Organic food consumption

A multi-theoretical framework of consumer decision making

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Abstract *An approach is introduced to combine survey data with multi-agent simulation models of consumer behaviour to study the diffusion process of organic food consumption. This methodology is based on rough set theory, which is able to translate survey data into behavioural rules. The topic of rule induction has been extensively investigated in other fields and in particular in learning machine, where several efficient algorithms have been proposed. However, the peculiarity of the rough set approach is that the inconsistencies in a data set about consumer behaviour are not aggregated or corrected since lower and upper approximation are computed. Thus, we expect that rough sets theory is suitable to extract knowledge in the form of rules within a consistent theoretical framework of consumer behaviour.*

Introduction

There is a growing demand for organic foods driven by consumers' perceptions of the quality and safety of these foods and by the positive environmental impact of organic agricultural practices. This growth of demand is expected to continue in the coming years. Although the situation differs from one country to another in terms of type and quantities of production, in all European Union (EU) Member States the number of organic farms has increased since the 1992 reform of the common agricultural policy (CAP). However, in total just under 2 per cent of all agricultural area is devoted to organic farming, on more than 1 per cent of all agricultural holding (Hau and Joaris, 2000).

From the producers' perspective there are two main reasons for the increasing interest in organic farming. The first is due to adoption of the 1992 Mac Sharry reform, under which are implemented the so-called accompanying measures based on the principle of decoupling, which involves the separation between market price and income support, through the compensation to directly support farm incomes. It is applied mainly through EC Regulation

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2078/92, which provides compensation for farmers who make a commitment to undertake more environmentally friendly agricultural production methods and less intensive agriculture. The agri-environmental measures introduced by the council regulation 2078/92 encourage conversion and maintenance of organic farming, providing for financial compensation to farmers for any losses of income incurred during the conversion. The second reason is linked to the possibility of higher financial returns for farmers in a saturated market. Organic food production seems to constitute an interesting market niche particularly attractive for small farmers who cannot benefit from the economy of scale effects of technologically advanced agricultural production (Shifferstein and Oude Ophius, 1998).

For environmental and ethical reasons there is political interest to increase the share of organic food production. This interest is strongly reinforced by the increasing number of crises in the agricultural system, like pig plagues, mad cow disease and the foot and mouth outbreak. The main barrier to increase production size is the willingness of consumers to buy organic food products, which are somewhat more expensive than most other food products. The question is thus how to stimulate the consumption of organic food products.

From a marketing perspective it is important to understand why consumers consume a certain level of organic food, when they change their consumption pattern, what their motives are, how the consumption of organic food consumption can be enhanced.

It is generally recognised that, despite the green trend in consumer values and attitudes, there are still different barriers to the diffusion of the ecologically oriented food consumption style. The barriers of organic food consumption stressed in the marketing literature include, for example, consumers' reluctance to pay higher costs, not only in money but also in time and effort, usually associated with organic products, and their unwillingness to accept sacrifices in the subjectively perceived quality of the organic variant.

In addition to this difficulty associated with conflict between personal and environmental benefits, organic food consumption is restrained by the complexity of the information related to the characteristic associated to products and the impact of the mode of production on the environment. A common understanding of what is meant by "organic" as well as the existence of internationally-recognised guidelines provide an important measure to ensure that consumers receive what they expect.

An organic label indicates that a product was produced using a certain environmentally-friendly agricultural practice. The term organic is referred to as a process claim, not a product claim. Products of organic agriculture are defined by technology and input used in the production process and not by inherent properties of the product itself. Despite the process claim, consumers often perceive organic products as representing an environmentally friendly mode of production as well as having certain intrinsic quality and safety characteristics.

In the past differences in these definitions were significant but the demand for consistency and international harmonisation of requirements for organic food both by traders and consumers has led to great uniformity. In the EU, the organic production of agricultural products is regulated by Council Regulation 2092/91. This regulation set out strict requirements which must be met before agricultural products, whether produced in the EU or imported from other countries, may be marketed as organic. In particular, the regulation restricts the range of products that can be used for fertilising and for plant pest and disease control, and requires each Member State to be set up an inspection system to certify compliance with these principles. In 1999, the Codex Alimentarius Committee adopted guidelines for the production, processing, labelling and marketing of organically produced food. These regulations set out the principles of organic production at farm, preparation, storage, transport, labelling and marketing stages. The Codex Alimentarius proposed definition is "organic agriculture is a holistic management system which promotes and enhances agro-system health, including biodiversity, biological cycles, and soil biological activity".

It emphasises the use of management practices in preference to the use of off-farm inputs. In fact, organic agriculture is one of several approaches to sustainable agriculture and many of the techniques used (e.g. intercropping, rotation of crops, double digging, mulching, integration of crops and livestock) are practised under many systems. What makes organic agriculture unique is that:

- almost all synthetic products are prohibited;
- soil building crop rotation is mandated (Le Guillou and Scharpè, 2001).

However, the way consumers make choices in buying food are rather diverse and complex. First, even though people may be concerned about environmental issues, it cannot be assumed that behaviour has changed accordingly. With regard to environmental issues the link between attitude and consumer behaviour is not straightforward. This is particularly the case when the products represent a conflict between environmental soundness and other perceived benefits, such as convenience performances and various quality attributes and prices. Uusitalo (1990) has pointed out that even though environmental quality is generally perceived as the most important social goal, "free riding" tendencies are present as soon as social goals interfere with the respondent's own utility (Wandel and Bugge, 1997).

Investigation and analysis of organic food purchase and consumption is well documented in the literature on consumer behaviour. Studies in this area mainly focus on the complexity of factors which drive food related tastes and preferences, and some authors have proposed models which attempt to categorise and integrate ethical and environmental values among the relevant factors (Siskos *et al.*, 2001).

Environmental concerns have been found to be a major determinant of buying organic food. A growing number of studies have demonstrated a great interest in health related aspects of food. The developments in the demand of food with higher quality and safety standards have been related both to higher incomes and the increased awareness of the importance of a healthy diet (Bellia, 1987; Carrà, 1999). Asp (1999) identifies a number of factors and barriers that influence food decision made by individual consumers. These include cultural factors, psychological and lifestyle factors and food trends, as well as barriers.

Grunert and Juhl (1995) assess the explanatory power of "values" for analysing consumer attitudes and buying preferences. Values are thus considered criteria to select and justify actions; values are both self-centred and social centred in the sense they are at the crossroads between the individual and the society. Using the Schwartz value theory, they describe 11 motivational domains of value, which are analysed using smallest space analysis, cluster and discriminate analysis.

Although there have been various investigations of determinants of past behaviour of organic food purchase, there are few tools to explore future developments of consumer behaviour. We propose the development of a dynamic approach of exploring possible scenarios of food consumption. Such an approach can be based on so-called multi-agent models, which simulate the behaviour and interactions of a large population of agents. A difficulty in applying multi-agent models is the empirical implementation of the individual agents. The contribution of this paper is the development of an approach to measure current and past motives of organic food consumption for classes of agents. This approach, based on rough set data analysis, is able to detect behavioural rules from surveys with consumers. These behavioural rules can be used in simulation models to explore possible future developments of organic food consumption.

The usefulness of rough set theory depends on the definition of attributes and objects. In the analysis of our data set we propose to use a conceptual framework of consumer behaviour to classify attributes and objects. This framework, the consumat approach, is a meta-theory of consumer behaviour based on theories from psychology (Jager, 2000). In various studies, the consumat approach is used to explore market dynamics based on different assumptions of consumer behaviour (Janssen *et al.*, 1999, 2001a, b). We expect that using the conceptual framework of consumer behaviour will be very useful for analysing the set up of and results from rough set data analysis. Furthermore, we expect that rough sets theory is suitable to translate survey data into behavioural rules for multi-agent computer simulation.

The outline of our paper is as follows. In the next section we discuss diffusion processes, the relevant theories on understanding the underlying decision processes of consumers, and multi-agent modelling of consumer behaviour. The section thereafter provides a brief overview of rough set data analysis. Then we discuss how to use rough set data analysis to relate it with multi-agent modelling. Finally, we discuss how the detected behavioural rules can be used to simulate future developments of organic food consumption.

Diffusion processes and consumer behaviour

Throughout history our food consumption patterns have been changing continuously. Remarkable changes took place as regards the type of foods we eat (e.g. the introduction of the potato in Europe, the consumption of organ meat), the way we grow our food (e.g. the introduction of pesticides, bio-industry), how we process our food (e.g. frozen food, microwaves) and our table manners (e.g. the introduction of the fork in medieval Europe, fast food). All these changes more or less slowly conquered the food consumption habits of the masses, may it be in centuries (the use of the fork) or within a decade (the microwave). Many factors determine the speed and degree to which such changes diffuse through the population. Theory on the diffusion of innovation provides an inventory of the factors that affect the rate of adoption of this diffusion process. Moreover, this theory draws a perspective on consumer characteristics that determine if people are "innovators", or belong to the group of people that follow later in adopting a new practice.

Diffusion processes

The innovation diffusion theory as introduced by Rogers (1962) is the most frequently cited publication in this field. The general conclusions of Rogers provide a means of analysing innovations and exploring the reasons of how food consumption changes. Rogers states that the cumulative number of adopters typically follows an s-shaped curve. The s-curve starts to rise slowly when the first innovators adopt the innovation. Following that, the cumulative number of adopters rises somewhat faster due to the early adopters. The curve is at its steepest when the early majority and late majority successively adopt the innovation. The curve increases at a slower rate when the laggards adopt the innovation slowly. Generally, early adopters appear to weigh their personal needs more, have a higher aspiration level (venturesome for the innovator and respect for the early adopter (Rogers, 1995, pp. 263-4)) and are more actively searching for information (Rogers, 1995, p. 274), whereas, late adopters appear to attach more weight to their social needs, have a lower aspiration level and search less for information. Moreover, early adopters are better at coping with uncertainty than late adopters (Rogers, 1995, p. 273). This may have consequences for the type of decision process they employ, because people that have a lower tolerance level for uncertainty may engage more in social processing (social comparison, imitation, see also Jager, 2000).

Rogers (1995) emphasises the importance of reaching a certain "critical mass" of adopters, beyond which the innovation will diffuse without much stimulation. This can be assumed to reflect the importance of having sufficient role models that increase the chance that the innovation is being spotted by less innovative people that engage more in social comparison and imitation.

The speed and degree to which an innovation diffuses (the slope and top-level of the s-curve) is related to several factors. Rogers (1995, p. 206) states that most of the variance (49 to 87 per cent) in the rate of adoption is explained by five attributes of the innovation:

(1) relative advantage;
(2) compatibility;
(3) complexity;
(4) trialability; and
(5) observability.

In addition to the attributes of the innovation, also factors such as type of innovation-decision, communication channels involved, nature of the social system in which the innovation is placed, and the extent of the change agents' promotional efforts affect the rate of adoption.

The general idea is that when an opinion leader has adopted, and a critical mass of adopters is reached (3-16 per cent), the innovation will diffuse without much promotion of change agents. Sometimes people may overadopt an innovation, for example when they innovate because of status reasons whereas the practical applicability of the innovation is relatively low. Rogers (1995, p. 216) explicitly mentions that this phenomenon should be studied further. We consider this effect of overadoption typically as an outcome of underlying behavioural dynamics, where people overvalue certain aspects (e.g. status) in making a decision. This makes clear that the decision process that people use is a critical factor in the innovation diffusion process. When they deliberate a lot they will perceive the innovation early. When they engage in imitation or social comparison they may learn about the innovation from others. But when they habitually repeat their behaviour they may remain unaware of the innovation. It is evident that the behavioural dynamics/decision processes that dominate/characterise a typical market will affect the rate and speed of innovation diffusion to a large extent.

For example, when people invite other people for a more formal dinner they often deal with important decisions with respect to which foods to serve and how these will affect their social identity. For example, you would not like to serve your boss a simple meatball, and a very experimental dish may also be a bad idea. Moreover, people may be uncertain because there is a large number of dishes and wines to choose from, and it is at first unclear how the guests may value these foods, both in terms of taste and social value for the occasion. This uncertainty causes people in general to talk frequently about food, and several magazines and television programmes are devoted to cooking. The market can thus be seen as affected by a social comparison processes, which may elicit a somewhat competitive market with fashion dynamics (see e.g. Janssen and Jager, 2001a). This may explain the various trends that can be seen in cooking, such as the popularity of the fondue in the 1970s, nouvelle cuisine in the 1980s, Cajun in the 1990s and the current trends such as slow-food, fusion cooking and locally grown food.

In estimating the chances for organic food, for example, as an innovation to diffuse in the market, the five attributes as identified above play a role as follows.

The relative advantage is normally interpreted in terms of economic profitability, social prestige and other outcomes. Research has consistently show that only the percived advantages of environmental innovation are one of the best indicators for their subsequent adoption. Thus, innovations in food consumption which are belived to be profitable are usually readly adopted. People are generally motivated to think about alternatives when their current behaviour is not fully satisfactory. Hence, when they are satisfied with their current behaviour they might remain unaware of the innovation and its (changing) characteristics (e.g. decrease of price). Moreover, it appears that relatively fast positive outcomes speed up the process of diffusion, whereas preventive and/or distant outcomes lower this rate of diffusion (Rogers, 1995, pp. 216-17). This also makes clear that when people decide, they do not engage in economic optimising (rational actor type behaviour), but rather use more simple heuristics or engage in biased information processing in their evaluation of the relative advantage.

The compatibility of an innovation refers to the extent to which it fits with sociocultural values and beliefs, previously introduced ideas and needs for the innovation. The higher the compatibility of the innovation, the faster its diffusion will proceed.

The complexity is related to the perception of how difficult the innovation is to understand and use. It has a negative effect on the rate of the diffusion, although the research is not conclusive on this effect (Rogers, 1995, p. 242). People that are very motivated to adopt a new innovation (e.g. organic foods) are more likely to spend cognitive effort in understanding this complexity, and hence will be better capable of dealing with it, thus benefiting from the innovation. However, people that are less motivated, and experience uncertainty because of the complexity, may decide to buy environmentally friendly produced foods by observing the outcomes of the early adopters and estimating how they could benefit from eating healthy food themselves (social comparison). However, these people may experience much more difficulty and frustration in dealing with the innovation than the early adopters, which is in line with the observations of Rogers *et al.* (1980).

The trialability is how much an innovation is easy to test before making a full commitment. It affects its diffusion positively, especially among the innovators and early adopters as these have no behavioural examples of other people that use the innovation (Gross, 1942; Ryan, 1948). The more people already adopted to the innovation, the less important this trialability becomes, because the experience of other people (social capital) can be employed in deciding to innovate.

The observability is the extent to which the features and benefits of an innovation can be observed and described to non-users. It is considered to be positively related with its adoption (Rogers, 1995, p. 244). Here we want to add that this observability relates to the innovation use, which may be public or private, and to the proportion of people that have already adopted the innovation. As regards the latter, especially the people that base their decisions on social information may perceive a low proportion of people using the innovation as a strong clue not to adopt.

The Bass model makes an important contribution to the study of innovation diffusion by modelling the process in a mathematical way. Bass (1969) proposed that potential adopters of a new innovation are influenced by two means of communication, namely mass media and word of mouth. The Bass model further assumes that there is a group of "innovators", that exclusively use mass media as a source of information, and "imitators", that exclusively use word of mouth. Whereas the Bass model approached the market as an aggregate, several researchers developed micro-level models to study the individual foundations of innovation diffusion (see e.g. Mahajan *et al.*, 1990). For example, Chatterjee and Eliashberg (1990) contributed to the modelling of innovation diffusion by introducing a micro-level model that allows studying the effects of heterogeneity in populations on the diffusion of innovations. Such a micro-level model is the basis of multi-agent modelling of consumer behaviour.

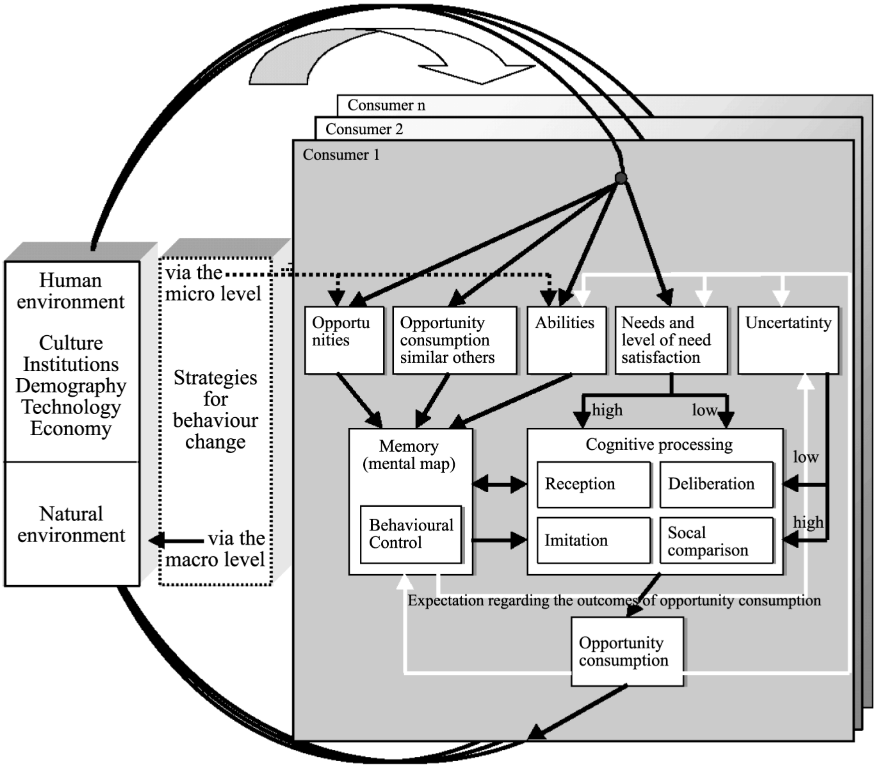
Consumer behaviour

Many behavioural theories, like theories about human needs, motivational processes, social comparison theory, social learning theory, theory of reasoned action and so on, all explain parts of the processes that determine consumer behaviour. Social psychology is often discussed to be in a pre-paradigm state. According to some scholars there is a need for a meta-theory of human behaviour. The multi-theoretical framework of Jager (2000) tries to offer such a meta-theory (Figure 1).

The figure indicates that consumer behaviour can be conceived as a cyclical process, in which the micro-level behaviour of many individuals and the macro-level outcomes mutually affect each other. The driving forces at the collective (macro) and the individual (micro) level determine the environmental setting for consumer behaviour. The collective level refers to technical, economic, demographic, institutional and cultural developments, and thus describes the world the consumers are living in. The individual level refers to the consumers, who have different needs which may be more or less satisfied, are confronted with opportunities for consumption, and have various abilities to consume these opportunities. Furthermore, consumers may be more or less uncertain, depending on the difference between expected and actual outcomes of their behaviour.

Modelling consumer behaviour

Computer simulation is an increasingly popular tool for social scientists to unravel observed social phenomena (e.g. Gilbert and Troitsch, 1998). Traditionally, social scientists statistically analyse data originating from surveys and controlled laboratory experiments. However, because these analyses are based on limited numbers of subjects and conditions, they are usually less suitable to identify the relevant dynamics of more complex



Source: Jager (2000)

Figure 1.
The conceptual model of consumer behaviour

systems. Computer simulation has become an additional tool for social science to perform a large number of controlled experiments with a population of agents. The description of these agents is based on theories from social science and artificial intelligence. The resulting models are often used to understand observed stylised facts.

A challenging additional step is to use survey data to simulate concrete phenomena. A problem of deriving such behavioural rules is the limited available methodology of extracting these behavioural rules. Statistical analysis is able to provide averages of a population, but is less suitable for finding concrete behavioural rules for a heterogeneous population of agents. The rough set data analysis approach, developed during the 1990s in the framework of artificial intelligence (AI) techniques, provides a method to extract the required behavioural rules, as we will discuss later.

In behaviour-based AI the term aimat, referring to artificial animal (coined by Wilson (1985)), is frequently used. The consumat approach (Jager, 2000) is a multi-agent simulation approach based on a multi-theoretical framework. The term consumat it introduced to specify the artificial human consumer, that is simulated agent whose rules are based on psychological theories.

The driving forces at the collective (macro) and the individual (micro) level determine the environmental setting for the consumat behaviour. The consumats are equipped with needs, which may be more or less satisfied, they are confronted with opportunities to consume, and have various abilities to consume the opportunities. Furthermore, consumats have a certain degree of uncertainty, depending on the difference between expected and actual outcomes of their behaviour.

The consumats may engage in different cognitive processes in deciding how to behave, depending on their level of need satisfaction and degree of uncertainty. Consumats having a low level of need satisfaction and a low degree of uncertainty are assumed to deliberate, that is: to determine the consequences of all possible decisions given a fixed time-horizon in order to maximise the level of need satisfaction. Consumats having a low level of need satisfaction and a high degree of uncertainty are assumed to socially compare. This implies the comparison of own previous behaviour with the previous behaviour of consumats having about similar abilities, and selecting that behaviour which yields a maximal level of need satisfaction. When consumats have a high level of need satisfaction, but also a high level of uncertainty, they will imitate the behaviour of other similar consumats. Finally, consumats having a high level of need satisfaction and a low level of uncertainty simply repeat their previous behaviour. When consumats engage in reasoned behaviour (deliberation and social comparison) they will update the information in their mental map, which serves as a memory to store information on abilities, opportunities, and characteristics of other agents. After the consumption of opportunities, a new level of need satisfaction will be derived, and changes will occur regarding their abilities, opportunities and the social and physical environment, which will affect the consumption in succeeding time steps.

In recent papers the consumat approach is used to understand market dynamics from a psychological perspective (Janssen and Jager, 2001a, b). They found that different types of market, such as lock-in of one type of product, of unstable fads-and fashion dynamics, can be explained from the minimum level of need satisfaction the consumats need to derive before they are satisfied, and the level of uncertainty they tolerate. Different types of market dynamics can be attributed to the cognitive process that dominates the decision making process. A consequence of this is that for some kinds of markets, where consumers are easy to satisfy but quickly uncertain, a large chance of (local) lock in exists due to the frequent imitation of the consumers. However, when the consumers are not easily satisfied, a high uncertainty yields a market with timely fads and fashions. Hence, in order to understand the dynamics of (organic) food consumption, it is important to detect how different market segments are characterised in terms of the different underlying consumer needs (e.g. subsistence, identity), the role of (social) uncertainty and heterogeneity of consumers as regards their preferences and abilities. Characteristics of consumats are drawn from distributions. These distributions can be informed by empirical analysis such as surveys. Some of these distributions describe the behavioural rules and what rules consumers use for making particular decisions. Simulations of consumats, using the rules extracted from surveys by using rough set data analysis, might be able to provide insight into individual decision making and the characteristics of the market, and provide a laboratory setting to test marketing strategies.

Rough sets as tools of data mining

Introduction

In recent years we have witnessed an interest in the study of consumers' behaviour for organic food. Various approaches have been developed aiming at describing, modelling and predicting the various way that consumers make a purchasing decision.

Data mining (DM) is a well-known theoretical research field attempting to explain observed variations in behaviours and values. A typical problem in market research application can be stated as follows. Given a database of survey data representing characteristics of customers, along with the information reflecting the kind of product to be purchased, identify some specific combinations of the characteristic occurrence which would increase the chances for the products to be purchased. Databases for marketing purposes are characterised by detailed data at the level of the individual consumer. However, this information needs to be turned into knowledge in order to become useful.

DM is a multi-stage process concerned with extracting useful information from a complex database and applying the results to decision making. DM tools detect patterns and rules and infer association and rules from them. The extracted information can be applied to prediction or classification model by identifying relation within variables. In recent years artificial intelligence techniques have gained increasing popularity for the identification of underlying structures in complex databases. In fact, a data system on organic food consumption can be regarded as a qualitative database that is suitable for classification and explanation.

However, according to a widely accepted description of Fayyad *et al.* (1996), DM is a useful approach but it is only a first step in a larger iterative and interactive process called knowledge discovery in databases (KDD). This process consists of the following steps: data warehousing, target data selection, data cleaning and pre-processing, data reduction and extraction of useful features, choosing the DM algorithm(s), model selection, interpretation of mined patterns, consolidation and use of knowledge.

Generally, data on a particular topic are acquired in the form of symbolic and numerical attributes. Analysis of these data gives a better understanding of the phenomenon of interest. The main objective of any data analysis is, therefore, to discover new knowledge that will be used to solve a problem or to make decisions. However, there are various problems with the data which may prevent this. In most cases, imperfections on the database are not noticed until the actual data analysis starts. For example, in the development of knowledge-based systems the data analysis is performed to discover and generate knowledge for building a reliable and comprehensive knowledge base. The reliability of that part of the knowledge base that is generated through data analysis techniques such as induction is, therefore, heavily dependent on the available data (Famili *et al.*, 1997).

In the context of this paper we propose the use of rough set data analysis (RSDA) as a tool to extract previously unanticipated knowledge from large databases. Its attractiveness as an application of KDD relies on the fact that it is based on minimal model assumptions and admits ignorance when no proper conclusion can be drawn from the data at hand (Ziarco, 1998). RSDA draws all its information from the a priori given data set. In other words, RSDA remains at the level of the empirical system: more formally, the numerical and the empirical system coincide and the scaling is the identity function. In RSDA, there is no numerical system that is different from the operationalisation of the observed data, and there are no outside parameters to be chosen, nor is there a statistical model to be fitted. In the practice of RSDA, however, there are numerous attempts to find an optimal RSDA model. In principle, there are two strands: the classical main approach concentrates on finding (near) reductions and short rules via a Boolean reasoning to explain the (endogenous) decision variable. It uses simple probability measures such as approximation quality, rough membership and rough inclusion which are obtained from within the data in order to estimate and optimise the explanation and prediction quality of various attribute sets. These measures are conditional on the choice of attribute sets. A second strand integrates the complexity of rules and the estimation of prediction errors into a common unconditional measure by employing various entropy functions. These methods are substantially different from the previous ones, and the clear structure of their relationship with the traditional rough set methods and their consequences still needs to be further explored.

RDSA is not part of all the processes in data discovery knowledge. In fact, data collection and selection are essentially not a part of RSDA, which assumes that enough care has been taken in these steps so that the operationalisation of data is sufficiently accurate to be a sound basis for analysis. Data pre-processing consists of several mechanisms to solve problems with the data structure at hand. Discretisation and missing data treatment are issues that were not part of the classical RSDA, but are today rather well developed (Deogun *et al.*, 1997).

Noise reduction does not apply to RSDA in the sense of a classical statistical KDD procedure, because RSDA has no concept of noise in a statistical sense. Nevertheless, reducing complexity by removing dependency within the data set is a procedure that reduces noise as well. Indeed, RSDA can be viewed as a pre-processing device to recognise the potentially important explanatory variables, for example for the construction of a multiple regression model in order to reduce the problem of multi-collinearity.

Data reduction is the main feature of RSDA, as it allows representation of hidden structures in the database.

Next, we will offer a brief introduction to the study of rough sets (Pawlak, 1991, 1992). However, in the context if this paper we will not give a formal description of the rough set theory, for which we refer to the extensive bibliography published on this topic (see, for example, Skowron and Polkowski, 1998).

Learning from vague information: algorithms for induction of decision rules

The rough set theory originally introduced by Pawlak (1991) is a mathematical tool to deal with vagueness and uncertainties in data analysis. The theory is based on the assumption that some information is associated with every object of the considered universe. Objects characterised by the same information are indiscernible (similar) from the point of view of the information associated to them. A set of indiscernible (similar) objects is called elementary set.

Knowledge, according to the rough set philosophy, is generated when we are able to define a classification of relevant objects, e.g. states, processes, events. By doing this we divide and cluster objects within the same pattern classes. These classes are the building blocks (granules, atoms) of the knowledge we employ to define the basic concepts used in rough set analysis.

For algorithm reasons knowledge about objects (consumers) is represented in the form of an information system. The information system consists of a finite set of objects (U), a set of characteristics or attributes (Q) with which these data can be described, a domain (V) of these attributes, and finally, an information function which permits the classification of a datum and its attribute to a given domain $f(x, q) \rightarrow V$ such that $f(x, q) \in V_q$ for every $q \in Q$ and $x \in U$. Hence, an information system can be expressed as quadruple $S = <U, Q, V, f>$.

The information system is represented in a finite data table in which rows correspond to objects and columns correspond to attributes. To each pair (object, attributes) there is assigned a value called a descriptor. Each row of the table contains descriptors representing information about the corresponding object of a given decision situation. In general the set of attributes is then partitioned into two subsets: condition attributes and decision attributes. The information system is also called a knowledge information system.

However, the methodological issue proposed in this paper refers to the use of rough set theory for extracting decision rules. A decision rule as an implication relation between the description of a condition class and the description of a decision class. The decision rule can be exact or deterministic when the class of decision is contained in the set of conditions, i.e. all the decision attributes belong to the class of the condition attributes. We have an approximate rule when more than one value of the decision attributes corresponds to the same combination of values of the condition attributes. Therefore, an exact rule offers a sufficient condition of belonging to a decision class; an approximate rule only admits the possibility of this.

The topic of rule induction has been extensively investigated in other fields and in particular in learning machine where several efficient algorithms software systems have already been proposed, for example the classical version of Quinlan's ID3 algorithm and the modified updated versions, probabilistic tree classifier PT, ELISEE method, and C4.5 system in a rule option (for a comparison of the implementation of the different algorithms (see Stefanowski and Wilk (1999)). Most existing learning systems handling uncertainties are based on probability theory. Some of them use the subjective Bayesian approach while others add statistical tools. A popular method is to induce a decision tree which must be transformed into rules (Stefanowski, 1998). Knowledge in the form of rules induced by learning from example is easily understandable. Rules are symbolic representations of knowledge. The induction of rules from examples is a typical approach of artificial intelligence. It is concordant with the principle of posterior rationality by March (1988). According to Slovic (1975), people make decisions by searching for rules which provide a good justification of their choices. However, a direct statement of decision rules requires a cognitive effort from the decision maker, being typically more confident making exemplary decisions than explaining them. Moreover, the learning system is frequently forced to deal with uncertainty derived from incomplete or conflicting evidence. The main focus of a rough set is rule induction from conflicting evidence, i.e. from inconsistent examples (two examples classified by the same values of attribute belong to two different classes).

However, the peculiarity of the rough set approach is that inconsistencies in a dataset are not aggregated or corrected since lower and upper approximation for each class are computed. As a consequence induced decision rules are distinguished as certain (exact) and approximate (possible) depending, respectively, on the use of lower and upper approximations.

A decision rule R is a logical statement of the form of if "C then D", where C is the condition part of a rule, and D is the decision part. More precisely, let $(U, A \cup \{\mathrm{d}\})$ denote an information system where U is a finite set of objects, A is a finite set of condition attributes, $d \notin A$ is a decision attribute that defines partition of objects into a set of decision classes $Y_1, Y_2, \ldots Y_k$. Let K represent the decision concept to be described by rules, i.e. decision classes Y_j. An elementary condition is defined as an expression (a rel v) where $a \in A$ and v is its value (or a set of values) and rel stand for relational operator, i.e. $=, \geq, \leq, \in$. Let C be a conjunction of q elementary condition, i.e. $C = c_1 \wedge, c_2 \wedge \ldots \wedge c_q$. Then $[C]$ is the subset of the example which satisfies the condition represented by C. Considering the concept K to be described, this subset is divided into the positive cover $[C]^+{}_K = [C] \cap K$ and the negative cover $[C]^-{}_K = [C] \cap U/K$. In order to evaluate discovered rules several measures could be used. Usually the following measures are used: absolute strength $(R) = |([C]^+{}_K|$ (and relative strength $(R) = |[C]^+{}_K|/|K|$; length $(R) = q$; level of discrimination of a rule

$D(R) = |[C]^{+}_{K}|/|C$. The level of discrimination is the probability an object satisfying the condition part of the rule belongs to the class pointed out in the decision part. If the level of discrimination is equal to 1 then the rule is able to predict exactly the class of the covered object, if it is less than 1 the prediction is approximate.

Using rough sets theory for generation of behavioural rules

Rough sets theory is a suitable candidate to transform survey data into decision rules for different types of consumers. If consumers are classified according to their demographic and socio-economic characteristics, we expect to trace decision rules when to consume a certain opportunity. For example, if consumers fall in category X on demographic and socio-economic characteristics and attributes have values Y then they consume a certain level of opportunities Z.

Survey data cannot provide us direct information on the use of cognitive processes, but it might provide information on the relative threshold of need satisfaction and uncertainty tolerance.

Multi-agent models are suitable tools to study macro-level phenomena from micro-level actions of a heterogeneous set of agents. Besides extracting possible rules as used by real agents, rough set data analysis may provide distributions of particular types of agents who differ in the rules they use for making food-related decisions. Such distributions can be used to generate large sets of consumats for the computational laboratory. Evidently, such a model should be able to reproduce current market dynamics, but may also be used to explore new policies. Such policies might be focused on the stimulation of the diffusion of organic food products. The computational laboratory might provide likelyhoods of the success of alternative policies. Sensitivity analysis can provide insights on which barriers have to be broken to introduce organic food products and how stable organic food products will be for invasions of other food products.

For example, when consumers are asked about the importance of certain characteristics of food consumption it may differ in the weight on availability/quality, trends/exclusiveness, price/design, etc. Rough set theory can supply information about what are the characteristics of consumers with relative levels of satisfaction and uncertainty tolerance.

We cannot measure cognitive processes from the subjects directly, especially in interviews. However, we may get some indirect information. For example, by asking whether they think it is important that people in their social network have the same pattern of food consumption, the amount of time they spend on making particular decisions, etc. There are different rough algorithms for rule induction. All of them aim at rule description of the decision classes but the type of induced rules can be different according to the perspectives for which they are used. As suggested in Stefanowki (1998), three different rough set based approaches to induction of decision rules can be identified:

(1) *Extracting a minimum set of rules: the classification strategy.* Well-known approaches for inducing classification rules have been constructed taking into account only the classification point of view. A large body of research in induction of classification rules addresses learning as a knowledge acquisition task in building classification systems. Here, classification rules are used to predict the class of an example, where the class could be the discrete variables representing, for example, the willingness to buy organic food. Most of them are focused on inducing a minimum set of rules. The algorithm LEM2 follows a heuristic strategy, which is typical of many well-known machine learning techniques. This strategy consists of creating a first rule by choosing sequentially the best elementary condition according to some heuristic criteria (Gzymala-Busse, 1992). Thus, learning examples that match this rule are removed and if there are some significant undescribed examples the procedure is repeated. Such algorithms are particularly useful in case we are interested in a decision list, where an interpretation of each rule depends on its position in the list. A disadvantage of this procedure can be the fact that the minimum set of rules contains only a limited part of interesting rules

(2) *Discovery oriented induction: the satisfactory strategy.* Since generally a database is replete with patterns and few of them are useful, there is the need to look for "interesting" rules. Generally, a pattern is interesting to the degree to which it is accurate and useful with respect to the knowledge discovery, and objective of the user. Thus, discovery of such decision rules is a difficult problem depending on the context of application and requires close interaction with the user because he has to define the requirements for deriving knowledge. Indeed, the meaning of terms like interesting rules or potentially usefully information depends on the interests and expertise of the user. For this purpose the algorithm Explore has been introduced (Mienko *et al.*, 1996). In the algorithm Explore the search for rules is controlled by parameters called stopping conditions (SC) that reflect users' requirements. The exploration of a rule is performed using an algorithm, which is repeated interactively for each class to be described. The main part of the algorithm is based on a breadth-first strategy, which generates rules of increasing size starting from the shortest one. The strategy start begins with the initial rules having an empty condition part. In each step all rules are evaluating again the threshold value of the strength and strength. Rules that are too long or too weak are discharged. Then the level of discrimination of remaining rules is evaluated and rules with acceptable values of these measures are stored. Rules with an unacceptable value of discrimination level are further specialised by adding new elementary conditions.

(3) *Extracting an exhaustive set of rules: the overall learning strategy*. This kind of rule description provides the richest information about patterns existing in a database. Besides strong rules it induces rules that are weak and very specific. There are also rules referring to the same or overlapping objects and rules having condition parts. These conditions are very demanding from the point of view of readability. Nevertheless, they could be useful both from the point of view of classification and discovery application.

When using rough sets analysis in combination with the conceptual model of behaviour, we try to identify those factors that play an important role in the decision rules for different consumers. First of all, these rules pertain to the different needs that may play a role in the consumption of food. Besides subsistence, also affection, understanding (experimentation), participation (sharing) leisure, creation and identity may be needs that more or less play a role here. People not only differ regarding the weighting of these needs (e.g. one may like experimenting in the kitchen, whereas the other not), but may also differ regarding how they prefer to satisfy these needs. Whereas one person likes raw vegetables, the other prefers a medium steak. Attention thus should be given to the preferences people have. The (un)certainty people have regarding the capacity of (organic) food to satisfy their different needs also plays an important role. Hence uncertainty touches on issues such as nutrition, health, animal welfare, environmental concerns and social (status) concerns. Next, attention should be given to the abilities people have. As regards food we may think of financial abilities, cooking abilities, knowledge regarding food and its origins and the social (cultural) environment as regards food. On the basis of rough sets analysis it would be possible to formalise the factors as mentioned above into the consumat rules. This would subsequently allow simulating the diffusion dynamics of organic food consumption, and experimenting with various assumptions and policy measures on these diffusion dynamics. Robust simulation results should be validated in practice before practical conclusions regarding policy measures aimed at stimulating organic food consumption can be drawn.

Conclusion

In this paper we have proposed an approach to link survey data to computational multi-agent models of consumer behaviour. Such an approach can be used to understand the conditions that foster the diffusion of organic food products. Rough set data analysis provides a suitable link between survey data and multi-agent models since it is designed to extract decision rules from large quantitative and qualitative data sets. The following step in this project will be the application of this approach to a survey dataset on organic food consumption.

Currently, application in marketing research of KDD tools, as rough set analysis, are rapidly growing. Using KDD methods, the marketer gains additional value from large amount of data through a broader and more effective analysis. DM is the overall process of finding interesting patterns from data. It is also referred to as interactive and iterative knowledge discovery in the database process, involving repeated application of a specific algorithm. Through the use of specific algorithms they attempt to source out discernible patterns and infer rules from those patterns. These rules can be useful to support revision and examine consumers' decisions. Moreover, from a marketing perspective of organic food products they allow the targeting and tracking of groups of customers as distinctive segments and thus indicate a marketing strategy which recognises special attributes of individual customers. Along with techniques from the emerging field of interactive marketing, KDD methods offer an opportunity for a strategic dynamic customer segmentation.

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