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Software Agents Role and Predictive Approaches for Online Auctions

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Abstract – *Software agents have become very significant these days. In almost all the activities they are being employed. Here the significance of software agents have been shown. This is particularly discussed with respect to the online bidding scenario. A light has been put on the model aspects of software agent being used for the interaction with bidder.The machine learning aspects are also being used for majority of findings these days. The relevant aspects are discussed here. The social media effect have also been shown in this paper.*

Key Words: Software Agents, Machine Learning, Social Media.

1. INTRODUCTION

In today's innovative technological era, software agents have become a vital framework towards the predictions made in online auctions. The reason for the same is their tremendous capability and adaptabilities. They can easily adopt to the dynamic incoming information and the changings behavioral patterns of bidders. These need not to be manually handled and least level of human intervention is required. This not only ensures their smooth functionality, but it provides quality results in online auction related predictions [1].

1.1 Bidder Interaction Model

To understand the online bidding interaction model in online auction it is important to explore the role of a bidding agent to know the automation in the auction process [2]. From this model, the different bidder interaction module can be identified. These are: Pre-buy Interactions, buy-process interactions and post-buy interactions. The pre-buy interactions include the product search, auction picker and the online bidding operations (Fig. 1.). In pre-buy search, the user searches among large collection of available products on the Internet. Whatever one decides it depends upon the requirement and other aspects of product like its features, price, delivery, etc. Then user searches for the relevant auctions available on web. Normally, abundance of auction for a specific product brings brighter chances of winning it. And not only winning is important, but it may result into the lower price for a particular product during the purchase process [3]. Here bidding agent needs to make intelligent decisions like it needs to roam on different websites across the web and decide in which auction to select to participate in. Bidding agent automation here requires to co-ordinate and communicate with other agents and set the bidding preferences accordingly [4]. To implement this strategy a bidding agent need to possess and develop high level of learning skills.

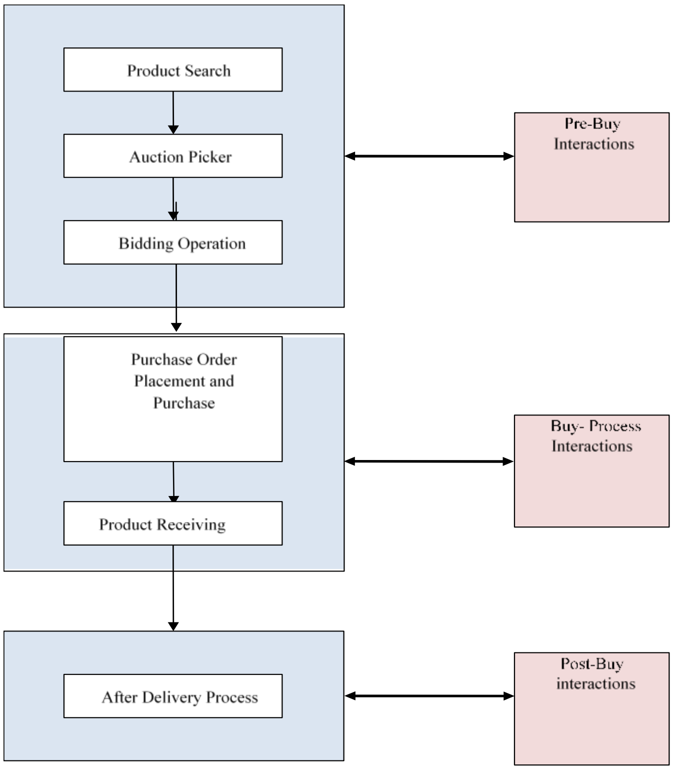

Fig. 1. Bidder interaction model [2].

In buy process interaction phase the subparts of the same are purchase order placement and product delivery. The final step, i.e. post buy interaction is very important not only for a bidder but for the auctioneer as well. Here the software agent can build bidder profile, later this can be further utilized in order to provide the after sale services. These services can be used to personalize the offerings later-on [2].

1.2 Characteristics of Software Agent

From the above discussed phases of bidding process, software agents possess different characteristics. These are explored briefly here:

1. Autonomous: Autonomous agent do not need an external interfere for its operations, at least directly it is not required. It controls its operations directly by its own learning model [5].

2. Proactive: In the real simulations, the intelligent agent should show proactive behavior. These goals exhibit the behavior in terms of the set objectives [6]. Here matching of pre and post conditions should be handled as described. A bidding agent will

make the decisions according to the own objectives and preferences and analyze the available alternatives. Accordingly, it predicts the results.

3. Reactive: The software bidding agent should be not only be responsive towards attaining the predefined goals but it must be able to respond to the arising situations from time to time. The changing environment and unexpected dynamic situations must responded by it in a very efficient way (Fig. 2.) [7; 8; 9].

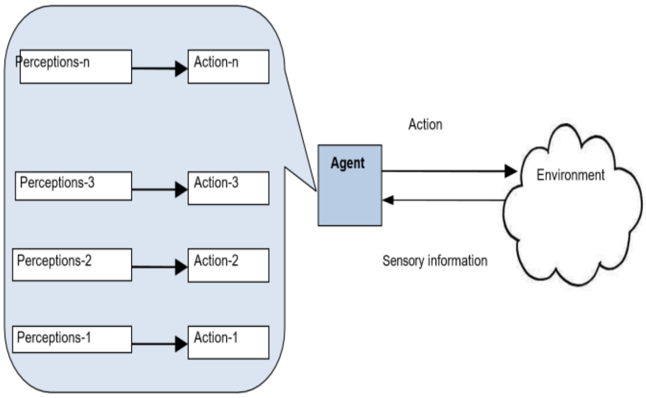

Fig. 2. Reactive software agent [8].

4. Social: The software bidding agent should be able to take instructions from the human counterpart so as to produce a common approach to other's problems as well. It should track how other bidders [9].

5. Intelligent: The software bidding agent must be smart enough so as to explore the surroundings in terms of similarities among bidding. This will assist it to find the surplus bids [10].

2. Machine Learning Approach For Price Forecasting

In Machine Learning Based approach [11] the steps can be as given below:

1. Colleting the data of online auction: Here data can be collected using the web crawlers and implementing them on a website like the e-bay.

2. Define set of features to be extracted, for example, seller features, item features, Auction Features, Temporal features, etc.

3. Creating Advanced or Meta-class features that are derived from an initial set of features like auction length, shipping charge, start of week etc.

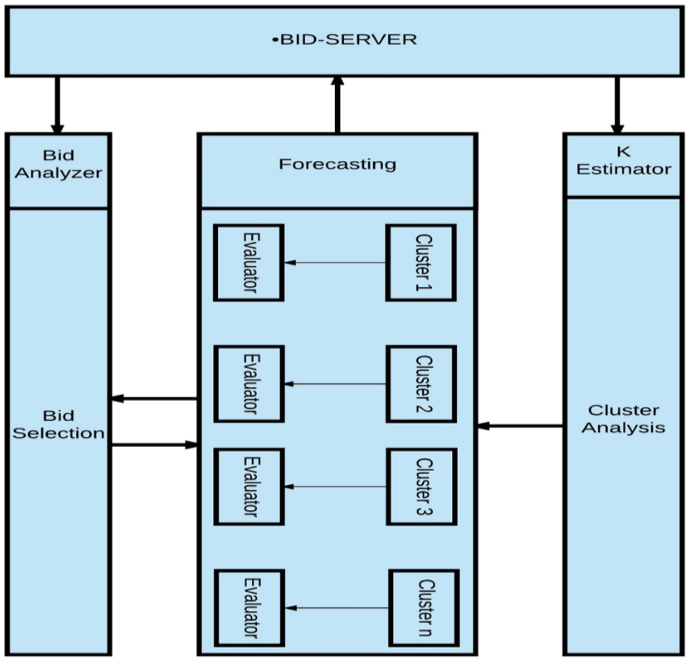

Fig. 3. Price forecasting agent [13].

Extracting features from the hidden information in the data using some classifiers/extractors etc.

Another example towards forecasting the price is based on forecasting agent [12, 13]. In this, the following four steps work to provide the output:

i) Collection of data from the bid server.

ii) Perform the clustering based upon the similarities in characteristics of online auctions.

iii) On the basis with the results from transformation of data into clustering, bid evaluators are invoked to estimate the final price of bid.

3. Significance of Social Media in Price Forecasting

The data of social networks have been playing a key role in every aspect of society. Researchers are trying to utilize the data produced, but till now it is largely untapped. The social media can be used to predict on real-world scenarios [14]. Application areas spreading from price prediction [14], recording social trends on a particular event, medical related or even society awareness, all these can be achieved. In social media, twitter can be used as one of the most important data sources [14]. This data generated comes from the common mass, so it reduces the chances of being biased.

The data achieved through social media platforms are in the form of short text strings having ideas of common people. So techniques like classification and clustering can be utilized in finding the meaningful information from these sources [15]. This micro blogging websites like Twitter, Facebook, etc. are emerging as a common medium as users have come and see and share the contents that are familiar to them [16]. If textual and networking integration of the data can be achieved, the result can be very surprising [16]. This type of approaches like sociological approach to handle noise and short texts (SANT) can perform this classification task efficiently [16]. Numbers of frameworks have been presented in this area. These frameworks are used for sentimental analysis. Though the data produced from social media are unstructured, and it is not easy to drill through this data [17].

It is very significant to identify the existing clusters in such unstructured data groups [18]. For this, genetic algorithm can play a key role [18]. Along with these extending applications of graph theory, the use of fitness function can play an important role in predictability of such data [18]. The static and real-time data generated by Twitter can be analyzed using a flexible framework [19]. This framework, or similar other frameworks require to have various modules, which include miner, classification, etc. [19]. The output generated here can be in the form of CSV files based on sentimental classification of data [19].

The agent-based modeling showed promising results in the last few years. In this type of research, it finds its wide applicability in health-related issues [20]. It ranges from epidemics to cardiovascular research areas. Replacing the humans fully by the computer is not considered to present a good solution to a problem. Rather the use of visual analytics has a good scope for decision making [21]. Even the complex information represented visually can prove to be very beneficial.

The volume of data generated by these social networking platforms is very large. So a model that is capable of analyzing not only the large volume, but the real time flow of data as well. This large data is very significant from a research perspective. There are approaches that combine probabilistic language model for analyzing the customer sentiments and combines it with classical approaches to give better predictability [22].

There are domains, which require real-time data analysis. These include using social media for emergency services [23]. Here visual analytics plays an important problem deriving the meaningful information. There are plugins available that can be used to check the credibility of tweets generated. These assist in evaluating the quality of information produced [24]. The sentiment analytics used in finding political scenarios or knowing more about the consumer feelings about a particular event [25]. Some researchers have filtered tweets based messages from syntactic filtering language modeling, near duplicate detection and set cover heuristics [26].

Work related to the messages provides the strength of the online sentiment analysis. This sent-strength can be different for different languages [27]. Linguistic analysis of a corpus can be used to build a sentiment classifier for deciding about the positive, negative or neutrality of a message [28]. The social media analytics finds its applicability ranging from analyzing public behavior [29]. Health-related monitoring issues [30], to how information is propagating through the social media [31].

4. CONCLUSIONS

The review presented here highlights few significant observations in the present research work. These include, firstly, the localization impact factor is quite significant. Here localization means the mass segment of people, having their views on a specific product or service. There needed to have a multidimensional model to observe the impact in a real sense. Thirdly, the predictive machine learning models can be worked upon for achieving the better results. The role of software agents in price prediction of online auctions can be elaborated. Data mining plays an important role in predicting the end price of online auction. There have been many approaches in data mining that provides good results. Multiple options can be integrated from the number of options available that tends to give the better results.

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