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AN APPROACH TO INTELLIGENT MODELING OF CUSTOMER BEHAVIOR AND DECISION SUPPORT IN COMPLEX MARKETING: MULTI AGENT SYSTEMS

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ABSTRACT

Traditional marketing research studies take a micro or macroeconomic viewpoint of the market place. [1] Consumers are studied as separate entities that make decisions on which products to purchase, and firms are studied as another type of entity that make decisions on what products to introduce to the marketplace. Consumer marketing research has more of a focus on the psychological perspective of consumer decision-making whereas managerial researchers take more of an organizational perspective. Rarely are the two approaches studied together. Although this is a simplistic mindset to marketing research, it does exemplify the mutually exclusive approach common to marketing researchers

In this paper the main focus is on the methodology, agent-based modeling (ABM), as a vehicle for studying complex adaptive systems. The primary goal of the paper is to develop multi agent systems for intelligent modeling of customer behavior and decision support in a complex competitive marketing environment. The proposed multi-agent system, including its architecture and implementation, are presented and demonstrated through an example integration scenario involving real planning and execution.

Keywords: Multi Agent Systems, Complex Marketing, End User Agent , Behavior Networks

Introduction

Increasing globalization helps international companies to gain more and more market share and more pressure is put onto local competitors. Companies have to develop new strategies to remain competitive. An essential part of the competitive position is the optimization of assortments and prices. In the daily decision making process there are many different alternatives and combinations from which the person in charge has to map out an optimal strategy The biggest problem is the enormous amount of alternatives and the complexity of internal relationships and external influences, such as competitor's prices and promotions, market trends, the economic situation and weather conditions. To solve this problem a number of approaches have been considered, e.g. regress analysis [12] in economics, which provides means for a more accurate forecast. More recent approaches in computer science include the use of neural networks [12, 11]. Yet all these approaches have significant disadvantages: regress analysis provides us with acceptable quantitative results; however, it allows for just a few factors to be included in the analysis and can only treat linear dependencies. Neural networks can cope with a much higher number of influencing factors and while single-layered networks

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can only model linear dependencies, multi-layer neural networks can even model nonlinear dependencies. The problem with neural networks is their fast rise in complexity, which renders them unsuitable when augmenting the number of factors. But more important is the fact that both approaches simply predict future values out of past experience without a deeper understanding of how the individual factors correlate. To sum, up these approaches can support the decision making process only up to a certain extent resulting in sub optimal solutions to be optimized by man. A fully satisfactory approach to this problem must be able to model and simulate the individual customer's behavior as a reaction to both internal and external influences. Given perfect information on the individual behavior of a customer we could then predict the overall behavior of a group by considering the sum of the predictions for all individuals. For a large group it would even suffice to consider a representative subgroup to determine the likely overall reactions to influences like promotions or changes in price or location

The Multi Agents approach used in this paper does just that. It simulates a representative set of individual behaviors by modeling each individual customer through an individual software agent. Note that the behavior is determined from real world data by using special learning algorithms to extract the relevant information where "real world" refers to data gathered by a company on its human customers. The area of user modeling which has a long history at DFKI [6] is closely related to the area of customer modeling. Multiagent based user modeling provides a rich basis of concepts for representing patterns of human behavior in agents. Schaefer [7] successfully uses dynamic Bayesian networks [8] to model users of dialog systems and to personalize the application flow.

The agent architecture uses also known models from psychology and economics. It models the relevant entities and external factors of a company in order to create a test scenario, where the agents react to the scenario according to their individual behavior patterns. As these patterns are derived from the actual behavior of individual human customers the system is capable of predicting realistic results.

What is a Multi-agent System

A multi-agent system is a loosely coupled network of problem-solver entities that work together to find answers to problems that are beyond the individual capabilities or knowledge of each entity. It is composed of multiple autonomous components showing the following characteristics:

- Each agent has incomplete capabilities to solve a problem
- There is no global system control
- Data is decentralized
- Computation is asynchronous

One of the current factors (and arguably one of the more important ones) fostering MAS development is the increasing popularity of the Internet, which provides the basis for an open environment where agents interact with each other to reach their individual or shared goals. To interact in such an environment, agents need to overcome two problems: they must be able to find each other (since agents might appear, disappear, or move at any time); and they must be able to interact

This section provides a case study describing how agent-based technology can be applied in business applications. The primary goal of the paper is to develop multi agent systems for intelligent modeling of customer behavior and decision support in a complex competitive marketing environment.

A Proposal for a Multi-Agent Architecture

The proposed multi-agent system, including its architecture and implementation, are presented and demonstrated through an example integration scenario involving real planning and execution.

Architecture

In this paper we use a holonic multiagent system (MAS), which supports agent groupings as *holons* so that each individual agent can be a member of different agent groups. A holon is an agent that represents a group of agents whereas each group member keeps its individuality [2]. We model each individual customer as an agent, which behaves according the customer's individual preferences. These preferences are extracted from real world data, such as customer cards, sales data and interviews. The customer's shopping behavior is represented in *behavior networks, which* are stored in the customer agents' knowledge bases. The behavior of a representative group of customers induces the overall sales figures, which support decisions what to sell at which price. In addition the MAS is connected to a *data warehouse,* which stores real data from the related market. [1]

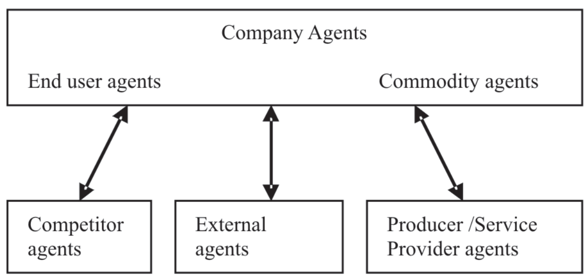

Figure 1: Multi Agent Architecture

Fig. 1 shows the current architecture where each element is modeled as an agent. The whole company is also represented by a *company agent* who provides detailed information about the specific company, such as assortment of goods, item prices and promotions, shelf layouts, sales data, costs and so on. The *end user agents* model the individual customers and their personal shopping behavior. The system is able to represent each customer individually as well as an arbitrary number of (possibly not disjoint) customer groups and subgroups. The largest group of customers, the group of all customers, is represented by a *end user group agent*. Similarly all items are represented as *commodity agents* who are grouped into predefined commodity groups modeled by *commodity group agents*. In addition, commodity can be dynamically classified in order to generate groups such as private brand commodities, all commodities that are lower than *n* Euros and so on. The group of all commodities is represented by the *meta commodity agent*. The architecture of the MAS supports also *competitor agents* which model relevant competitors. These agents provide information about the competitor's prices, promotions and strategies. They may have links to common customers and items. We can have *producer/service provider agents,* which mainly provide information about the current range of products, their prices and promotions as well as details about forthcoming products. Important external effects and influences e.g. current season, economic situation and weather conditions are represented by *external agents*. These are information agents who collect and administrate the relevant data from external services or the internet. They generate simple forecasts or (if provided with insufficient data) request more detailed prognosis from external services (such as e.g. the daily weather forecast).

End User Agent

According to the literature, the classification of a customer can be based on a variety of criteria or similarities, e.g. there are many different concepts and models of customer groups developed in marketing [10] and psychology, such as the “Sinus- Milieus” from Sinus Sociovision [4] or the “Euro-Socio-Styles” from CCA/Euro panel [5]. Metaphorically speaking the characteristics of a customer [3] competes for the greatest influence on the customer’s decision. For this reason it is important to consider the customer’s characteristics and factors themselves as *characteristic agents*. Each *characteristic agent* represents a single factor of the customer’s behavior, such as price and promotion consciousness or brand loyalty. Collectively, these agents form a multiagent system of their own, the *society of characteristic agents*. From this point of view the customer’s (shopping) behavior is the result of the interaction of its characteristic agents, a view that conforms to Marvin Minsky’s “society of mind” [3]. The predictions of the shopping behavior and preferences of customers are represented in the end user agents. Any individual customer that is known to the company through empirical surveys, the use of customer cards, electronic payment or direct contact is represented as an individual end user agent. End user agent administrates the knowledge and information about a related customer and his behavior. The knowledge consists of a *personal profile* (information about age, income, gender, domicile etc.) and a special model of the customer’s individual buying preferences. We consider the customer’s behavior as an interaction of many different factors e.g. characteristics, addictions, needs and environmental influences. These factors may correlate or even contradict each other. For example, it is interesting whether the quality sensitivity outweighs the price sensitivity for a certain offer or not, i.e. whether a very low price can “persuade” a customer to purchase a low-grade product or not.

End User Group Agents

In order to support complex groupings of customers in our system, each *end user agent* can be a member of one or more *end user group agents*, which are represented as holonic agents. Thus, we are able to simulate a certain group of customers either by simulating all related individual group members (higher accuracy) or by simulating the average group behavior (higher computational efficiency) depending on situation at hand. Customer groups can be built beforehand or dynamically at runtime where the criteria can vary, for examples similarities concerning the personal profile (same age, gender or domicile etc.) or patterns of shopping (similar baskets of goods, same product interests, similar price consciousness etc.) or a combination Evaluating the actual distribution of customers over typical customer groups by comparing the shopping data of individual customers to typical shopping baskets is important. This will allow for a detailed ratio analysis of the customer groups of a company and thereby to fine-tune the weighing of the group based simulation results.

Behavior Networks

The empirical data, i.e. the characteristics of individual customer shopping behavior, was primarily extracted from customer cards data, questionnaires and from general marketing knowledge. It can be represented in behavior networks, i.e. Bayesian nets. The quality of the customer simulation and prognosis depends mainly on how exact and realistic these characteristics and thus the shopping behavior of individual customers can be modeled. We can base our approach on a rule system where customer data is encoded in a set of rules, which are associated with conditional probabilities. The rules can be stored in a specific network structure - the behavior network - to represent the dependencies between them. Bayesian networks are an example of such network formalism. We can model the behavior of a customer by generating a specific Bayesian network [9] or each relevant commodity group. We extract these networks by data mining patterns of behavior from individual customer data. In addition, we can integrate the individual dependencies of single customers of external influences, e.g. weather, economic situation or seasons into the behavior networks.

Agent-Based Simulation

The decision about assortment, prices and promotions is based on assumptions concerning future external influence factors as well as the current situation and the result is a set of internal changes and promotions likely to lead to the company's business objectives. Finding optimal sets of changes and promotions is the main challenge. The problem is that the company's primary objectives can vary between e.g. profit maximization, cost reduction and increasing the number of customers. So, first, a possible future scenario for the company can be defined in accordance with the current situation on the basis of predicted external influences and planned internal changes. Based on this scenario a prediction about the possible impact of planned changes can be generated. From the result the most important key figures are computed to indicate the degree to which the defined business objectives will be accomplished. To allow comparison and evaluation of the different scenarios more than one simulation run on computer can be computed. Finally the combination of changes and promotions is chosen, which has the highest probability to fulfill the defined business objectives. In the simulation, the customer agents and item agents are presented with the current scenario. Their response indicates the individual preferences with respect to all affected products. When "questioned" the agents return the amount of units for each individual product, which the customer is expected to purchase in the scenario under consideration. This is currently based on the specific behavior of the commodity group networks with all affected networks being configured with the specified values of the influence factors for each defined action. The propagation algorithm of the behavior network [9] computes the expected values for all purchased products of the commodity group. Items are not represented as single units in the network but as a set of abstract attributes. Therefore, the "answer" of an agent is not a list of products, which its customer is expected to buy but instead an abstract description of them, e.g. "five high-priced brand products" of a specific commodity group. The simulation will comprise several steps. Initially, all relevant item agents give a description of their items in the form of an attribute list containing e.g. price category, placing, quality and promotions. These attributes are then matched with those of the feature agents and the feature agents are confronted with these item descriptions. The relevant feature agents react internally with quantified acceptance or rejection and the feature agents then "negotiate" the overall reaction of the customer agent with respect to the relevant commodity group. Again the result is a list of item descriptions, which the customer is expected to buy. The list of attributes can be mapped to specific items. Based on this the expected amount of units sold per product is computed. A quantified prognosis about the behavior of all customers is obtained by summing up the expectations. Using this approach it is also possible to integrate *virtual customers* into the simulation, representing typical customer groups instead of individual customer's e.g. young families, students or senior citizen. The quantitative distribution of these prototypes of customer groups is determined by an analysis of sales slip data or questionnaires and is then used for the simulation. The use of behavior networks serves also an explanatory purpose as it allows a new kind of evaluation: besides computing scenario rankings and key figures it is also possible to give detailed verbal and graphical explanations for the simulation results. For example a direct connection between increasing the price of a product and loss of customers to a discounter may to be due to the extreme price sensitivity of a certain group and this is what the system reveals. A selective simulation of customer groups is possible since the customer groups are modeled as holons and the system explicitly forecasts the effects on specific customers and/or customer groups. Thus, a simulation is highly scaleable as the system can optionally simulate all, only some or just the individual customers.

Conclusion

In this paper we presented a multi-agent system that is capable of supporting intelligent modeling of customer behavior and decision support in a complex competitive marketing environment. The proposed multi-agent system, including its architecture and implementation, are presented and demonstrated through an example integration scenario involving real planning and execution. MAS-based approach models a real market with all items, customers and relevant external influences, where the holon-paradigm supports arbitrary dynamic agent groupings. With this approach, a set of software agents with specialized expertise can be quickly assembled to help gather relevant information and knowledge and to cooperate with each other, and with other management systems and human managers and analysts, in order to arrive at timely decisions in dealing with various enterprise scenarios. The work presented here represents only the first step of our effort toward agent-based enterprise integration Further research and experiments are needed to extend the current work and to address its shortcomings. Although common communication languages that exist today do not impose many constraints and requirements on the internal structure of agents, it may be beneficial to have a common framework for the agent's internal structure within a single agent system. We are currently considering lightweight blackboard architecture for such a framework, which, among other advantages, may provide flexibility for agent construction, agent component re-usability and plug-and-play. Future research will improve the model of the customer agents by enhancing the society of feature agents. By defining adequate measurements of similarity, customers are divided into groups and represented as holons. The simulation results will be empirically evaluated in comparison to realistic sales data of the past to predict the effects on the future.

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