CBR BASED LEARNING IN E-AUCTIONS

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ABSTRACT

The advent of e-commerce has brought about a radical change in the process of auctions that can be achieved by using agents. One of the important capabilities of agent is learning from the environment. In this paper, the authors are proposing case based learning for agents in online e-auctions. Case-based reasoning (CBR) is a problem solving paradigm based on the principle that similar problems have similar solutions has inherent learning capability. In auctions, CBR has been proposed to store past histories of similar auctions with their solutions which helps agent to learn from past experience. Proposed bidding agent that uses CBR (CBR-agent) participates in the auction and performs better than those bidders who have no past knowledge about similar auctions. Empirical evaluation is done and the performance of CBR-agent is calculated by comparing its success percentage and average winning price with that of other agents participating in auctions.

Keywords: Learning, Case-based reasoning, E-Commerce, Agents

INTRODUCTION

Auctions are very important and useful applications of E-commerce [5]. Auction is a process of buying and selling things by offering them up for bid, taking bids, and then selling the item to the highest bidder. Auctions are broadly classified into two categories viz., forward auction and reverse auction. Forward auction consists of one seller and many buyers. The seller puts items up for sale and bidders compete by posting bids. These drive the bid price up. Seller can choose not to sell below a given level by fixing a reserve price. In a reverse auction, the competition is among the sellers rather than the buyers. It is a specialized auction format that allows individuals/organizations to procure goods and services at the lowest possible price. Prospective buyer can list any items that he wishes to buy, and then sellers bid to provide the best price. Generally auctions if not specified are assumed to be forward auctions. There are different types of forward auctions which could be ascending or descending of bid values. Some of popular auctions are English auction (also called reserve price auction), Dutch auction and Vickrey auction [5].

The complexity and diversity of auctions inspire an automated alias to a person rather than the person itself. The automated alias is a Software agent which can be defined as a component of software that is capable of acting exactingly in order to accomplish tasks on behalf of its user [7].

Agents are extensively used in E-commerce [9,10] applications. For the agent to behave like humans it should have the ability to learn and improve from experience. Case-based reasoning (CBR) is a problem solving paradigm which incorporates problem solving, understanding and learning and integrates all with memory processes. CBR based systems are classified into two types, namely, problem solving and interpretive, based on the reasoning tasks handled by the system [4]. In problem solving CBR, cases suggest ballpark solution which is then modified for the new case. These types of systems handle design, planning and diagnosis problems. In case of interpretive CBR, the purpose is to use old cases for providing criticism and justification in the new case. A typical example of this is in legal cases where the justification of the case is based on the arguments generated in the previous case. The principle of CBR follows a cyclic process of retrieval, reuse, revise and retain [1].

The research in CBR has been driven by the primary desire to model human behavior. Roger Schank (Schank-82)[4] worked on dynamic memory and showed the advantages gained in problem solving and learning due to reminding of earlier situations and situations patterns. There is not much work done in the area of bidding in auction using CBR technique. One of the areas where CBR has been used is in disease deduction where authors [11] show the usage of CBR in determining medicine for diseases using Homeopathy. Some of the other works in the area of CBR is reported in [6] for distributed case-base retrieval. Multiagent brokerage system using CBR is one technique which has been proposed by Sun and Finnie[12].

The CBR framework has been proposed for the agents to acquire learning capability while participating in online auctions. The past experiences of similar auctions in terms of various attributes are stored in Case Base with final bid values and/or past bid patterns. Hence, a repository of old cases is maintained in this approach. Any new problem is solved by extracting similar case from the repository and is adapted for the current auction. The Case Base is enriched with the solution of current case by adding it as new case or updating the existing similar case. In this manner, system learns similar to the way human learns from experience [3]. Learning is achieved both through success as well as failure in winning an item. The CBR-agent is implemented as a web service that takes user preferences as input and then connects with the auction server to participate in the auction. The private valuation of the item is extracted through Case Base which is implemented using XML. Private valuation is the assessment of individual bidders for an item.

Proposed System for Automated Learning in Agents

The proposed system for bidding in auctions using CBR strategy is shown in Fig. 1. CBR system consists of cases with their solutions. Case in CBR is an auction and a solution of the case is maximum bid value. The case consists of various attributes arranged in hierarchy shown in Fig. 2.

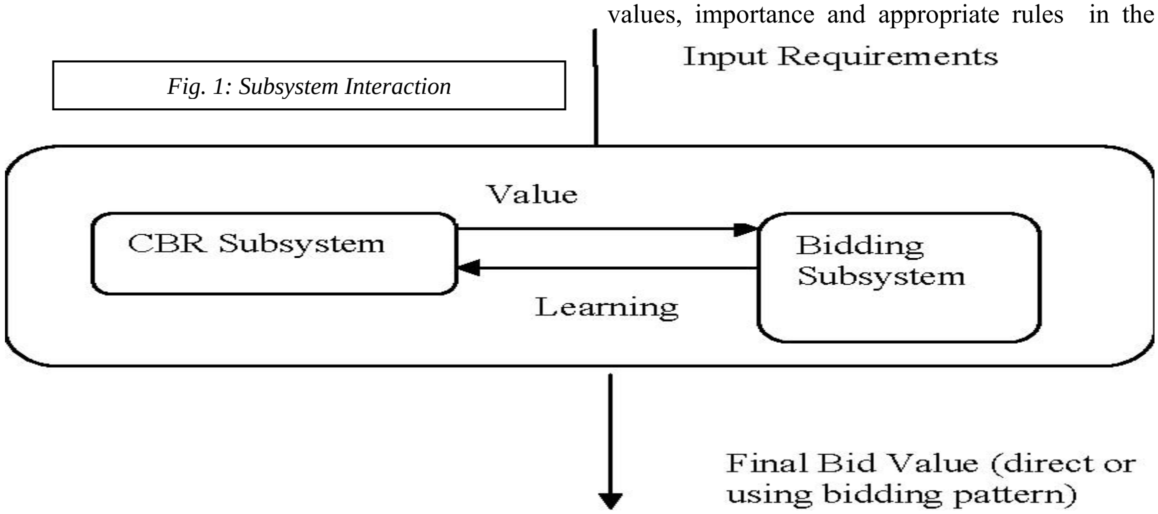
2.1 Subsystem Description

In the proposed system, the bidding CBR-agent takes the requirements and the preferences as input from the user and gets the final bid value (if possible) as output for participating in online auction. The system is made up of two subsystems namely CBR Subsystem and Bidding Subsystem. Such design is proposed to give the flexibility to the system to work for any type of auction and for any domain. The goal of the CBR Subsystem is to give the final bid value (price), till which the CBR-agent should bid, using past history consisting of previous bidding values and/or bidding patterns. The Bidding Subsystem decides the bidding strategy based on the type of auction taking place and the need of the user. It also captures the result i.e. either the winning data or losing data and gives it to the CBR subsystem to be stored into the Case Base for future learning. The solution is firstly explained for any generic scenario and then an example for ticketing process in an airline is shown.

2.2 CBR Subsystem

CBR subsystem is the intelligence component of the system. It gives the maximum value from past experience which should be bid for winning an auction. The past experience is depicted in form of hierarchical (tree) structure consisting of many layers. Each layer is corresponding to an attribute or parameter which defines some property of an item having number of values. For example, an item 'shirt' has color as a parameter with the values as red, blue and green etc. Leaf nodes contain the result of a case (value or bid pattern - ref section 3). One branch starting from root to leaf node represents one case (auction). Domain expert defines the list of parameters, the corresponding values, importance and appropriate rules in the

Fig. 1: Subsystem Interaction



Case Base. In Fig. 2, the hierarchical structure of a generic case-base is shown. RootN represents the root node and indicates the item or the domain (for example airline domain). There are four parameters shown by P1, P2, etc. Each parameter Pi can have number of values depicted by PiV1, PiV2, PiV3 etc. There is also an importance factor (I) attached to each parameter such that sum of all importance is equal of 1. A rule can also be attached with each layer which can help in adapting the old case to the new case. Suppose if layer is of class parameter (economy, business) in airline domain, then the rule " if class is business then cost of economy class is x% less than business class else if class is economy then cost of business class is y% more than economy class" can be attached to this layer. It also enable search for approximate values for certain parameters.

The CBR subsystem takes the requirements that need to be matched with the current auction from the user. Search for similar case is made in the repository and if exact match is found then the corresponding value is returned as a maximum valuation of the current case. In case of inexact match, the sum of importance of matched parameters is calculated and if it is more than some threshold then value is returned as a result of search else the system returns that 'no match is found'. Further, parameter is considered to be matched if there is variation of x% from the stored value (numeric) of that parameter. The rule attached to the parameter will specify the corresponding deviation % from original value. The leaf node can contain one or more values for handling fluctuations. Rules (like return MAX, AVG or MIN as the value) can also be attached to the leaf node holding the values of the case depending whether user is aggressive, moderate or mild.

2.3 Bidding Subsystem

- In case of exact match, irrespective of winning or losing auction, the winning value of an auction is fed back to Case Base.
- In case of inexact match and the sum of importance of matched parameters is more than some threshold, then if CBR-agent wins, the value is fed back to the CBR system otherwise if CBR-agent loses, new branch containing all parameters starting from topmost match is created and added at appropriate node in the Case Base.
- In case of inexact match and the sum of importance of matched parameters is less than

The bidding subsystem is the main interface of the system. The goal of this subsystem is to strategize the bidding strategy, get the user preferences and needs, validate if the auction is in synchronization with the user preferences and needs.

User Preference and Needs

Firstly, this subsystem gets the user preferences and requirements. The preferences are given along with the scale of need for that parameter. The need of the user can be high, medium or low. In case, the need of the user is high it is assumed that the user finds this preference very critical and hence, only p% variation is allowed. Subsequently, the figure of medium and low can be defined as q% and r% respectively where $p < q < r$. Based on the matching of user preferences and needs the CBR-agent decides if the auction is appropriate to participate in or not.

Bidding Strategy

This is the flexible component of the bidding subsystem. This component decides the bidding strategy based on the type of auction and the need of the user and is rule based. There is a configurable rule defined for each type of auction. In case of English Auction, the CBR-agent can decide to bid x% greater than the current highest bid value till its private valuation is not reached. Different types of auctions will have different rules defined. This component allows the system to participate in any type of auction and for any domain.

2.4 Learning in Case Base

Learning in case-base systems is through experience irrespective of whether CBR-agent wins or loses. The following different situations may arise and depending upon the situation, the cost is updated or new branch is generated. The starting position of the branch depends upon the value of the attribute which exactly matched.

some threshold, then new branch containing all parameters starting from topmost inexact match is created and added at appropriate node to the Case Base.

With this learning strategy, the Case Base becomes stronger and more exhaustive. This will lead to better results. The learning component makes the system wiser with experience as it happens in human beings.

2.5 Explanation of Concept using a particular auction example

Consider a case of an auction of airline ticket. This ticket is being sold using a Dutch Auction (in this auction prices of the item fall till someone bids for an auction or threshold price is reached). The parameters defined by the auctioneer are the source and destination points (Delhi → Tokyo), number of hops (2), class of seat (Economy), hours of journey (14) and the name of airline (Thai Airways). The user gives preferences as follows:

• Name of airline (need=low, Singapore Airways),
• Source and destination (need=high, Delhi → Tokyo) and
• Number of hops (need=low, 1).

These preferences are matched by the system with auction parameters. Based on the need defined for each variable, it is decided that participating in the auction is appropriate or not. If name of airline and number of hops do not match, then since the preference for these is low, the auction will be considered appropriate for the user. Parameters of the auction rather than the user preferences are matched with the Case Base. Suppose the Case Base has a branch with the parameters airline name (Thai Airways), Source and Destination (Delhi→ Tokyo), Number of hops (3), class of seat (business) and hours of journey (14). There is no exact match but the system based on importance of these parameters finds this case suitable for reuse after applying rule attached with cost of ticket. The rule says that business fare is to be reduced to economy fare by some%. The reduced fare will be returned as a private valuation (X). The auctioneer will put the price of the ticket as Y. If Y > X, then CBR-agent waits for appropriate price. The auctioneer will continue to decrease the price if he is not getting any bidder. As soon as the price reaches ≤ X, the agent will bid for the ticket and win it. This learning will be fed back into the system. In case of English auction (increasing price auction), the agent will continue to bid till the price X is reached. There is a possibility in this case that agent will win the auction at a price less than X. This will not be possible in Dutch Auctions.

CBR BASED LEARNING USING BIDDING PATTERN

In earlier section, the solution of the case as private valuation value(s) was stored but here the bidding pattern (in the form of a polynomial) instead of value is stored. Fig. 3 shows a bid pattern for an English auction. The pattern of maximum bidding values in any auction is observed and stored as a result of a case (auction). It is very useful to find the expected maximum bidding value for a running auction by using the similarity of pattern stored in the Case Base. If Case Base does not contain similar pattern, the CBR system returns 'no match' found. Fig. 3 shows the bid pattern graph for auction1 (which is stored in Case Base) and partial graph of auction2 (currently running). Observed graph of auction2 matches with the graph of auction1, so during auction, maximum bid value will be computed using graph of auction1 and returned as a maximum bid value to CBR-agent who wants to participate in that auction. Similar approach can be used for Dutch auction as well.

In case if CBR-agent is observing multiple auctions, it can match pattern of each auction with patterns in Case Base and choose an auction with minimum expected closing value.

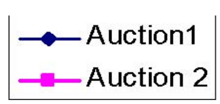
Max. Bid Value

3.1 Structure of Case Base

The challenge in this problem was to define a Case Base which could capture the required attributes which could help the CBR-agent in getting the best possible pattern. The case base shown in Fig. 4 could have some of the following parameters.

• Type of item which is being auctioned (TIC) - These can be common items like airline tickets or they can be precious items like paintings, etc.

• Duration of the auction (DA) – This indicates the total number of hours the auction is open. This would help the user in getting the pattern for similar size of auctions.



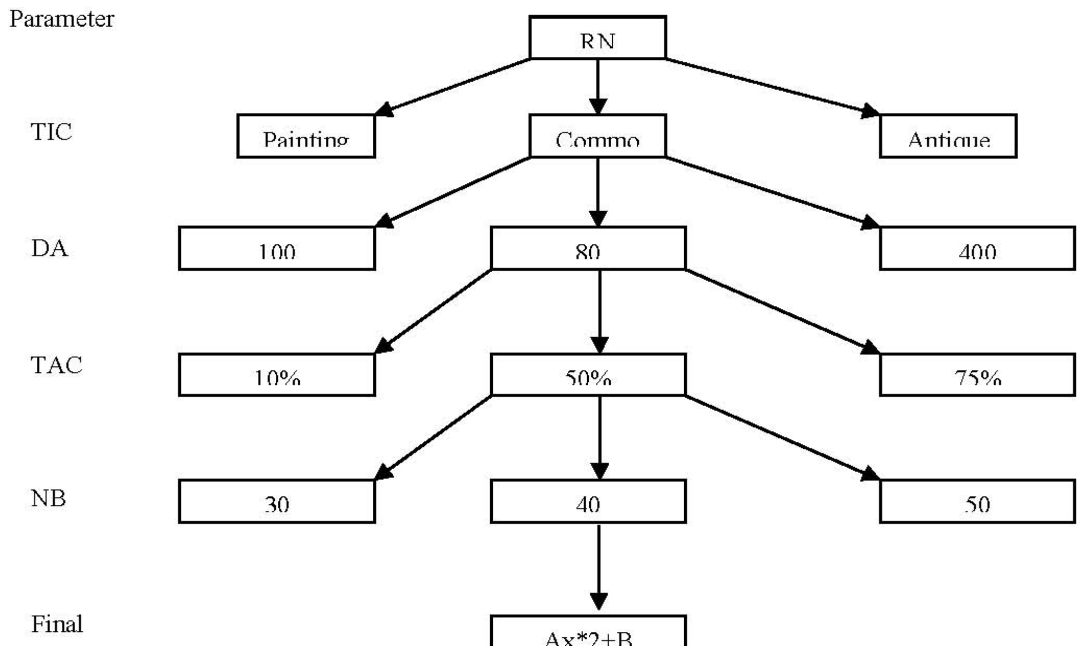


Fig. 4: Hierarchical Representation of a Repository

- Type of auction (TA) – This parameter can have values like English auction, Dutch auction, etc.
- Item – This is the actual item.
- Time of auction completed (TAC) – This covers the time in percentage which has been completed. This is the most important parameter because if the pattern is matching in percentage terms the final matching can occur.

- Number of bidders (NB)
- Pattern observation duration – This could have values ranging from 10-30%, 2060%, etc.

The sample Case Base is shown in Fig. 4. In a typical auction scenario, the CBR-agent will participate in an auction after observing certain pattern. The CBR-agent would give this pattern to the CBR system along with parameters like, the period of auction completed, duration of the auction, etc. The CBR system compares the parameter values in Case Base and depending on the importance of these parameters, indicates if the match has occurred or not. If similar match has occurred, it would return the maximum closing value of the item using the most probable pattern.

4. IMPLEMENTATION

The CBR based bidding agent is implemented as a web service. This service takes user preferences as input and then connects with the auction server to participate in the auction. The private valuation of the item is extracted through Case Base. As part of prototyping, the auction server is implemented as a web service. The communication with the auction server is using XML.

4.1 Implementation of Case Base

The Case Base is stored in XML as it gives flexibility in defining hierarchical structure with capability of attaching heterogeneous data such as

values, rules etc. The major functionality associated with the Case Base is creation, insertion, searching, deletion and storage of multiple values. Search, match and update operations of the Case Base are implemented using Java Libraries for XML reading and writing, which provide parsers for XML documents. These parsers allow us to map a XML document to a tree data structure, which gives us O(n) search and insert time complexities, where ‘n’ is the number of levels in the Case Base.

4.2 Performance Analysis

For doing empirical evaluation of CBR-agent, an auction environment is simulated which consists of multiple auctions of the same item with multiple bidders participating in them. The performance of CBR-agent is calculated by comparing its success percentage and average winning price with that of other agents participating in auctions.

Simulation Environment

In the experiment, total number of six English auctions running simultaneously for the same item and duration (start and end time of each auction is same) are taken. There are 30 bidders in addition to CBR-agent and one control agent (described below) participating in these auctions with constraints of minimum of 2 bidders (out of 30) participating per auction. The private valuation of the bidders is between 60-80 range. The auctions are simulated in such a manner that different auctions close in different ranges as private valuation is also influenced by the auction house (depends on region, reputation, business rules etc.) in which bidders are participating. For example, auction 1 would continuously close in the range 60-70 while auction2 would close in the range 62-72 and so on. This has been done so as to verify the ability of the CBR-agent to choose the correct auction for bidding. The evaluation is done in two scenarios.

- **Scenario 1** – The bidders would follow the range specified for auctions in which they are participating

- **Scenario 2** – The random bidders (maximum 2 per auction) would bid in the range 60-80 in the auctions irrespective of the range of the auctions. This has been done so as to observe the behavior of CBR-agent when certain random bidders enter the auction. These bidders do not follow the normal private valuation of the item but have different method of doing private valuation.

The bidding strategy chosen for the bidders is that they either bid x% more than the current highest bid value or their private valuation whichever is lower. The CBR-agent is analyzed against control agents in 30 and 100 trials (number of times auctions are running) in order to get the randomized comparative analysis in similar conditions. The CBR-agent is modeled based on exact match in Case Base. Therefore, a single branch of a CBR structure has been taken in the experiment as the simulated auction is being conducted repeatedly for the same item. Performance of CBR-agent is evaluated against two control agents.

- **C1 -** the control agent who bids in the auction with the same private valuation as that of the CBR-agent . However, C1 randomly chooses the auction where it decides to bid.

- **C2 -** the control agent who is the best performing out of 30 bidders participating in the auctions. These bidders choose any auction randomly and random private valuations based on two Scenarios mentioned above.

The results of simulation have been populated for the two scenarios in the form of graphs for winning comparison analysis and average winning price of CBR-agent with respect to two control agents in different situations. These are based on the method of getting the private valuation for CBR-agent and C1 as well as the length of trials required for building the Case Base. Each auction has its winning price in each trial. Case Base will keep averages of each auction winning prices which is continually upgraded in each trial. The private valuations for CBR-agent and control agent C1 are either MAX, AVG or MIN types. MAX valuation is the maximum average winning values, AVG valuation is the average of average winning values and MIN valuation is the minimum average winning values of all six auctions. Performance of C2 agent in MAX, AVG and MIN situations are shown in the tables and graphs for comparison purposes. Initial Case Base structure might be empty (no observed data) or is constructed by observing few initial trials by CBR-agent. CBR system continuously keeps on learning on each trial from the behavior of each auction. The experiment is carried out for total of 30 and 100 trials in which CBR-agent is participating.

Scenario 1 – No unpredictable behavior of the bidders

Winning Percentages and Average Winning Price with private valuation as MAX, AVG and MIN are given in tables 1 & 2 respectively with corresponding graphs in Fig. 5, 6, 7 and Fig. 8. The graphs and data in the tables clearly indicate the improved performance of CBR-agent in comparison to the control agents with respect to winning percentage and average winning price.

INTERPRETATION OF RESULTS

- Results of this experiment stabilize when number of trials increase.
- In case of MAX and AVG, CBR-agent outperforms as compared to control agents.
- In case of MIN, CBR-agent performs much better than C1 and comparable to C2.

Table 1: Winning Percentage

		MAX			AVG			MIN		
Total Observations	Total Trials	CBR agent	Agent C1	Agent C2	CBR agent	Agent C1	Agent C2	CBR agent	Agent C1	Agent C2
0	30	86.67	76.67	26.67	83.33	36.67	30.00	26.67	0.00	33.33
10	40	93.33	80.00	33.33	96.67	40.00	36.67	40.00	3.33	43.33
50	80	96.67	73.33	30.00	96.67	33.33	33.33	63.33	3.33	40.00
0	100	88	77	25	89	33	28	31	3	25
30	130	93	80	26	90	31	23	39	8	25
50	150	94	74	27	93	40	25	43	2	27

Table 2 Average Winning Price

		MAX			AVG			MIN		
Total Observations	Total Trials	CBR agent	Agent C1	Agent C2	CBR agent	Agent C1	Agent C2	CBR agent	Agent C1	Agent C2
0	30	71.39	74.54	78.38	69.80	71.98	72.13	67.33	0.00	72.60
10	40	69.66	74.35	75.13	70.19	71.71	78.27	68.23	68.75	68.92
50	80	69.46	74.60	74.36	69.98	71.60	75.26	68.00	68.50	68.95
0	100	71.03	74.73	71.71	70.49	71.5	73.87	67.2	67.9	73.67
30	130	70.53	75.11	76.95	69.97	71.97	74.32	67.8	68.25	75.05
50	150	70.67	74.84	77.2	70.54	72.25	73.59	67.63	68.98	71.54

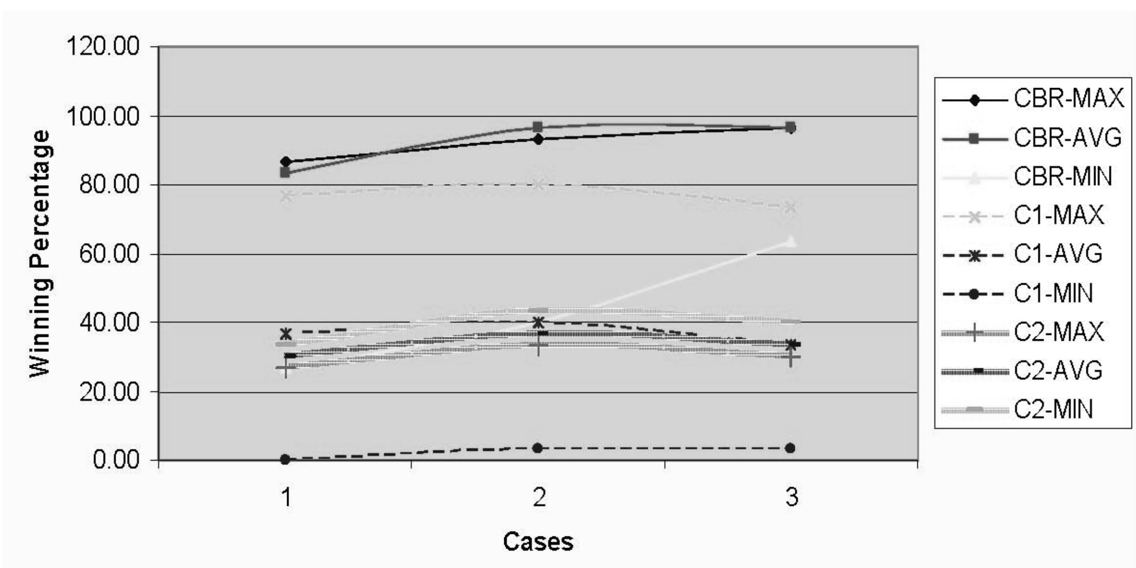
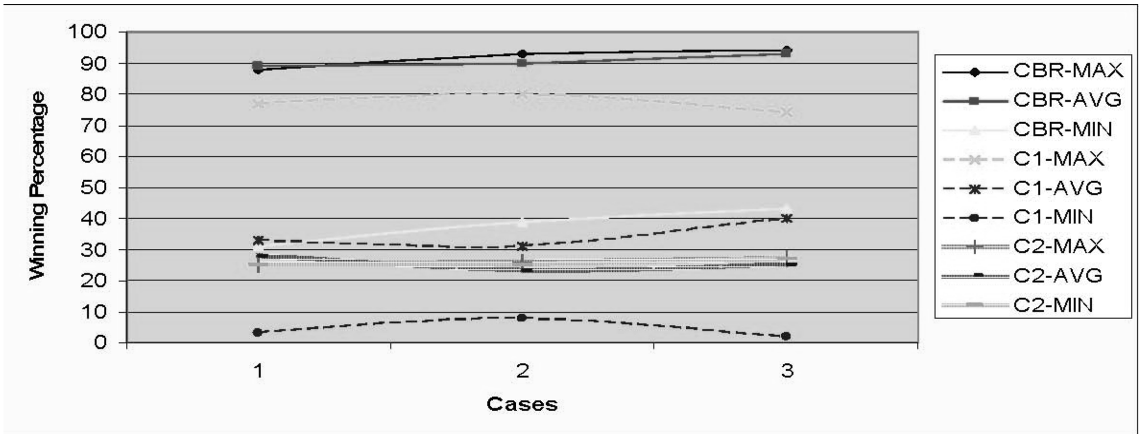


Fig. 5: Winning Comparison Analysis for 30 trials Fig. 6:Winning Comparison Analysis for 100 trials



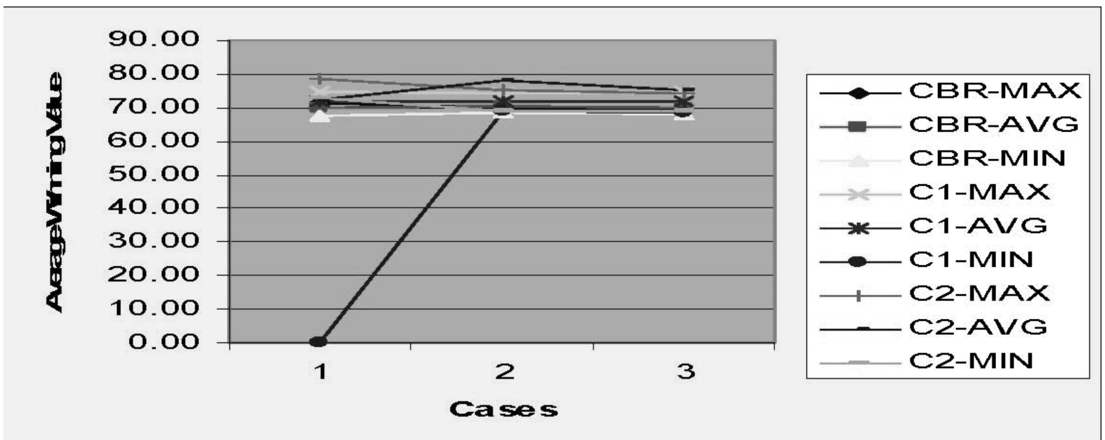


Fig. 7:Average Winning Value Comparison for 30 trials

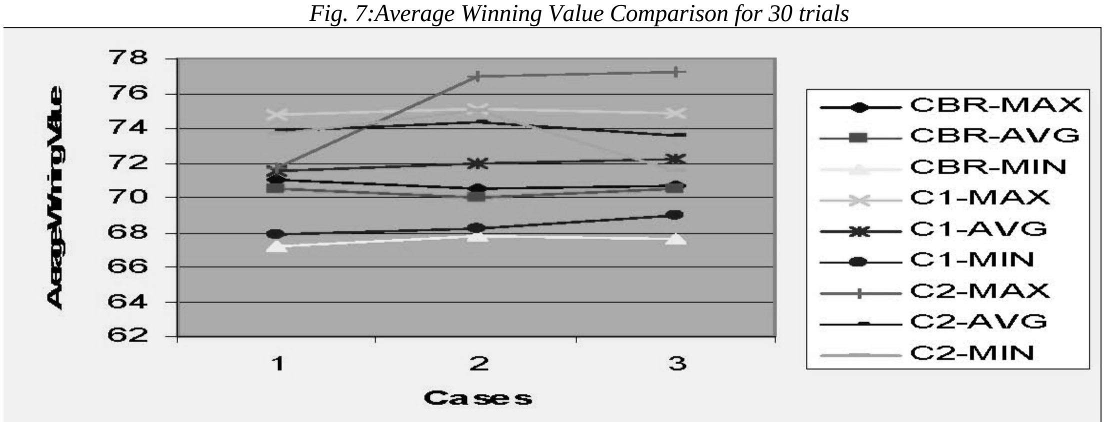


Fig. 8:Average Winning Value Comparison for 100 trials

Scenario 2 –Unpredictable behavior of certain percentage of bidders

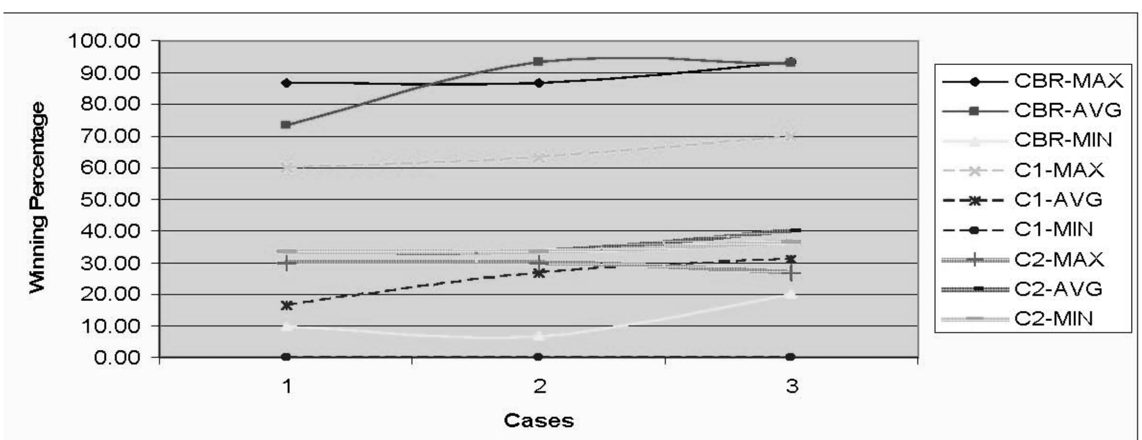
In this case, certain percentage of bidders is made to participate in auctions with the private valuation confirming to the overall range of 60-80 but not to the specific auction range. This has been done so as to evaluate the performance of CBR-agent in environment where there is a possibility of certain bidders having unpredictable private valuation. Winning Percentages and Average Winning Price with private valuation as MAX, AVG and MIN are given in tables 3 & 4 respectively with corresponding graphs in Fig. 9, 10, 11 and 12. The graphs and data in the tables clearly indicate the improved performance of CBR in comparison to the control agents with respect to winning percentage and average winning price. The strategy of the agent should be dynamic to cater to the needs of the changing environment. Based on the winning patterns it should be able to change the target auctions.

Table 3: Winning Percentage

		MAX			AVG			MIN		
Total Observations	Total Trials	CBR agent	Agent C1	Agent C2	CBR agent	Agent C1	Agent C2	CBR agent	Agent C1	Agent C2
0	30	86.67	60.00	30.00	73.33	16.67	33.33	10.00	0.00	33.33
10	40	86.67	63.33	30.00	93.33	26.67	33.33	6.67	0.00	33.33
50	80	93.33	70.00	26.67	93.10	31.03	40.00	20.00	0.00	36.67
0	100	71	62	35	49	30	37	23	13	41
30	130	74	67	28	49	25	33	26	4	46
50	150	77	61	30	54	31	40	32	15	37

Table 4: Average Winning Price Fig. 9:Winning Comparison Analysis for 30 trials

		MAX			AVG			MIN		
Total Observations	Total Trials	CBR agent	Agent C1	Agent C2	CBR agent	Agent C1	Agent C2	CBR agent	Agent C1	Agent C2
0	30	71.5	73.8	72.9	70.4	70.28	70.87	66.18	0	73.15
10	40	70.6	73.5	67.7	70.2	70.7	64.4	65.3	0	71.9
50	80	70.1	74.2	72.1	69.3	71.2	73.6	65.6	0	74.9
0	100	73.6	74.19	72.39	72.44	72.44	73.22	70.34	70.65	71.54
30	130	73.4	74.48	72.39	72.58	73	72	69.95	69.3	71.4
50	150	73.5	75.1	72.4	72	71.95	72.15	70.34	70.86	72.04



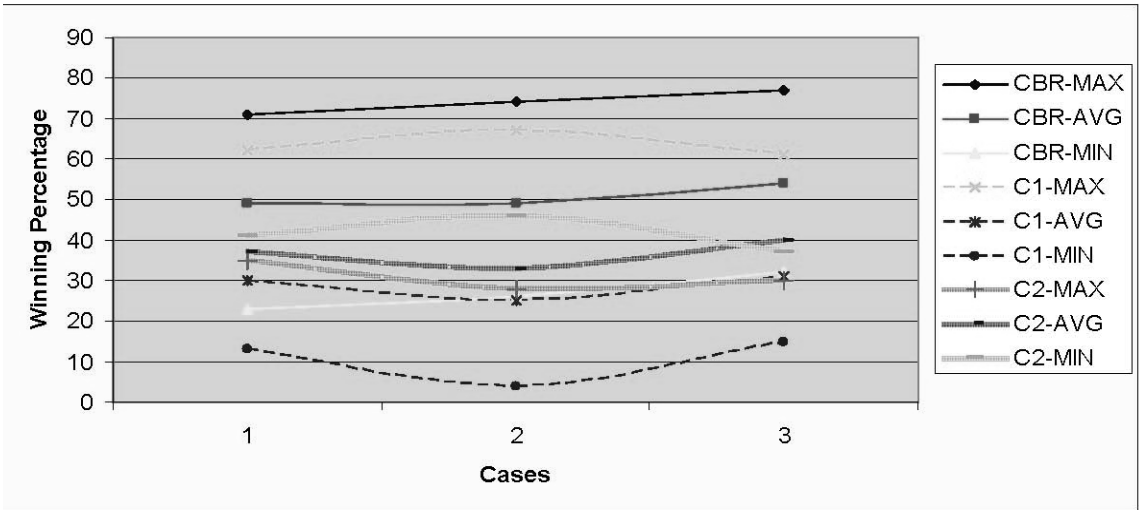


Fig. 10:Winning Comparison Analysis for 100 trials

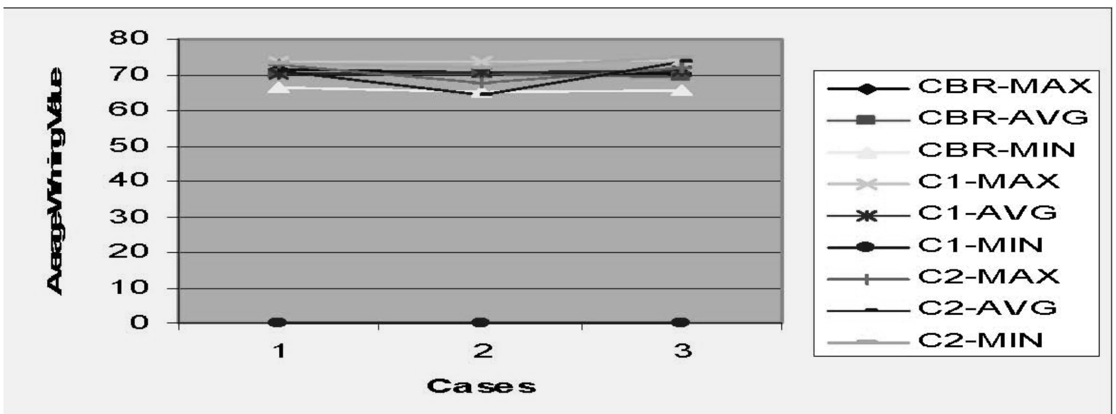
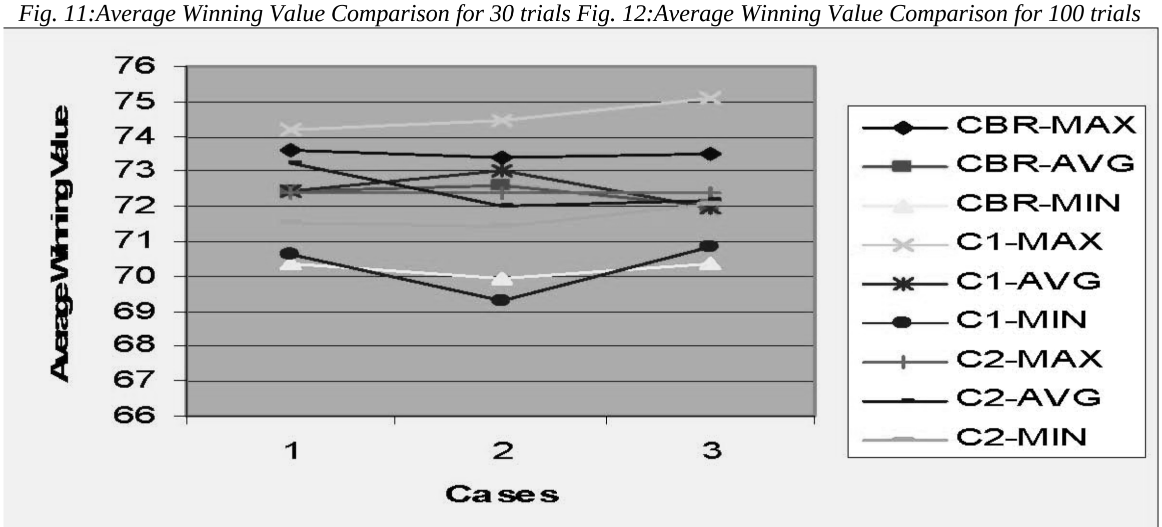


Fig. 11:Average Winning Value Comparison for 30 trials Fig. 12:Average Winning Value Comparison for 100 trials



RESULTS OF EXPERIMENTS

The experiments led to several conclusions:

- CBR-agent performs better both in average winning percentage and winning price than C1 (having same maximum valuations as that of CBR-agent) & C2 when MAX and AVG valuation values are taken into account. In case of MIN valuation value, CBR-agent performs better than C1.

- In scenario 1, CBR-agent performs similarly in winning percentage in case of MAX and AVG cases. However, the performance of C1 falls dramatically in AVG case as with respect to MAX case. This indicates that knowledge of the private valuation alone is not sufficient. This is further collaborated by the results of MIN. However, in scenario 2, the winning percentage in case of MAX and AVG cases is not similar because of the unpredictable behavior of the bidders. The other conclusions remain the same.

- CBR agent has visibility of other auctions and can suitably choose the auction depending on the auction trend at the end of each trial.

- If CBR agent has no initial observation data but learns in each trial and if number of trials increase, then its performance increases. The length of trial is proportional to the learning gained by the system.

- If percentage of observation data increases, then winning percentage also increases. This is true for both scenarios. However, in scenario 2, because of the unpredictable nature of bidders some data might not comply with this.

In general, it is conclude that

- An agent that has a visibility across multiple auctions is better than the one which has a visibility of only one auction.

- By capturing the feedback from the environment in CBR structure, the agent shows better results.

- The private valuation and the choice of the auction are two most important things which can determine the winnability of the item.

- The knowledge of the correct private valuation shows an improved performance but is even better if the knowledge of both the things (visibility of auctions and private valuation) is available.
- The agent shows considerable improved performance in case number of trials is more because of its continuous learning approach.

CONCLUSION

In this paper, the CBR system has been proposed for the agents to acquire learning capability while participating in online auctions. The CBR structure stores the past experiences of similar auctions with various attributes along with their values and final bids / bid patterns. For any new auction, CBR based agent tries to get private valuation value from the similar auctions held in the past. Similar case (auction) from the Case Base is retrieved and is adapted for the current auction. The Case Base is enriched with the solution of current auction by adding it as new case or updating the existing similar case. Learning is achieved both through success as well as failure in winning an item. It has been shown through simulation that CBR-agent performs better in winning auctions as well as winning prices than other test agents in same environment. This is possible as CBR-agent has a visibility across multiple auctions and has the knowledge of the correct private valuation. Learning capability of CBR system helps CBR-agent learn and perform better. The CBR-agent is implemented as a web service and Case Base has been implemented using XML.

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