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Intelligent Agent Based Approach to Sales Operations at eStores

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Intelligent Agent-based Approach to Sales Operations at E-stores

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ABSTRACT

In our paper, we consider the application of Intelligent Agents in supporting the operations in an Internet-based store (e-store). We consider and discuss different opportunities for employing Intelligent Agents to improve the performance of an e-store's operations, including sales, forecasting demand and supporting order fulfillment. We provide a framework for the application of such agents, show available sources of information, and discuss challenging issues in modeling learning and decision processes for agents.

Keywords

Intelligent Agent Application, Internet-based Stores, E-stores, Sales Operations, Sales Support Operations.

INTRODUCTION

Information is considered to be the key element in achieving a successful business in today's competitive marketplace. It has been understood that integration of information systems is the first step for the full utilization of information value. The need for integrating information systems within an organization has led to the birth and growth of Enterprise Resource Planning (ERP) applications. On the other hand, the ever-growing interest of businesses in supply chain management necessitates the external integration of information.

The high speed of today's transactions and the vast amount of information available due to the integration impose a challenge to decision makers in the operations level. A viable approach to processing and decision-making in today's demanding environment is the use of Intelligent Agents (IA's). Intelligent agents are software programs that *perceive* the environment through their *sensors*, make *autonomous decisions*, and affect their environment through their *actuators*. An agent *rationale* invokes actions that best satisfy a set of predefined *goals* (for a formal definition of an agent, see for example Luck and d'Inverno, 2001). Application and implementation of IA’s have been the focus of many studies. Applications of IA's have been considered in various areas including e-commerce (Guttma, Moukas and Maes, 1998; Rahwan, Kowalczyk and Pham, 2001; Ye, Liu and Moukas, 2001) and supply chain management (Mehra and Nissen, 1998; Shen, Ulieru, Norrie and Kremer, 1999; Shen and Norrie, 1998; Swaminathan, Smith and Sadeh, 1998). The two main concerns of these application studies are to identify the agent's goal set and its decision models. Implementation studies, on the other hand, focus on the structure of agents, communication between agents, and security issues (Da Silva, Choren and de Lucena, 2004; Guan and Zhu, 2002; Marques, Silva and Silva, 1999).

Abdoli and Choobineh (Abdoli and Choobineh, 2003) provide a conceptual framework for implementing a sales agent at Internet-based stores (e-stores). They also discuss the challenging issues in modeling the agent including customer identification and sales tactic selection. In this paper, we extend their work in two directions. First, we provide a more detailed plan for implementing the sales-agent. We consider a two-level structure consisting of a *master sales agent* (MSA) and many *personal sales agents* (PSA). PSAs are reactive agents that interact with visitors, preprocess visitors’ surfing activities, and make final decisions regarding the use of sales tactics. The MSA is a proactive agent that decides on the use of system-wide tactics based on available information including those provided by PSAs. We also extend the work of Abdoli and Choobineh by introducing two other supporting agents for sales operations, namely, *demand-forecasting agent* (DFA) and o*rder-fulfillment agent* (OFA).

The rest of the paper is organized as follows. In the next section, important supporting operations for sales in e-stores are discussed. A general framework for application of IA's for those supporting operations is provided. Moreover, challenging modeling issues are discussed and some modeling approaches are suggested. The paper concludes with a summary of research and future directions.

E-STORE OPERATIONS

Sales and sales-supporting operations of e-stores are often more challenging than those operations of their brick-and-mortar counterparts. In the following, we discuss the challenges that e-stores face with respect to sales and sales support operations such as demand forecast and order fulfillment.

By making various storefronts easily accessible, the Internet has made the shopping experience more efficient for many customers. The ease of access to e-stores via the Internet has increased the number of online customers, thus driving the growth of Internet storefronts (e-stores). The growth of e-stores, consequently, lowers the *search cost* (the cost of comparing services/products) for Internet shoppers. Finally, the ease of use and lower search costs have reduced the likelihood of customers being loyal to a particular store. The combination of the above factors has made it challenging for e-store owners to attract visitors and convert them into buyers and loyal customers. This disadvantage of e-stores is more pronounced when considering the lack of human contact. The success of stores depends partly on the performance of their salespersons who take full advantage of their face-to-face contact with customers. In e-stores, however, the face-to-face contact is not applicable. E-stores can use visual/audio technology to imitate the face-to-face contact in brick-and-mortar stores; nonetheless, the use of such technology is not popular. This is most likely due to the large number of customers, low buyer-to-visitor ratio, and limited resources (e.g. bandwidth required to support visual/audio communications).

The lack of physical boundary –the main difference between e-stores and brick-and-mortar stores– has also affected the operations routine in e-stores. In brick-and-mortar stores, most customer orders are fulfilled at the store. In e-stores, however, customers are invited from geologically dispersed areas and orders most often need to be shipped to them. This leads to certain advantages and disadvantages for e-stores. The advantages include having the ability to choose a providing source from a larger set of providers, and providing the opportunity to avoid the costs of holding inventories; practices which are supported and encouraged in e-commerce literature. Nonetheless, having to make order fulfillment decisions based on single customer orders (rather than forecasts of store-wide sales) increases the burden of decision makers. In order to maintain a low (or zero) inventory, e-stores need to have a more precise understanding of customers' demands and need to be able to react to sudden shifts in customers' interests. These consequently increase the risk of failure in on-time delivery and customer dissatisfaction.

The application of IA's provides a plausible approach to challenges that e-stores face. IA's can use information available to e-stores to: 1) assist customers with recommendations and persuade them to make a purchase using promotions, 2) improve order fulfillment by initiating proper shipping and handling transactions, and 3) support planning operations through frequent and accurate forecasting demands. In the following section we provide a conceptual framework for implementing three groups of IA's that can satisfy the above applications.

APPLICATION OF IA'S AT E-STORES: A FRAMEWORK

Figure 1 shows our general framework for the application of three groups of IA's that can improve the performance of the e-stores' operations. Our framework presents the interconnections and flow of information between agents (circles) and informative nodes (ovals) in e-stores. In our framework, bold arrows distinguish the outflow of information from agents. Different types of agents communicate with each other directly or indirectly (through informative nodes). This framework initiates a decision support system that interacts with customers in the storefront and provides informational support to supply-end operations. In the rest of this section, a brief introduction to informative nodes in the framework is provided, followed by a separate presentation of each agent's operation.

Informative Nodes

Informative nodes represent the IA's perception of the environment. These nodes contain pre-existing information in the system and/or knowledge learned and created by other agents. Pre-existing information is extracted from available information to e-stores that include database systems and websites' server log-files. Table 1 provides the list informative nodes used in our framework. A brief introduction to each node is followed.

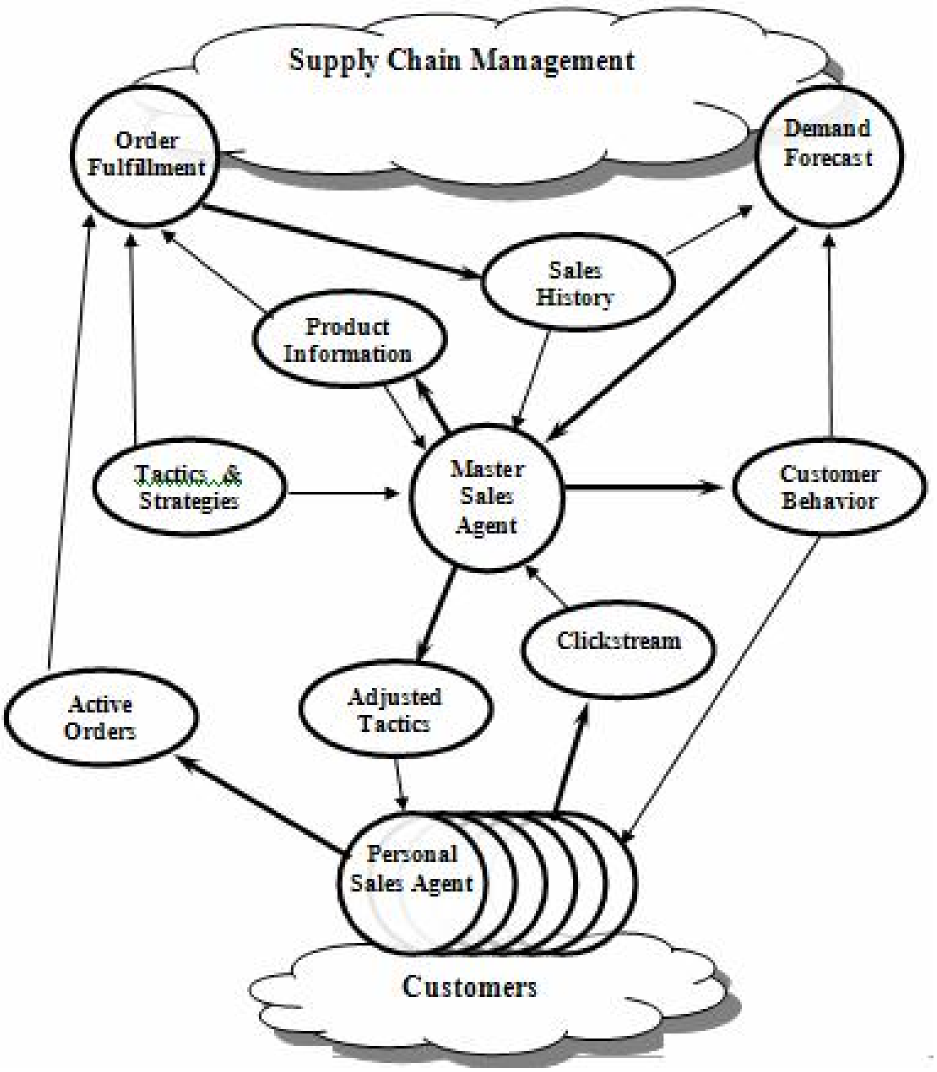

Figure 1. The general framework for application of IA's in e-stores.

Informative Nodes	Pre-Existing Information	Learned Information
Clickstream	√	√
Customer Behavior		√
Active Orders	√	
Sales History	√	
Product Information	√	√
Tactics & Strategies	√	
Adjusted Tactics		√

Table 1. List of informative nodes and their generating sources.

Clickstream

Customers' visiting actions are recorded in server log-files and can be used for estimating customer visiting characteristics, including visiting intention and purchasing interest. The sequence of actions taken by a customer is commonly called *clickstream* and usually is extracted from server log-files. In our framework, we consider the option that personal sales agents (PSAs) update clickstream node directly.

Customer Behavior

This node represents the agent's perception of the customer's visiting intention and shopping interest. The intention and visiting objective of customers are not observable. Nonetheless, agents can use available information (e.g. clickstream, demographic data, and purchase history) to learn about customers' interests and intentions. Table 2 shows some details of available information (Demographic data can be supplied by Customer Relationship Management database which is not shown in our framework). The master sales agent (MSA) can use this information to update the customer behavior node.

Information Type	**Fields**
Server Log-Files (Click-stream)	Page Viewing Time
	Number of Pages Visited
	Type of Pages Visited
	The Sequence of Actions Taken
Customer Relationship Management (Demographic data)	Age
	Gender
	Income
	Location
Sales (Purchase History)	Last Purchase Date
	Last Purchased Amount
	Sales Tactic Used

Table 2. Examples of customer-related information available to e-stores.

Active Orders

This node provides the list of outstanding orders made by customers. This information is usually held by the sales database. In our framework, PSAs can update this node; however, no learning process is required.

Sales History

"Sales History" simply includes the history of sales made by each customer. This information is usually held by the sales database. In our framework, order-fulfillment agent (OFA) can update this node; however, no learning process is required.

Product Information

This node includes the inventory status of products as well as their specifications and relevance (functional relationship). Inventory status is easily accessible from the inventory database, but not all product relationships are readily available. The MSA can use clickstream to identify (learn) unobservable (non-transparent) relationships between products. Such approaches have been used for recommending products based on previous customer's preferences. For example, amazon.com provides visitors with a list of recommended books based on the purchase history of customers with similar interests. Table 3 shows a list of product related information.

Tactics and Strategies

This node provides both goals and action sets required for applications of MSA and OFA. These sets are provided by the e-store managers. The main goal of the e-stores, usually financial growth, can be interpreted as multiple detailed objectives such as increasing the monetary value of sales and reducing the cost of shipping.

The action set includes the possible tactics that can be used to satisfy one or more of the detailed objectives. These tactics may affect the product price, the product specification, and/or customer service. *Price discrimination* tactics (with long-term life-cycle), and *promotional discounts* (with short-term life-cycle) affect the product's price. Up-sizing tactics increase the volume of sales, for example, by adding other products. Also, supportive actions directly target customer satisfaction. Table 4 provides some examples for each tactic types.

Adjusted Tactics

Tactics and strategies provide the ground for sales decision support; however, they may represent conflicting directions. For example, reducing shipping costs can be in conflict with increasing customer satisfaction. Also, using some tactics (e.g. reducing the price) can increase the sales of a store and its market share, but it also can reduce the profit margin per sales. Accordingly, using sales tactics is a two-edged sword, and is considered an important issue in marketing and has been extensively studied (for example, see Zeithaml, 1987).

The MSA can proactively refine and adjust tactics and objective functions based on the market trends and customer behavior. "Adjusted Tactics" node represents the sales tactics that have been adjusted for use based on the collective interest and intention of all customers at the current time.

Source	Information Type	Field
Inventory Database	Quantity	On-hand Inventory
		In-Order Inventory
		Rate of consumption (Demand)
	Monetary	List Price
		Replenishment Cost
		Inventory Cost
	Transparent Association	Possible Substitutions
Log-Files	Non-Transparent Association	Accessories
		Products frequently bought together

Table 3. Examples product-related information available to e-stores.

Target	Sales Tactics	Examples
Price	Price Discriminations	Loyalty Program
		Group Discount
		Volume Discount
		Nonlinear Pricing
	Promotional Discount	Seasonal Sales/ Rebates
		Excess Inventory Sales
		Individual Discount
Product	Sales Up Sizing	Cross Selling
		Up Selling
		Bundling
Customer	Supportive Offers	Bandwidth
		Technical Support
		Fast/Free Delivery
		Advertisement
		Shelf Presentation

Table 4. Examples of sales tactics grouped based on their target.

Sales IA's

Abdoli and Choobineh (Abdoli and Choobineh, 2003) proposed the use of a sales agent that utilizes its perception from customer behavior and its knowledge of product specifications to adjust a set of given sales tactics. The agent uses the adjusted sales tactics to provide a customer with promotions and offers for improving the sales performance of the e-store (e.g. increasing the probability of purchase). Here we present a multi-agent approach with the same objective. Our approach considers the following two agents: 1) a *Master* sales agent (MSA) that provides periodic system-wide adjustments to sales tactics (e.g. setting price modifications or seasonal sales) based on the recent behavior of all customers; and 2) a group of *Personal* sales agents (PSAs) that select sales tactics by comparing online actions of customers to suggestions provided by MSA. We consider MSA to be a proactive agent in the sense that it is goal-oriented. The MSA uses available information to learn customer behavior and the relation between customer actions and effects of sales tactics. To satisfy the e-store's goal, MSA creates and updates the set of adjusted tactics. PSAs are considered reactive agents. They use the adjusted sales tactics and the knowledge of customer behavior produced by the MSA to assign a tactic to a customer based on his/her online actions.

In an e-store, the number of concurrent visiting customers can be very large, while computing and communication resources are limited. Moreover, not all customers have long history of visit, or spend enough time in a single visit to provide adequate learning opportunity to terminal agents (here PSAs). Our two-level structure incorporates the learning element of an Intelligent Agent approach with no side-effects on the effectiveness of terminal agents: First, it reduces the processing burden of PSAs to improve their response time. Second, it allows sharing observations for similar visitors to strengthen the learning process. Finally, by considering the option that PSAs can update clickstream directly, we can eliminate processing step that extracts clickstream data from the log-files. PSAs can filter non-informative, short sessions to increase system's performance by saving recording and retrieving times.

Figure 2 shows the interaction of our sales agents with a hypothetical e-store's database systems. Information used by agents is supported by sales, customer relationship management (CRM), inventory, and product information databases, and server log-files. Sales, CRM, and inventory databases are part of traditional information systems for both e-stores and brick-and-mortar stores. However, server log-files are an explicit part of the e-store information system. Product characteristics may be available to both types of stores in a database format; nonetheless, some of the subtle relationships between products can only be documented in e-stores using information provided by server log-files. Such product relationships, called non-transparent relations, can be extracted from visitors' viewing actions. Recommender agents exploit these relationships to assist/persuade online visitors. Tactics and Strategies and Website Database are other external information required for implementing our sales agents. Other required information, such as customer behavior and adjusted sales tactics, can be generated and shared internally between different sales agents.

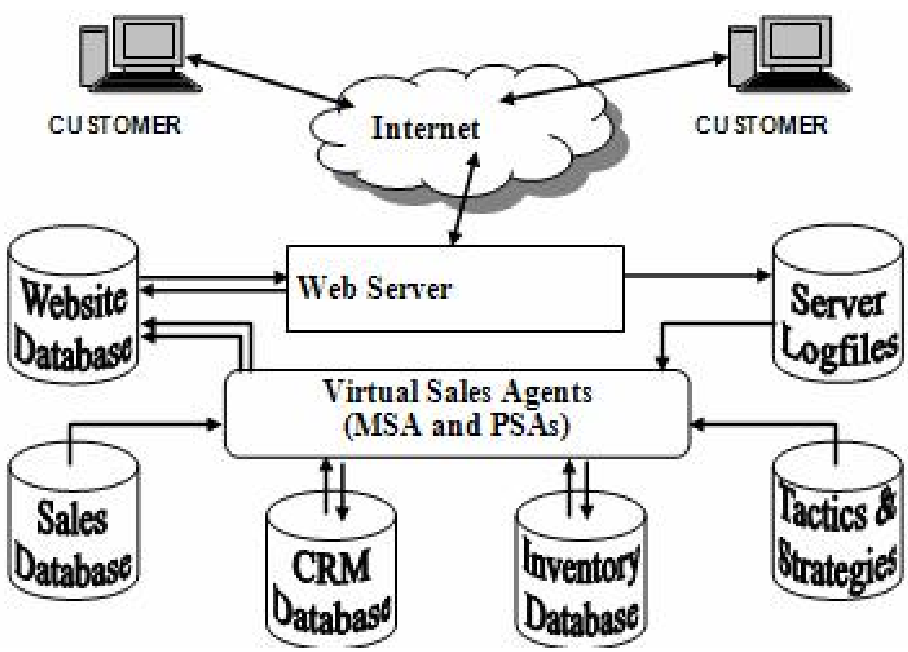

Figure 2. Sales Agents and their interaction with a hypothetical e-store.

Order-Fulfillment Agent (OFA)

Today's e-commerce offers e-stores the use of a large number of providers and supports the high speed of transactions. This, in return, requires e-stores to face more frequent purchase/replenishment operations. Therefore, e-stores can only fully utilize their advantages (operating globally and holding zero-inventory) if they support their sales operation with a reliable and fast order-fulfillment operation. Such an operation relies on access to a set of vendors as well as a selection process that accounts for vendor reliability and shipping alternatives. Let us consider the simple case that vendors are negotiated and selected in advance. A reactive OFA can handle the shipping process of all active orders (updated by PSAs). As soon as an order is activated, the OFA will select the appropriate vendor and shipping method based on the information provided by order itself, product specifications, and available shipping methods (given as tactics). Information of fulfilled orders finally is added to the sales history that is used for future analysis.

The above simple approach can be extended in two directions. First, OFA can cooperate closely with the supply chain management system of the e-store. In some cases, e-stores can benefit from the vendors' competition by postponing their negotiations until an order is made. The OFA can initiate the negotiation process and support the process by providing the shipping costs and constraints to the negotiating agent(s).

Another improvement can be made by assigning one OFA to each outstanding order. Then allowing OFAs to distribute orders (by creating new OFAs) and/or mix orders (by merging some OFAs together) in different stages of shipping. In the latter case, OFAs are more valuable when they coordinate shipping processes of more than one store.

From implementation point of view, a two-level approach (similar to our sales agents) can combine both suggested extensions. The master agent will manage the distributing/mixing operations for the other OFA agents. It also will cooperate with negotiating agents (or perform their tasks if no such agent is implemented). Figure 3 shows the relationship of the OFA(s) with e-store database systems and other agents in the system.

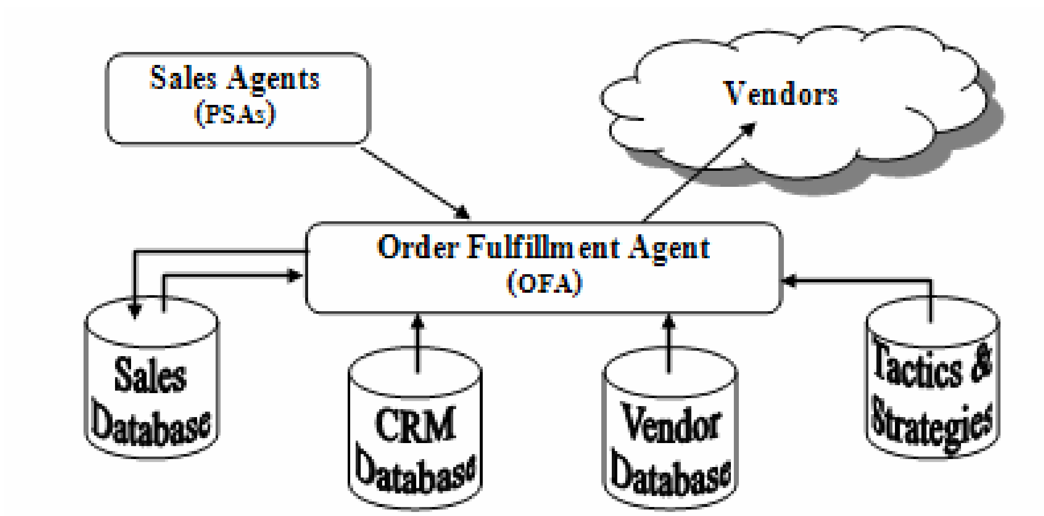

Figure 3. Interaction of the OFA with e-store database systems and PSAs.

Demand Forecasting Agent (DFA)

Forecasting demand is an essential part of planning operations for all stores. Demands are usually forecasted periodically based on patterns of sales made in the past. These forecasts are then used for long-term planning such as vendor acquisitions and forward contracting. In e-stores, long-term planning may not be a necessity; nonetheless, frequent and accurate demand forecasts can provide useful insights for both acquisition and sales operations. Negotiator agents (in e-commerce) can use forecasts of demand to strengthen their bonds with to-be-needed vendors or reduce the acquisition time by initiating negotiations for future purchases. Furthermore, the MSA can use demand forecasts for adjusting sales tactics (e.g. offering seasonal sales when demand in diminishing).

In general, demands are forecasted based on the sales history. To improve the accuracy of forecasts, we allow DFA to benefit from the knowledge created by MSA (i.e. MSA's perception of customer intention) for a better interpretation of sales history, and consequently, a better demand forecast. In this approach, DFA accounts for customers' intention through weighting sales patterns by the sales tactics used prior to each purchase. Figure 4 shows the interconnection of the DFA with existing databases and agents in the system.

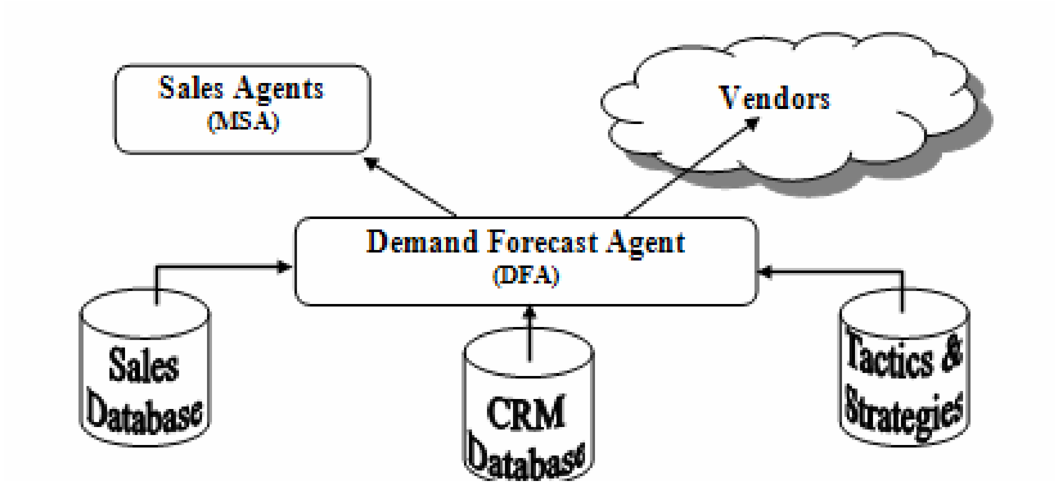

Figure 4. Interaction of DFA with e-store database systems and other agents.

SALES AGENTS AT E-STORES: MODELING ISSUES

We considered the areas that IAs can provide support to e-stores' operations. In our framework, we introduced three different IAs and discussed the way that they perceive environment and the actions that they can take. Regarding implementation, available sources of information and those to be learned were discussed. From other implementation issues, including modeling agents' decision engines and software development, we only consider the modeling issue. Some of required models for our application of IAs are: 1) a *customer identification* model for the MSA that creates knowledge of customer online behavior from available information such as clickstream and sales history; 2) a *tactic-effect* model that allows MSA to learn the effects of tactics used on customer purchasing behavior; 3) a *tactics adjustment/selection* models that give the MSA the ability to set store-wide sales tactics and guidelines for PSAs on personal tactic selection; 4) a *demand* model that provides bases for forecasting demands, and discovers the non-transparent associations between products, and 5) optimization models for quantifying action (tactic) selection problem needed by (reactive) agents such as PSAs. We focus on customer identification and tactic selection models, and provide some guidelines for developing such models.

Customer Identification

Customers' online behavior have been of researchers interest for different reasons, including to understand surfing goals, common paths taken, and factors affecting outcomes of customers' visits. In studies that the visitors' goal and the associated paths are of interest, the sequence of visiting actions is exclusively modeled. Markov models are used as a common tool for studying clickstream. For example, Markov models are used for representing webpages visited to forecast the next action of online visitors (Pirolli and Pitkow, 1999, and Sen and Hansen, 2003). They also are used for modeling the sequence of documents requested over the time to predict and pre-fetch to-be-requested documents.

Other related works in this area are the studies that have marketing incentives and are interested in modeling purchasing behavior of customers. These studies commonly estimate the probability of purchase and/or classify customers based on their purchasing habits. The common sources of information for such studies are surveys (Pedersen and Nysveen, 2005) or summary of viewing activities in a session (Moe, 2003).

In our research, we are interested in learning customers' searching behavior from sequence of online actions, as well as purchasing behavior from purchasing outcomes of visiting sessions. Markov models that are usually used for modeling search behavior can be adapted to present purchasing outcomes as follows. A Markov model provides a set of probability of visiting webpages w based on recent webpages visited h, denoted by $Pr(w|h)$. The probability of purchase can be supported by considering a subset of webpages PURCHASE consists of all confirmation pages in the e-store's website, and then calculating expected probability of visiting such a subset in a given session, i.e. $E\left[\Pr(w \in PURCHASE \mid h)\right]$.

In a similar approach, a dynamic multinomial probit model is used for predicting the purchase conversion rate (Montgomery, Li, Srinivasan and Liechty, 2004). In this study, webpages are aggregated based on their functionality into eight categories including *order*; then, the probability of visiting *order* category is used as the probability of purchase. Nonetheless, this model does not provide a detailed representation of the customers' search behavior. Our approach represents the details of customers' search behavior and offers the ability to predict the product of interest. The measure of customer interests on products can complement the probability of purchase in providing a better assessment of the customers' value. Consequently, we can improve the performance of MSA and PSAs using a better estimate of customers' value.

Tactic Selection

In brick-and-mortar stores, salespersons have a little (if no) authority in using many sales tactics. In fact, most sales tactics are usually employed and updated by the sales manager after processing recent sales data. Moreover, implementing most tactics is costly (e.g. changing price tags; advertising seasonal sales). Therefore, tactic updates are infrequent. In e-stores, on the other hand, employing sales tactics are not as costly and tactic adjustments can be frequent. In our framework, PSAs can theoretically process available information and select sales tactics frequently on their own (a decentralized decision system). Nonetheless, we suggest using a centralized decision system (similar to brick-and-mortar stores) to increase the response time of PSAs and improve the MSA's learning process by sharing (aggregating) information of similar customers. In our suggested approach, PSAs can use different tactics frequently, but the MSA does not adjust those tactics frequently.

Implementing a tactic selection process has following two challenges: 1) the effect of tactics on customer behavior is unknown *a priori*, and 2) the diversity of tactics types makes comparing them challenging. These challenges are addressed below.

Estimating Tactics' Effects:

Statistical methods can be used in conjunction with the customer identification model (discussed earlier) to estimate the effect of each tactic on customers. For example, the average increase in the probability of purchase before and after employing a tactic can be used as a measure of tactic effects. Markov decision models (Choi and Liu, 2002) are another alternative for learning tactics effects. The application of IAs is a natural approach to learning such relations over the time.

Tactics Unification:

To make tactics comparable, we consider the tactic selection problem as a resource allocation problem. In this approach, a nominal price and demand is set which defines the nominal revenue/benefit of the e-store. Then an amount is allocated as the *Maximum Allowed Discount* (MAD) that sets a lower bound to the store's revenue/profit. In this setting, tactics can be represented uniformly by their associated cost. This turns the tactic selection into a resource allocation problem in which MAD is allocated to sales tactics such that the e-store performance is maximized.

CONCLUSION

We considered the application of intelligent agents (IA's) in sales and sales support operations for e-stores. For sales, we proposed a two-level agent structure. The MSA proactively learns the customers' behavior, the effect of tactics on customers, and adjusts store-wide tactics based on the current market trend. PSAs reactively apply available adjusted tactics to customers based on the knowledge of customer behavior created by the MSA. We also considered using agents for forecasting demands and fulfilling orders. These agents can also provide support for the existing supply chain management operations.

We also provided some insight on how existing database systems of e-stores can be used for implementing operations support agents. Utilizing existing databases has some advantages and disadvantages. Ease of development and independence of implementation phases are two advantages of this approach. Agents' software programs do not need to build and maintain their data internally. Moreover, most agents can be implemented and operate regardless of the status of other agents. Nonetheless, using legacy databases imposes some restrictions which might reduce the flexibility of agents in both implementation and operation phases. This is less likely if a well-designed database system is in place.

We proposed some modeling approaches for dealing with challenges of learning customers' behavior and selecting tactics. For tactics selection, we suggested adapting a resource allocation approach in which different types of tactics are transformed to comparable monetary resources. For modeling customer behavior, we proposed combining two groups of studies in this context. These studies are marketing related studies, concerned with the customers' shopping intentions, and search behavior related studies, focused on customers' surfing interests. Our motivation for combining these two approaches is to assign a monetary value to the probability of purchase and use the resulting measure as the customer value. The customer value can be used by MSA for adjusting sales tactics.

Our research will continue with a focus on developing required models and verifying their performances. The software development and implementation is the next step in our research, which can be extended to consider the integration with other agent technologies currently proposed and used in e-commerce and supply chain management.

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