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Pricing Algorithms in Online Auctions

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Abstract— In today's era of the Internet, economies have changed the way than they were a few years back. Now buyers and sellers have started preferring to go online for completing the process. This not only saves the efforts applied but plays a significant role for profit graph to touch the sky as well. One important constituent of this "Online Economic Revolution" is Online Auctions; in this paper, we compared the pricing algorithms available presently. We conclude by showing some performance related aspects of online auctions.

Keywords— Algorithm, End Price, Bid, Online Auctions, Prediction.

I. Introduction

Introduction: In an online auction, auction is held on the internet. Online auctions come in variety of forms, but most popularly these refers to ascending English auctions, first-price sealed-bid, Vickrey auctions, descending Dutch auctions, or a combination of different auctions, taking elements of one and merging them with another. The scope and range of these auctions have been powered by the Internet to a level beyond what the initial observers had anticipated [1].

A. History

Online auctions were going on even before the release of the first internet browser i.e. NCSA Mosaic. Instead of users buying & selling items using the internet they were trading by text-based newsgroups and emails. Though, the first internet-based business activity related to online auctions that made noteworthy sales began in May 1995. In September of the same year eBay also started trading [2]. This type of companies used ascending bid i.e. English auctions and were the first of their type to take advantage of the new technological advancements. The internet offered new advantages such as the use of computerized bids through electronic forms, a search engine for quickly finding the items and the ability to allow users to view items by their categories [2].

B. Categories of Online Auctions

Basically there are six types of online auctions:

i) English auctions

In live sense, English auctions are those where bids are declared by either a bidder or auctioneer and winners pay what they bid to get the object. English auctions are known to be the most common type of third-party on-line auction design used and is observed to appear the most simple of all the types [3] . The common operational way of this form is that it is an ascending bid auction in which bids are open for all to see. Winner is who placed the highest bid [3]. English auction is popular because of the fact that it uses a structure that people find known and intuitive and therefore lowers the transaction costs. It also exceeds the limits of a traditional English auction where it is required to be physically present, making it more and more popular even though there is an exposure to various forms of frauds [3].

ii) Dutch auctions

Dutch auctions are the opposite of English auctions where the price begins high and is methodically lowered until a buyer admits the price. Internet sites which offer Dutch auction services are known to be confusing and the term 'Dutch' have become common practice for the use of a similar-price rule in a single unit auction as opposite to how it is actually planned for that of a declining price auction [2]. However, with actual online Dutch auctions that show descending price, it was established that auctions have on average a 30% more ending price than first-price auctions with assumption indicating to bidder impatience or the outcome of endogenous entry on the Dutch auction [3].

iii) Vickrey Auction

A Vickrey auction, occasionally known as a Second-price sealed-bid auction, uses very similar rule as a first-price sealed bid. Though, the highest bidder and winner will merely pay what the second highest bidder had bid. Online auctions where bidders employ a proxy bidding system is a close likeness to that of a Vickrey model for single item auctions, however because of the fact that the bidder is capable to modify their bid at a later time means it is not a true form of the Vickrey auction [4]. The Vickrey auction is advised to check the incentive for buyers to bid tactically, due to this fact it needs them to tell the truth by providing their actual value of the item [5, 6].

iv) Reverse auction

In Reverse auctions the roles of buyer and seller are opposite. Multiple sellers compete with each other to get the buyer's business and prices normally decrease with time as new offers are presented. They do not follow the typical auction design in that the buyer is aware of all the offers and may pick according to his preference. Reverse auctions are used basically used in a business reference for Procurement [7].

The term reverse auction is normally mixed up with Unique bid auctions, which are more similar to traditional auctions due to the fact that there is only one seller and several buyers. Though, they follow a related price reduction concept except the lowest single bid continuously wins, and each bid is kept confidential [8].

v) Bidding fee auction

A Bidding fee auction entails customers to pay for bids, which he can increase an auction value one unit of currency at one time. In criticisms that compare this type of auction to betting, because users can use a substantial amount of money without getting anything in return ([9], [10], [11], [12], [13]). The auction owner earns money in two ways, the buying of bids and the real amount made from the final price of the item [14].

vi) First-price sealed-bid

In First-price sealed-bid auctions a single bid is put by all bidding parties and the single maximum bidder wins, and pays the bidding amount. The difference among this and English auctions is that bids are not openly presentable or declared as opposite to the competitive nature which is produced by public bids. From a different point of view, the first-price sealed-bid auction is somewhat alike to the Dutch auction; that is, in both auctions the participants will be adopting the alike bidding strategies [15].

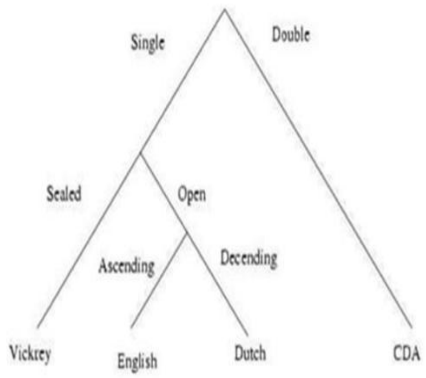

Fig.1 Taxonomy of Electronic Auction [16]

II. MODELING THE ONLINE AUCTIONS

1) Forecasting the results from available Data:

Irrespective of methodology, most processes for creating predictive models combine the following steps: [17]

1. Project Definition: Decide the business objectives and preferred results for the project and convert them into predictive analytic ideas and tasks.
2. Exploration: Examine source data to conclude the most appropriate data and model building method, and scope the effort.
3. Data Preparation: Select, extract, and renovate data upon which to produce models.
4. Model Constructing: Create, test, and validate models, and assess whether they will meet project metrics and objectives.
5. Deployment: Use model results to business conclusions or processes. This varies from sharing actual facts with business users to embedding models into uses to automate conclusions and business procedures.
6. Model Management: Manage models to improve performance, control access, support reuse, standardize toolsets, and minimize redundancy issues.

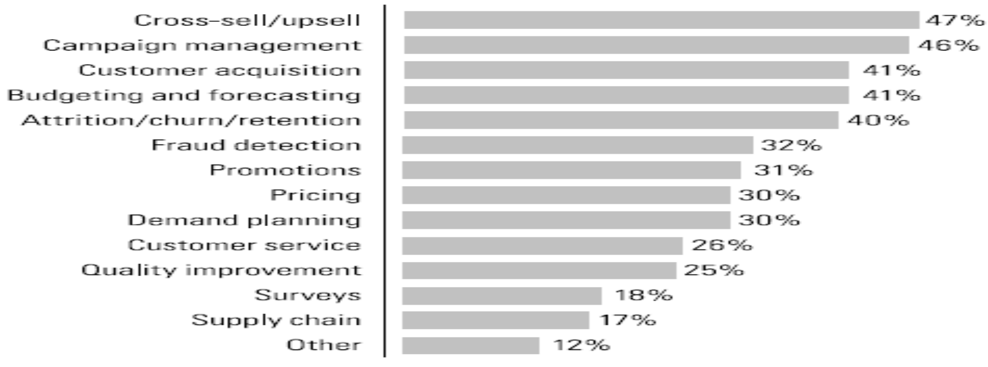

Fig.2 Types of data used to create the predictive models [17]

Predictive models use a variety of tools to discover and examine source data. Most analytical tools offer some exploratory competences. Basic tools allow analysts to compile descriptive statistics of various fields, though few others incorporate more powerful data profiling tools & techniques that analyze the features of data fields and identify relationships between columns within a single and across the tables. Data profiling tools are very common in data Quality projects and are offered by most prominent data quality and data integration retailers. A small ratio of analysts use innovative visualization tools that let users explore features of source data or analyze model results visually.

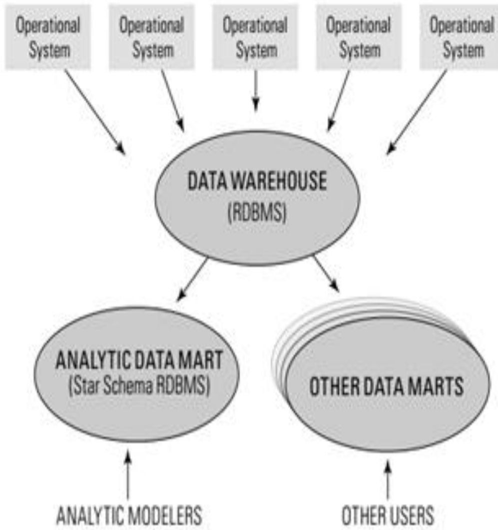

Fig. 3 Architecture for predictive analytics [17]

III. DATA COLLECTION

There can be traditional sources for online auction data such as from company through purchase or by working relationships. Internet is a major source for online auction data [18]. There are certain websites like www.ebay.com, www.saffronart.com which make certain information open to all. Other than traditional techniques for data collection two other technologies for the same are:

1) Web Crawling: Here researchers write certain program that collects data in an automated manner [19].

2) Web Services: In this technique the website made the data available [20]. There are framework available for data collection using web services.

IV. PROJECTING THE PRICE OF ONLINE AUCTIONS

In process of determination of auction price clustering method is very useful. [21]. Based on clustering and other statistical measures good results can be achieved. For cluster analysis software agents can be used.

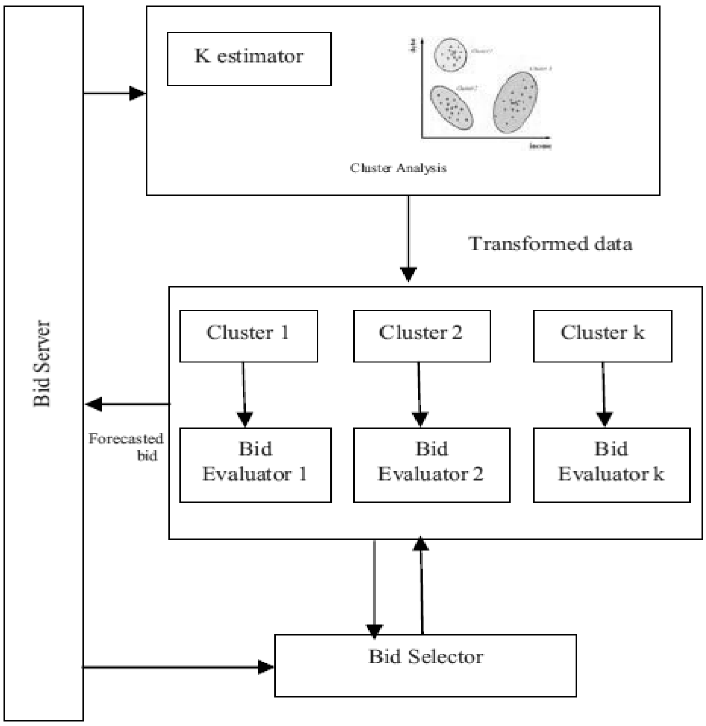

Fig.4 Price Forecasting Agent [21]

Clustering method is used to estimate the final-price of an online auction for independent agent dependent systems. In the proposed technique the input auctions are divided into groups of comparable auctions depending on their various characteristics. Normally partitioning is done by using k-means algorithm. The value of 'k' in k-means algorithm is set by applying elbow method that uses one way analysis of variance (ANOVA) [21].

In an another approach for predicting prices of online auction [22] it is analyzed that how data mining methods can be logically used in price determination. Here large number of auctions are verified by using the decision trees. The bidders are categorized as shown in diagram below:

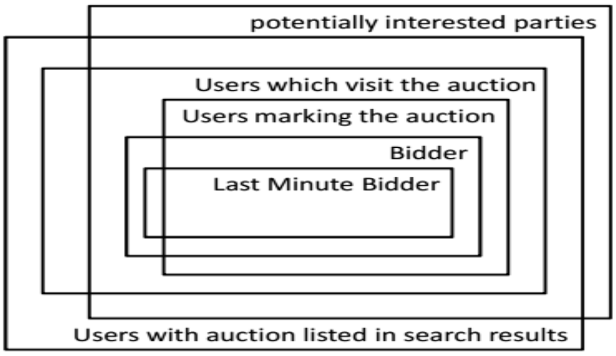

Fig.5 Users Classification [22]

Various aspects of importance that effect the price can be categorized as:

i. Product
ii. Presentation
iii. Seller Reputation
iv. Procedure for Auction

It is observed that the above factors are important and have influence on determining the final price of an auction. This is not very accurate because of the irregular distribution of data so a new approach that relies on mixed models can be more beneficial. Using mixed approach may avoid the challenges of functional approach i.e. challenges related to data analysis [23].

In another method of price prediction using time series and clustering method the result improvements has been achieved [24]. In most of the approaches the results are mainly derived through functional characteristics of data but rather other ways of doing the same i.e. prediction using multi attributes and using time series data ([25], [26], [27], [28]).

As the problem of predicting the price of online auctions is not a static problem it is associated with the dynamic decision making as the data is being generated quite irregularly and the behaviour of bidder is not known in advance. Such type of problems are known as On-Line Algorithmic Problems. An online algorithm where the future input is not known while in case of offline algorithms the input is known in advance [29, 30, 31]. Some of the commonly dealt financial problems by online algorithms are: ([32], [33], [34], [35])

i. Online Search Problems
ii. Online Replacement Problems
iii. Online Leasing Problems
iv. Online Trading and Portfolio Selection Problems

One example of online financial program is Google's AdSense program [36]. This uses vickrey auction [4] for pricing the web space. Google Inc. earned its 30% of total revenue from Ad Sense during the fourth quarter of 2012 that comes around $4.27 billion. So this shows that if the inline decision making is monitored it can definitely aid in increasing the profit earning. The types of Ad Sense used are:

i. Content based Ad Sense
ii. Feed based Ad Sense
iii. Search based Ad Sense
iv. Mobile content based Ad Sense
v. Domain based Ad Sense
vi. Video based Ad Sense

Functioning of Ad Sense: ([37], [38], [39])

i. Java Script code is inserted in to webpage this is Ad Sense Code.
ii. Whenever the webpage is opened it uses JSON to fetch information from Google's Server. [37].
iii. The cache of page is used to get the high frequency keywords
iv. There are targeted pages also which are chosen by advertiser and the money is paid on cost per mile (CPM) or as per pre decided for every one thousand advertisements displayed ([40], [41]).
v. In referral system Google adds money to account of those who downloads the software for this purpose [42]. This referral system was retired by Google in August 2008 [43].
vi. The search performed by visitor is also recorded for advertisement display.
vii. To prevent the duplicate use of Java Script code by unauthorized webpages, the Ad Sense customers are to state the webpages for advertisement display.

V. CAN WE IMPROVE?

Performance has always been a major issue in every technological facilitations, and so is here. There are continuous efforts by researchers to improve the performance of online auctions. By performance, it is how many online auctions per minute have been processed [44]. Workloads characterization ([45], [46]) of various auction sites show very interesting observations. For example if the bid arrival is closely observed, it can be noted that in last few minutes the bid arrival rate is very high. So there is need to develop an efficient closing time scheduling algorithm that can evenly distribute the no. of closings so as to produce fairly a uniform distribution of bids on auction website [44]. Now this bid arrival and selection is just like the concept of demand and supply. There need to be a balance between two and it always require a good modeling of the same. Models like BARISTA (Bid Arrivals In STAges) [47] introduce a family of distributions which will approximate the bid arrivals distributions in hard close online auctions. Some researchers have used genetic algorithms to simulate the bidding trends in online auctions [48].
Another approach from performance aspect can be to have a close observation on the load on bid dealing website [49]. The significance of this can be explained like; as it is well known fact the websites are maximum overloaded in last moments. Now if due to this reason of overload, the bidder is not able to place the bid then seller might have financial loss. So policies regarding this type of situation can be framed through experimentation on benchmark online auction system ([50], [51], [52]).

VI. CONCLUSIONS

In this paper we have reviewed area of online auctions. As it is quite clear that now as marketplace is shifting from physical to online. So there is lot of scope of research with challenges like price determination or efficient bidding system etc. Here we studied various techniques like clustering, k means etc. for determining the price of online auctions. There are certain factors like product, presentation, reputation, process of selling that have impact on final price of online auctions. The data collection sources i.e. physical & online automated have been discussed here. And in last the performance of bidding as a process has been discussed. After having a comprehensive review it can be concluded that there is scope of improvement in the process of online auction, this improvement can be in terms of either the predictive price analysis or in terms of the performance of web services offered

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