Q < Q_{max}$ latent clusters are known to be locally optimal solutions. The model-based clustering approach, proposed by Van Hattum and Hoijtink,⁴ is elaborated such that clusters are not only separated, but also combined.

USING INFORMATION CRITERIA IN A DECISION TREE

Reduction algorithm

An important reason for choosing the model-based clustering algorithm, described in Section 'Model-based clustering algorithm', is because it is based on two conjectures with respect to the geometry of model-based clustering models. The main implication of these two conjectures form the point of departure for the reduction of the statistically optimal solution into a solution suited for marketing purposes. The model-based clustering algorithm starts with one cluster, containing all customers. Clusters are split and reallocated between clusters, until the cluster solution reaches its globally optimal solution with Q_{max} clusters. All cluster solutions with fewer clusters than this global optimum are known to be locally optimal solutions in which the clusters

Figure 1: Decision tree.

are non-overlapping combinations of the Q_{max} clusters.¹⁴

In order to reduce the number of clusters, the model-based clustering algorithm is used in reverse order. Or, using an agglomerative method, the globally optimal solution with Q_{max} clusters is reduced. This is illustrated using the example in Figure 1. In this example $Q_{max}=4$. Part I of Figure 1 shows the four clusters. With $Q_{max}=4$ there are $\binom{4}{2}$ possible 'ways' to combine two of the Q_{max} clusters in order to get solutions with $Q=3$ clusters. These solutions with $Q=3$ clusters are locally optimal solutions, but can be very useful from a marketing perspective. The possible solutions with $Q=3$ clusters are shown in part II of Figure 1. More general, with Q clusters there are $\binom{Q}{2}$ possible 'ways' to combine two of the Q clusters, resulting in $\binom{Q}{2}$ different cluster solutions with $Q-1$ clusters. As $Q-1 < Q_{max}$ these $\binom{Q}{2}$ cluster solutions, with $Q-1$ clusters, are all known to be locally optimal solutions. In order to pick the 'best' locally optimal solution from these $\binom{Q}{2}$ cluster solutions, an information criterion^{16,17} is used.

Basically, information criteria impose a penalty on the likelihood that is related to the number of

parameters estimated.⁵ In general, information criteria have the following form:

$$Criterion = -2\log L + Pd \quad (1)$$

Here $\log L$ is the log-likelihood function, P is the number of parameters in the model and d is some constant. Where $-2\log L$ is the measure of fit and Pd is the measure of model complexity. The constant Pd weights the increase in fit against the additional number of parameters estimated. In statistics this penalty has always been a topic of discussion,^{5,18–20} resulting in criteria with different penalty functions. Some well-known information criteria are: Akaike Information Criterion¹⁸ (where $d=2$), Consistent Akaike Information Criterion^{5,20} (where $d=\ln(N+1)$), Bayesian Information Criterion^{5,21} (where $d=\ln(N)$) and so on. As information criteria can be seen as the distance between the current model and the true model, the model with the lowest value for the information criteria is most preferred.

But despite of all the discussion about which information criterion is the best, the choice of which information criteria, or, in other words,

the choice of which penalty function, is no point of discussion in this article. The reason for that is, when comparing the $\binom{Q}{2}$ cluster solutions with $Q-1$ clusters, the number of parameters, P , and the number of customers, N , are equal for each cluster solution. So, for each of the $\binom{Q}{2}$ cluster solutions with $Q-1$ the same penalty applies. As such this article uses $-2\log L$ as criterion function to decide which of the cluster solutions is the best.

Above described agglomerative method and the use of the $-2\log L$ criterion in selecting the 'best' locally optimal solution, are incorporated in a decision tree. The root of this decision tree represents the globally optimal solution with Q_{max} clusters and the leaves represent the $\binom{Q}{2}$ locally optimal solutions with $Q-1$ clusters. Using $-2\log L$ in each branch of the tree, a decision has to be made, resulting in the 'best' locally optimal cluster solution with $Q_{desired}$ clusters.

The above is illustrated using the example tree in Figure 1. In this example $Q_{max}=4$, that is the statistically optimal number of clusters and $Q_{desired}=2$, that is the desired number of clusters, suited for the intended marketing purposes. The root of the decision tree is shown in part I of Figure 1. With $Q_{max}=4$ there are $\binom{4}{2}$ possible (locally optimal) solutions with $Q=3$ clusters. The possible solutions with $Q=3$ clusters are shown in part II of Figure 1. Looking at the $-2\log L$ values which are indicated on each edge, the minimum $-2\log L$ value is at the $Q=3$ solution in which clusters 1 and 4 from the $Q_{max}=4$ solution are combined. This solution is considered to be the 'best' locally optimal solution with $Q=3$ clusters. From this 'best' solution with $Q=3$ clusters, the decision step is repeated again. There are $\binom{3}{2}$ possible solutions in which two of the three clusters are combined. These possible (locally optimal) solution are shown in part III of Figure 1. From this part, it can be seen that the minimum $-2\log L$ value is at the solution in which clusters 2 and 3 from the $Q=3$ solution are combined, resulting in the 'best' locally optimal solution with $Q_{desired}=2$ clusters.

Application

As described in Section 'Model-based clustering algorithm', running the model-based clustering

algorithm with the data set at hand and a cluster model with the 149 BSR items, renders a globally optimal solution with $Q_{max}=35$ clusters. But, according to the main applications of these conjectures, when the globally optimal solution has $Q_{max}=35$ latent clusters, all other solutions with $Q<35$ latent clusters are known to be locally optimal solutions. As was stated earlier in this article, time and money are limited in marketing companies and using all these $Q_{max}=35$ clusters are not desired. So, taken into account the six criteria of good market segmentation, the statistically optimal solution with $Q_{max}=35$ clusters should be reduced to a solution suited for the intended marketing purposes. This reduction in number of clusters is achieved using the algorithm, described in Section 'Reduction algorithm' and evaluated using the six criteria of good marketing segmentation, described in Section 'Using segmentation in marketing'.

But what is $Q_{desired}$ in the Dutch housing market? It may be clear that marketers try to find a cluster solution that is a trade off between the statistically optimal solution (in this application 35 segments) and a solution suited for the intended marketing purposes. Also MacLachlan and Mulhern² acknowledge this interaction between statistics and marketing: *in any empirical problem, the researcher must necessarily use a substantial dose of subjectivity and domain knowledge. This can be aided by computation of some statistical indicators, but ultimately the decision, regarding the number of clusters to use in any particular problem, will be the result of viewing those indicators in the light of the marketing decision problem at hand.* The decision about the desired number of clusters in the Dutch housing market is supported with the help of the six criteria of good market segmentation (as described in Section 'Using segmentation in marketing'). To what extent these criteria are being positive or negative is determined using a substantial dose of subjectivity and domain knowledge of the researcher.

As was mentioned earlier in this article, it is undesirable to interpret, describe or making differentiated marketing plans for 35 clusters. A solution with 30 or 25 clusters also takes too

much time to describe and interpret. That's why the researcher decides to describe and interpret the reduced solutions with 15 clusters and the solutions with smaller number of clusters. Of course, this is a rather subjective decision, but it is an assessment between domain knowledge, available time and money. In order to determine what $Q_{desired}$ is, the cluster solution with 15 clusters is further reduced, until the most effective and most profitable solution is found.

When interpreting these cluster solutions, the reduced solution with $Q_{desired}=6$ clusters is the most effective and most profitable one. This is shown using the six criteria of good market segmentation:

1. *Identifiability*: A cluster must be clearly defined. It must be clear who is in the cluster. Table 3 shows for each BSR item (for simplification, only the BSR items about a person's character traits and a person's values are shown), the cluster-specific probabilities. Using these

cluster-specific probabilities for the BSR items and the cluster-specific probabilities for the observable items, that are demographical items, economical items, housing items and so on, in Table 4 (for simplification, only a few observable items are shown), each of the six clusters is described. This results in the following cluster descriptions:

- *Cluster 1*: Persons from this cluster strive for harmony in every aspect of life and harmonious relations with all people they meet in daily life. Harmony between family life and career, between friends and neighbors, relations in general and the rules and values of society. Families with children have a higher probability to occur in this cluster. Persons in this cluster are not ambitious in their career. They are low and moderate educated and have an average income. They think it is important to know your neighbors by name. Social cohesion in their neighborhood is an important factor. Also living closely to family

Table 3: Cluster-specific item probabilities for the $Q_{desired}=6$ (or best local mode) solution

Cluster	1	2	3	4	5	6
Cluster size	28.80%	18.80%	18.10%	5.10%	19.70%	9.50%
<i>BSR question about character traits</i>						
A little bit shy	0.08	0.26	0.03	0.08	0.32	0.12
Easygoing	0.17	0.17	0.15	0.03	0.03	0.34
A little bit impatient	0.22	0.20	0.33	0.13	0.28	0.14
Honest	0.58	0.67	0.46	0.39	0.60	0.60
Assertive	0.12	0.03	0.16	0.27	0.05	0.10
Critical	0.25	0.13	0.36	0.59	0.34	0.12
Interested in others	0.57	0.55	0.34	0.38	0.29	0.39
Gentle	0.16	0.25	0.10	0.05	0.19	0.13
Jovial	0.07	0.04	0.06	0.03	0.07	0.12
Neat	0.13	0.24	0.15	0.03	0.12	0.08
Ordinary	0.25	0.53	0.21	0.02	0.51	0.26
Capable	0.04	0.03	0.13	0.03	0.06	0.03
Spontaneous	0.54	0.32	0.19	0.26	0.06	0.42
Character	0.16	0.06	0.3	0.49	0.16	0.18
Adventurous	0.08	0.02	0.06	0.29	0.06	0.19
Sympathetic	0.23	0.24	0.15	0.27	0.18	0.25
Energetic	0.11	0.11	0.20	0.21	0.05	0.16
Self-confident	0.14	0.09	0.27	0.28	0.14	0.08
Leader	0.08	0.03	0.31	0.15	0.06	0.13
Classy	0.03	0.01	0.07	0.09	0.02	0.02
Serious	0.13	0.35	0.32	0.14	0.38	0.19
A little impudent	0.06	0.03	0.08	0.09	0.03	0.05
Commercial	0.02	0.02	0.27	0	0.11	0.05
Cozy	0.59	0.48	0.22	0.34	0.29	0.56
Self-assured	0.10	0.03	0.17	0.18	0.13	0.16
Deliberate	0.05	0.19	0.20	0.10	0.36	0.08
Passionate	0.08	0.01	0.03	0.22	0.01	0.08
Serene	0.09	0.17	0.23	0.03	0.35	0.11

Table 3 *continued*

<i>Cluster</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>
Intelligent	0.20	0.06	0.36	0.70	0.23	0.19
Opinionated	0.17	0.11	0.21	0.21	0.25	0.25
Helpful	0.51	0.67	0.20	0.11	0.33	0.53
Down-to-earth	0.18	0.37	0.33	0.05	0.55	0.17
Enthusiastic	0.36	0.14	0.18	0.35	0.04	0.28
Balanced	0.10	0.13	0.23	0.15	0.19	0.10
Cheerful	0.32	0.25	0.12	0.27	0.10	0.38
<i>BSR question about values</i>						
Self-belief	0.61	0.61	0.63	0.52	0.57	0.56
Self-advancement, growth	0.39	0.15	0.36	0.56	0.19	0.18
Enthusiasm	0.32	0.26	0.26	0.17	0.17	0.33
Enjoying life	0.75	0.68	0.68	0.54	0.57	0.70
Social harmony	0.22	0.25	0.11	0.06	0.27	0.12
Friendship	0.67	0.78	0.46	0.37	0.52	0.82
Social alliance	0.25	0.32	0.21	0.26	0.23	0.27
Passion	0.19	0.02	0.12	0.38	0.06	0.28
Solidarity	0.10	0.13	0.12	0.11	0.25	0.16
Intimacy	0.16	0.11	0.13	0.27	0.1	0.17
Privacy, tranquility	0.32	0.52	0.35	0.35	0.62	0.26
Respect	0.63	0.76	0.57	0.35	0.58	0.63
Security	0.46	0.68	0.20	0.26	0.38	0.14
Anonymity	0.01	0.04	0.02	0.02	0.11	0.03
Rationality	0.04	0.03	0.16	0.05	0.14	0.04
Status	0.01	0	0.03	0	0.01	0.04
Recognition of performances	0.16	0.10	0.31	0.24	0.23	0.20
Heroism, glory	0	0	0.02	0	0	0.03
Being unique, different	0.10	0.01	0.06	0.43	0.06	0.07
Independency	0.25	0.35	0.50	0.44	0.55	0.36
Success in life	0.11	0.05	0.31	0.11	0.08	0.25
Challenge, stimulation	0.17	0.04	0.30	0.39	0.10	0.30

Table 4: Cluster-specific probabilities for the observable items, for the $Q_{desired}=6$ (or best local mode) solution

<i>Cluster</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>
Cluster size	28.8%	18.8%	18.1%	5.1%	19.7%	9.5%
<i>Age</i>						
20–29 years	0.08	0.14	0.13	0.22	0.06	0.14
30–39 years	0.22	0.17	0.26	0.24	0.20	0.29
40–49 years	0.25	0.21	0.25	0.22	0.24	0.28
50–59 years	0.23	0.24	0.19	0.17	0.25	0.18
60–69 years	0.13	0.12	0.11	0.09	0.17	0.08
70 years and over	0.08	0.12	0.04	0.03	0.08	0.03
<i>Education</i>						
High	0.13	0.29	0.46	0.51	0.23	0.24
Middle	0.66	0.52	0.49	0.44	0.57	0.65
Low	0.21	0.19	0.05	0.06	0.20	0.11
<i>Type of family</i>						
Single family, young	0.01	0.10	0.05	0.10	0.01	0.03
Single family, old	0.11	0.38	0.10	0.15	0.10	0.08
Family with children	0.44	0.17	0.39	0.31	0.39	0.50
Family with adults, young	0.04	0.05	0.11	0.12	0.05	0.09
Family with adults, old	0.41	0.30	0.35	0.31	0.45	0.30
<i>Social economic status</i>						
A – high	0.11	0.11	0.26	0.24	0.11	0.14
Bb	0.25	0.24	0.37	0.33	0.29	0.30
Bo	0.22	0.24	0.22	0.25	0.27	0.24

Table 4 *continued*

<i>Cluster</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>
C	0.38	0.37	0.14	0.16	0.31	0.30
D – low	0.04	0.04	0.01	0.01	0.02	0.01
<i>Income</i>						
Lower than average	0.22	0.34	0.09	0.17	0.16	0.15
Average	0.35	0.31	0.17	0.20	0.32	0.29
Higher than average	0.43	0.34	0.75	0.62	0.53	0.56
<i>Type of house</i>						
Own house	0.67	0.47	0.79	0.67	0.72	0.75
Rental	0.33	0.53	0.21	0.33	0.28	0.25
<i>Domain-specific statements</i>						
It is important to live in a dynamic environment	0.01	0.03	0.05	0.10	0.02	0.03
A neighborhood with the same type of people is important	0.09	0.12	0.16	0.11	0.14	0.09
Anonymous living is important	0.02	0.06	0.03	0.04	0.04	0.01
Cozy living is important	0.47	0.37	0.27	0.30	0.35	0.45
Exclusive housing is important	0	0.02	0.06	0.06	0.01	0.02
Functional living is important	0.10	0.14	0.23	0.25	0.18	0.13
I prefer to live like a hermit	0.38	0.51	0.32	0.26	0.33	0.25
It is important to have a lot of social contacts in the neighborhood	0.23	0.19	0.17	0.18	0.23	0.23
It is important to have many visitors in my house	0.15	0.11	0.11	0.21	0.1	0.21
It is important to live free, with a lot of space	0.33	0.38	0.51	0.51	0.46	0.35
It is important to live in a house that is different from others	0.03	0.05	0.10	0.17	0.05	0.07
It is important to live luxurious	0.03	0.06	0.17	0.12	0.04	0.06
My house is always open for everybody	0.42	0.31	0.30	0.38	0.32	0.49
My house is basically a place to sleep	0.01	0.03	0.01	0.02	0.01	0.01
It is important to have privacy	0.49	0.59	0.57	0.50	0.56	0.43
It is important to live secure	0.58	0.52	0.53	0.43	0.57	0.53
It is important to have social cohesion in the neighborhood	0.43	0.33	0.32	0.37	0.36	0.49
It is important to live solitarily	0.01	0.04	0.03	0.03	0.03	0.01

and friends is important. Most of the persons in this cluster have never left their birthplace. Persons from this cluster prefer to live near schools, shops and parks/playgrounds, where children can play and people can meet and chat. In general, terraced houses can be found in this cluster.

- *Cluster 2:* Persons from this cluster are mainly oriented on their peer group and the rules and values of this group. Following these rules and orientation on the peer group creates a feeling of security and belonging. Persons in this cluster choose to live in an environment where they can live, work and shop. An important aspect in their neighborhood is privacy and anonymity. Their houses must be a safe place to live in. In general, low-educated persons with low income have higher probability to be in this cluster. Also the age of these persons is

in general higher. This cluster contains in general more single households.

- *Cluster 3:* Persons from this cluster are career oriented and aspire a certain (high) status in life in connection with certain status symbols and conspicuous consumption. This goes along with manifestative behavior and attitudes as well as a need for control. Translated into their housing, these persons prefer to live in large, detached houses such as villa's, bungalows and penthouses. They prefer to live in a neighborhood with their own type of persons. Luxury housing and status objects are important aspects. Social contacts and coziness in their neighborhood are not appreciated. Bonding with their house and neighborhood is low, with in general higher and faster moving rates. Families with children can also be found in this cluster. Compared to the families in Cluster 1,

families in this cluster are not as comfy. These families are more dynamic; each family member goes his own way, showing conspicuous consumption wherever possible. Persons in this cluster are in general high educated, with a high income. They have the highest social economic status, with a lot of prosperity. A lot of directors/CEOs can be found in this cluster.

- *Cluster 4:* Persons from this cluster are self-conscious and self-confident in their attitude towards (choices in) life and energetic, vital and passionate in their behavior. Persons in this cluster prefer living in an apartment, in a large town or city center. Living in town is interesting, as you can lead your own life. The creative and independent character will certainly be shown in the choice of houses. In general young, well-educated persons can be found in this cluster. They are on the eve of a successful career. Also more single households can be found in this cluster.
- *Cluster 5:* Persons from this cluster are, in terms of description, a combination of the persons in clusters 2 and 3. They are always trying to find a good combination between family and career. Persons from this cluster are also oriented on their peer group and the rules and values of this group, but not as strict as persons from cluster 2. These persons are in general middle aged and on the eve of becoming 'empty nesters'. This new phase in life leads to different demands in housing. Bonding with their residential place is because of their work, children or sports, rather than family and friends. In general persons in this cluster are sportive, social and like to be busy with their houses and gardens. Houses that can be found in this cluster are in general (semi)detached and luxury apartments.
- *Cluster 6:* Persons from this cluster are, in terms of description, a combination of the persons in clusters 1 and 4. These persons can best be described by the word 'normal'. They are called 'Monsieur Toutlemonde' in France, 'Joe Sixpack' in The USA, 'Otto Normalverbraucher' in Germany or 'Jan Modaal' in the Netherlands. They are the

common suburban family man; in general middle educated, middle aged, working as an employee with an average income, part of a family with an average number of children, living in a terraced house in a normal environment and so on.

Given these descriptions the six clusters are clearly defined. It is clear who is in the cluster.

2. *Substantiality:* A cluster must be large enough to ensure the profitability of developing a differentiated marketing strategy. From the row 'Cluster size' in Table 3, it can be seen that all six clusters has substantial weights, that is cluster 1 = 28.8 per cent, cluster 2 = 18.8 per cent, cluster 3 = 18.1 per cent, cluster 4 = 5.1 per cent, cluster 5 = 19.7 per cent and cluster 6 = 9.5 per cent. Whether these substantial clusters are profitable enough, can be decided after a differentiated marketing strategy has taken place.²² However, the descriptions of the six clusters provide relevant information on how to communicate with them and to set-up all kind of (differentiated) marketing strategies;
3. *Accessability:* A cluster must be reachable through promotional or distributional marketing activities. According to the literature this criterion is less appealing in psychographic segmentation.⁵ However, in above described motivational segmentation study, demographical, economical and housing-specific items are used in order to further describe the six motivational clusters. Using these observable items the clusters become more accessible. For example, when a financial company wants to target (future) mortgage owners, probably the best target audience can be found in cluster 3 (persons who are high educated, have a high income, own large houses and always looking for the best mortgages) and cluster 4 (on the eve of a successful career, with probably a high income, large houses and an increasing demand of mortgages). Or, when there are promotions for families with children, probably the best target audience can be found in clusters 1, 3 and 6;
4. *Responsiveness:* A cluster must respond uniquely to marketing activities. This criterion is not unequivocally supported in the literature for

psychographic segmentation bases.⁵ From Wedel and Kamakura⁵ it can be concluded that domain-specific segmentation bases, like is used in this application, score moderate on the responsiveness criterion. However, the responsiveness of above described cluster solution is supported by the fact that five of the six clusters identified, have successfully been used in differentiated marketing applications. For example, in an application a Dutch energy supplier sent (differentiated) cluster-specific questionnaires to all the customers in their database. For each of the five motivational clusters a cluster-specific questionnaire was made. Furthermore, a standard (undifferentiated) questionnaire was sent to a control group. In the end it was shown that the response percentages for the groups, that received (differentiated) cluster-specific questionnaires, were higher than the response percentage in the control group.²³ In another application about an European mail order company specialized in gardening products, it was shown that, using a randomized experiment, sending cluster-specific catalogues to their customers, stimulated buying behavior and increased sales.²⁴ See the track record on www.smartagent.nl for an overview of projects where these motivational clusters have been used in differentiated marketing activities. From this point of view, the six clusters are responsiveness;

5. *Stability*: A cluster must be stable in time, at least for a period long enough for identification of the clusters, implementation of a differentiated marketing strategy and to produce profitable results. In the literature this criterion is also not unequivocally supported.⁵ However, from a theoretical point of view, the clusters are expected to be stable.⁵ The stability of above described cluster solution is supported by the fact that four of the six clusters identified, have successfully been used in (inter)national marketing and are still workable in day-to-day business (see the track record on www.smartagent.nl for an overview of the projects where these motivational clusters have been used). From this point of view, the six clusters are stable, and given

the number of projects involved, have been successful and profitable.

6. *Actionability*: A cluster and the differentiated marketing strategy must be consistent with the goals and core competencies of the company. As the BSR questionnaire for the domain housing do not only contain psychographic items, but also domain-specific items such as, housing preferences, price preferences, branding of new housing projects and so on, the six motivational clusters are actionable. The full descriptions of the six clusters provide relevant information on how to communicate with them and to set-up all kind of (differentiated) marketing activities. For example, in order to
 - determine what kind of houses need to be build and where to locate them (terraced houses with parks and playgrounds for cluster 1, large, luxury houses for cluster 3 and apartments in the city center for cluster 4);
 - to (cross/up) sell mortgage products, that is to stimulate orders in (other and/or more) mortgage products (clusters 3 and 4);
 - determine what kind of facilities such as shops, playgrounds, parks, transportation, schools, are desired and where to locate them (schools and playgrounds in the neighborhood of where persons in cluster 1 live, more parking places for the in general higher average number of vehicles per person in cluster 3 and so on);
 - do promotions for empty nesters (cluster 5);
 - do promotions for amusement parks or funfairs (clusters 1 and 6).

As Wedel and Kamakura⁵ conclude, domain-specific psychographical segmentations are in general the most effective segmentation studies. Above described BSR segmentation study in the domain housing is such a domain-specific psychographical segmentation. Using the six criterion of good market segmentation, it is shown that the solution with six motivational clusters is effective and profitable. As such the statistically optimal solution with 35 clusters is reduced to the optimal solution for the intended marketing purposes. In fact, the results of the segmentation study, as described in the research report Woonbeleving 2000,¹¹ has successfully been

used by several housing corporations and real estate managers.^{25–27} Furthermore, Jenkinson²⁸ and Van der Putten²⁹ mention in their work that this (type of) segmentation study is one of a few that has actually been transformed in real marketing actions.

DISCUSSION

In marketing, there is a wish of dividing a market as effectively as possible. Resulting in a market segmentation with as few clusters as possible to fully describe the market, and finally, to solve the marketing problem at hand. From this point of view it is clear that it is possible that there may be a difference between the statistically optimal solution and the solution suited for the intended marketing purposes. From a marketer's point of view this globally optimal solution may contain too many clusters to interpret or to make differentiated strategies for.

This article proposed an algorithm to reduce the statistically optimal number of clusters to a smaller number, suited for marketing purposes. Point of departure for this is the statistically optimal solution. Using an agglomerative method and an information criterion, a decision tree is used to combine clusters till a useful number of clusters for the intended marketing purposes are reached.

This article illustrated the reduction algorithm using a marketing application where the Dutch housing market was segmented. Using a model-based clustering algorithm, it turned out that the statistically optimal cluster solution was a solution with 35 clusters. Or, in other words, the total housing market in the Netherlands could be divided into 35 clusters; 35 different groups of customers, that had the same views, motivations and attitude with respect to housing. But as time and money was limited, interpreting, describing or making differentiated marketing plans for these 35 clusters, was too expensive. Using the domain knowledge of a real estate consultant, there was a wish to reduce the number of clusters to a smaller number suited for marketing purposes. Using the proposed reduction algorithm, the statistically optimal solution with 35 clusters was reduced to a solution with six clusters. Using six

criteria of good market segmentation, this reduced cluster solution was evaluated and was found to be profitable and effective for further (differentiated) marketing activities. This conclusion is further supported by the fact that housing corporations and real estate manager are still working with the results of the segmentation study and researchers acknowledge the useful (and rare) marketing application of the segmentation study. Finally, the reduction of clusters has successfully been used in day-to-day business of The SmartAgent Company.

This article showed that, using six criteria of good market segmentation, an information criterion and two conjectures, describing the geometry of model-based cluster models, the statistically optimal solution can be reduced to a solution suited for the intended marketing purposes.

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APPENDIX

BSR questionnaire

When you think of a particular car, you may also think of the typical person driving such a make or model. Now, when you think of housing and of the way in which you live (or would like to live), what kind of people go with that? How do these people live, what are their character traits, their hobbies, occupations and so on?

Q1. Which character traits fit the best for the person that has the same opinion about housing as you do?

☐ A little bit shy	☐ A little impatient	☐ Easy going
☐ Adventurous	☐ Assertive	☐ Balanced
☐ Capable	☐ Cheerful	☐ Classy
☐ Cozy	☐ Critical	☐ Deliberate
☐ Energetic	☐ Enthusiastic	☐ Leader
☐ A little bit imprudent	☐ Gentle	☐ Helpful
☐ Honest	☐ Intelligent	☐ Interested in others
☐ Jovial	☐ Sympathetic	☐ Neat
☐ Opinionated	☐ Ordinary	☐ Passionate
☐ Self-assured	☐ Self-confident	☐ Serene
☐ Serious	☐ Down-to-earth	☐ Commercial
☐ Spontaneous	☐ Strong character	

Q2. Which family or household types fit the best for the person that has the same opinion about housing as you do?

☐ A family where everyone goes their own way	☐ Artistic household
☐ Bachelor	☐ Broad-minded family
☐ Busy dynamical family	☐ Cozy old-fashioned family
☐ Happy family	☐ Harmonious family
☐ Ideal family	☐ Isolated family
☐ Not suited for family life	☐ Perfect family
☐ Quiet family	☐ Rigid family
☐ Single	☐ Sportive family
☐ Stable family	☐ Aristocratic household
☐ Striving for a family	☐ Warm family

Q3. Which occupations fit the best for the person that has the same opinion about housing as you do?
Occupations can be done both by males or females.

☐ Account manager	☐ Activity guide	☐ Beauty specialist
☐ Member of the board	☐ Business-man/-woman	☐ Social worker
☐ Commercial assistant	☐ Commissioner	☐ Designer
☐ E-business	☐ Entrepreneur	☐ Financial planner
☐ Freelancer	☐ Full-time house wife	☐ House-husband
☐ Journalist	☐ Male nurse	☐ Manager
☐ No occupation	☐ Nurse	☐ Part-time house-wife
☐ Photographer	☐ Artist	☐ Anchor man
☐ Programmer	☐ Project manger	☐ Public servant
☐ Receptionist	☐ Scientist	☐ Secretary
☐ Shop assistant	☐ Shopkeeper	☐ Social worker
☐ Sports teacher	☐ Student	☐ Stylist
☐ Temporary employee	☐ Truck driver	☐ Unemployed
☐ Vets assistant	☐ Volunteer	

Q4. Which hobbies, interests and/or leisure activities fit the best for the person that has the same opinion about housing as you do?

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☐ A sociable evening with friends	☐ Active sports	☐ Adventurous holidays
☐ Top-notch achievement	☐ Astrology	☐ Being at home quietly
☐ Build a successful career	☐ Camping	☐ Cars/motor bikes
☐ Classy parties	☐ A day out	☐ Dine out together
☐ Do odd jobs around the house	☐ Gardening	☐ Going out together
☐ Going to a discotheque	☐ Golf	☐ Investing in stocks
☐ Make dream come through	☐ Religious matters	☐ Swimming
☐ Playing chess	☐ Reading magazines	☐ Shopping
☐ Snow boarding	☐ Working out	☐ Surfing the Internet
☐ Visiting friends and relatives	☐ Team sports	☐ Visiting a pub
☐ Watching TV		
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Q5. Which values fit the best for the person that has the same opinion about housing as you do?

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☐ Anonymity	☐ Challenge, stimulation	☐ Enjoyable life
☐ Enthusiasm	☐ Expression, uniqueness	☐ Friendship
☐ Heroism, glory	☐ Independence	☐ Intimacy
☐ Passion	☐ Privacy, tranquility	☐ Rationalism
☐ Recognition of performances	☐ Respect	☐ Security
☐ Self-belief	☐ Self-expression, growth	☐ Social alliance
☐ Social harmony	☐ Solidarity	☐ Status
☐ Success in life		
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