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Automated Negotiation Agents in Modeling Gaussian Bidders

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ABSTRACT: The purpose of automated negotiations, as a novel field of study in Artificial Intelligence, is focused on autonomous agents that can appear as humans' intelligent representatives, attend negotiations with other agents, and attain acceptable outcomes. The so-called automated negotiating agents are implemented such that they can beat as many opponents as possible in different kinds of domains. Like what happens in our daily negotiations, agents in automated negotiations do not reveal their preferences explicitly. Numerous research studies have heretofore accentuated that an opponent model would be a great salvation to reduce this uncertainty, since it can be of much assistance in making wiser decisions in the next steps, reaching ideal eventual utility, and more satisfaction, accordingly. Although most opponents in our world have single-peaked preferences, the functionality of negotiating agents in modeling single-peaked opponents has not been studied. Gaussian agents are one important sort of single-peaked agents that utilize the Gaussian function to ascribe the ranking of each negotiation item. The Gaussian opponent's bliss point estimation is of high importance during a negotiation. Therefore, we first proposed a variety of Gaussian bidding agents and then focused on how accurately Automated Negotiating Agents Competition (ANAC) attendees during 2010-2019 would model these bidder agents. The results of our experiments revealed that existing ANAC agents are performing well regarding individual utility and social welfare on average, but they are poor in modeling Gaussian negotiating bidding agents.

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1- Introduction

Nowadays, with the expansion of the Internet, there is a tremendous desire to make time-consuming and tiring tasks automated. One of these tasks is negotiation which refers to the offer exchange between some parties to reach an agreement [1]. Negotiation is practical in a myriad of situations amongst which we can refer to daily shopping as well as international decision-making [2]. Automated negotiation has received high attention in diverse disciplines including economics, artificial intelligence, politics, management, and e-commerce [3, 4]. An automated negotiation usually includes two or more automated agents that negotiate under a specified turn-taking protocol for a finite amount of time in bilateral or multilateral negotiations, respectively [5-7]. Agents are autonomous and hence, have control over their behavior as well as their internal state [8-10]. Despite game theory in which the alternatives in joint outcome space and their respective utilities to all parties are known to all participants, in automated negotiations, the utilities corresponding to the joint known space of alternatives are private information to each party [11]. Even in Bayesian games agents interact through imperfect but still complete information. In another field of study, group decision-making, the realized votes of the group members to known alternatives are aggregated into a social choice [12, 13], which again differs from negotiation encountering in which the problem is pertinent to each agent for what to bid and when to accept. In automated negotiations, the agent is not aware of their opponents' information space. Such an agent is programmed once, attends a negotiation to fulfill its owner's needs, makes offers and counter-offers, and none of the negotiation steps includes direct human supervision or intervention.

The Automated Negotiating Agents Competition (ANAC) [14] is an international event that aims to advance automated negotiations by holding annual competitions and rewarding the winners. Attendees from all around the world ought to implement their agents according to the BOA architecture [15] which constitutes the initialism of the Bidding strategy, Opponent model, and Acceptance strategy. The Bidding strategy decides what to bid when the opponent's turn approaches, while the Opponent model creates a model of the opponent's features, and the Acceptance strategy decides if the agent should reject or accept the opponent's received bid. Simulating real-world cases, the agents are interdicted from explicitly exposing their preferences. This is mainly done to reduce communication costs and avoid agents' exploitation

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of each other. In this regard, every agent needs a proper opponent model to predict some attributes of its opponent [16-18]. In addition to the bidding strategy and acceptance strategy, opponent modeling is also private.

In automated negotiations, agents utilize 1) Bayesian or 2) frequency-based opponent models. Bayesian models rely upon strong hypotheses about the opponent's behavior and utilize Bayes' rule to update and hence, decrease them during negotiation. However, it is not wise to rely upon such assumptions when the opponents' preferences are not known. Frequency-based models consider how the received bids' weights and evaluation functions' values change and estimate their utility, accordingly. Therefore, ANAC attendees often utilize methods that enable their agents to beat as many opponents as possible to win the competition.

Single-peaked preferences, as a salient sort of preferences, have been studied in different disciplines such as mathematics [19], economics [20], artificial intelligence [21], etc. A single-peaked agent prefers one alternative (the peak) most and it gives the agent the highest satisfaction e.g. he/she likes the color blue more than other colors. Such agents utilize a single-peaked function to rank negotiation items. The single-peaked utility is also among the functions that are considered for SLA (service level agreement) using negotiation for allocating resources [22]. Although some mediated negotiations evaluated the social surplus when the agents' preferences are single-peaked [23], according to the ANAC repository [24] and our investigations, the present study is specifically concerned about the design and implementation of BOA agents with single-peaked preferences as well as comparing other agents' capability toward modeling single-peaked preferences in automated negotiations. Therefore, we have utilized the Gaussian function (due to its capability in producing diverse single-peaked shapes) to create 27 single-peaked bidder agents. Afterward, we examine the efficiency as well as the accuracy of 14 opponent models extracted from the agents of ANAC 2010-2019 in confronting the Gaussian bidding agents using experiments utilized in Zafari and Nassiri-Mofakham [1]. The results of these experiments reveal that the most accurate opponent model is a Bayesian one, while the opponent models that surpassed in individual utility and social welfare are frequency-based.

In this regard, Section 2 elucidates single-peaked preferences in the previous studies. Sections 3 and 4 describe prerequisite concepts, Section 5 discusses the experimental setups for accuracy as well as performance experiments, and Section 6 illustrates the experiments' results. Finally, Section 7 concludes our work.

2- Literature Review

In the previous paper [25], we investigated winner agents of ANAC in modeling single-peaked agents in an experimental approach without getting into details. The present paper extends it by rendering comprehensive details of the problem, approach, experiments, and results.

Only a few automated negotiation studies have been conducted on the matter of single-peaked agents. Ito and Klein [23] focus on designing nonlinear multi-issue negotiating protocols rather than evaluating the agents' opponent models. Klein et al. [26] introduce evaluation functions as a part of the bidding strategies of negotiating agents and test the agents' bidding behaviors like those in the prisoner's dilemma game under the developed protocols. They are the agents with hill-climbing and simulated annealing methods to be able to search the optimum, the peak, in their own single- or multi-peak utility spaces. They also arm these agents with opponent modeling to find the type of counterparty bidding, climbing, or annealing. These protocols and agents have been the basis for ANAC protocols [14] and classic agents in the repository [24].

However, there has been copious research in the area of single-peaked preferences' applications in different disciplines. In the following, we will explicate some of them.

One routine task conducted in multi-agent systems is the aggregation of the preferences to attain a joint decision e.g., an aggregate ranking of alternatives. It has been revealed that when the setting contains no restriction, we will face some inevitable setbacks, amongst which we refer to Condorcet cycles. A Condorcet cycle appears when the setting entails three alternatives, and the agents' preferences are unrestricted. As a result, it won't be feasible to attain an aggregate ranking consistent with the outcomes of all pairwise elections [27]. Some other equally essential problems with general settings are stated in Arrow's impossibility theorem [28] and Gibbard-Satterthwaite's theorem [29], amongst which we can refer to the inability to fulfill properties like strategy-proofness, voting paradoxes, non-dictatorship, unanimity, etc. All of these problems are avoidable if there exists a restriction on the preferences of agents [27]. The most notable such restriction is the one introduced by Black [30], known as single-peaked preferences. These preferences form the basic tenets of abundant studies in the analytical political sciences [31]. Single-peaked preferences are also well known for their significant importance in Social Choice Theory e.g., in the renowned median voter theorem [32]. This theorem states that the equilibrium point of voting is the peak of the median voter (the voter whose peak is located in the median so that half of the voters have smaller and another half have bigger peaks than this value). Another instance is fair allocation while preferences are single-peaked, like what Juarez *et al*. conducted. Their research focuses on the allocation of a fixed amount of a divisible resource and proved that the best solution is using a "uniform rule". This solution maximizes efficiency, envy-freeness, and worst-case surplus [33]. Beynier and his colleagues' research investigated efficient and fair resource allocation of the house market to some agents [34] such that every agent has a house. Their research revealed that utilizing a crawler would guarantee Pareto optimality, strategy-proofness, and individual rationality, as long as the preferences are single-peaked. Interestingly, Bade's research [35] showed the same results and based on his research, Tamura *et al*. expressed that in resource allocation, the probability distribution of allocations a crawler chooses from arbitrary endowments

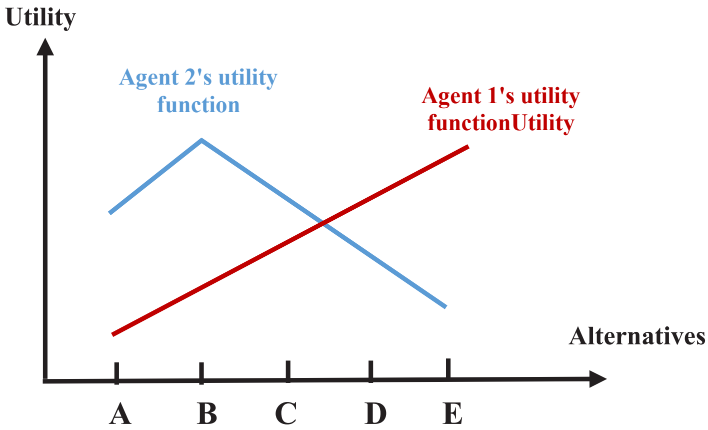

Fig. 1. An instance of two single-peaked utility functions

likens to the one selected by the random priority rule. In the case of a cake-cutting problem, which refers to a divisible resource (cake) allocation amongst n agents, Wang et al. represented a protocol in a standard model which has linear complexity and leads to an envy-freeness solution [36]. Later on, Bhardwaj et al. acclaimed that Wang and his colleagues' mechanism suffers from losing a lot of welfare; therefore, they introduced some other mechanisms that are also Pareto-efficient [37]. As for the single-peakedness recognition in a preference profile, Fitzsimmons and his colleagues [38] investigated incomplete preference profiles. This research revealed that the problem of single-peakedness recognition for incomplete profiles consisting of partial orders is NP-complete. In another research related to single-peakedness recognition, Escoffier et al. [39] represented a polynomial-time procedure for arbitrary graphs.

When an agent is said to have single-peaked preferences, it implies that up to a critical point, called the peak, an increase in the agent's endowment raises its welfare; while beyond the peak, the opposite is true [40]. For instance, in Fig. 1 the issue values of negotiation are $[A, B, C, D, E]$. For agent 1, E is preferred to D, D is preferred to C, C is preferred to B, and B is preferred to A, respectively. In the case of agent 2, B is preferred to C, C is preferred to D (and A), and D (and A) is preferred to E, respectively. B is the peak point for this agent, which is preferred to all other values. In other words, having a continuous preference relation R_i defined over $\mathbb{R}_+$ and p_i as a strict preference, each R_i has a unique maximum $p(R_i) \in \mathbb{R}_+$ such that, for each pair $x_i, x_i \in \mathbb{R}$, there is $x_i P_{i'} x_i$ as long as either $x_i < x_i \le p(R_i)$ or $p(R_i) \le x_i < x_i$ holds [40].

3- Preliminaries

An automated negotiation has a scenario with two or more preference profiles, a negotiation domain, and a protocol [41]. The role of the protocol is adjusting the interaction between agents and it comprises the rules for exchanging bids as well as the time [41]. In the present study, we use the Alternating Bids Protocol (AOP) [42] in our experiments that take place as bilateral negotiations between all agents in a tournament style so that every agent plays both sides for fair play. Randomly, one of the agents offers a bid and hence, initiates the negotiation. Subsequently, the second agent has two options: 1) it can reject the bid and make a counteroffer or 2) accept it. These agents continue exchanging bids until they reach the deadline with no accomplishment or they arrive at a compromise. The deadline is specified as either time or rounds. In the present work, we measure the deadline as rounds. A domain includes all possible bids that negotiating agents can make. It consists of negotiation issues and a set of all feasible values for every issue. Every domain contains two preference profiles or more to be assigned to the negotiating agents. Here, Ω denotes the negotiation domain. Every preference profile is a private component that determines the desirability of issue values from that agent's point of view. A bid is shown as a vector $\vec{W}$ and has n elements as $\omega_1, \ldots, \omega_n$ so that every w_i takes a value from the set $\{v_{i1}, v_{im_i}\}$ [1]. Here, m_i refers to the number of all possible values for the issue i so that $1 \le i \le n$. Each preference profile is shown as $\{\vec{w}, \cup(\vec{w}) | \vec{w} \in \Omega\}$ and includes a utility function $U(\vec{w})$ that maps every bid $\vec{w} \in \Omega$ to a utility in $[0,1]$. It should be noted that we use the preference profiles that have been utilized in ANAC and later on, incorporated into ANAC's repository (cf. 5-2). Therefore, every negotiation value has been assigned

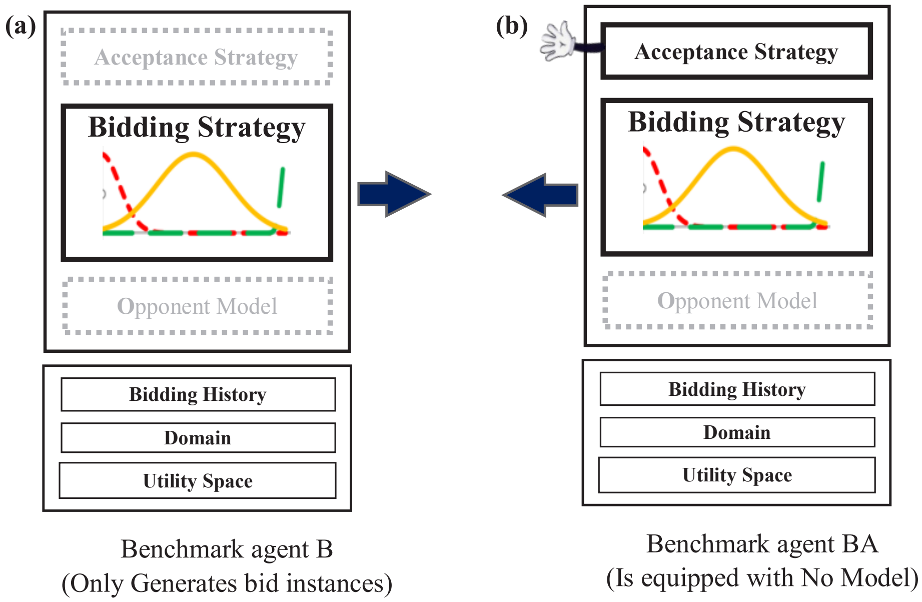

Fig. 2. The architecture of benchmark bidding agents for evaluating opponent model of counterparties: a) B: utilizing Bidding Strategy component, b) BA: utilizing Bidding Strategy and Acceptance Strategy components (adapted from [1]).

a utility in the preference profiles. In the current research, ANAC agents utilize the domains' preference profile without applying any change, while our single-peaked agents reassign a new utility to every negotiation value based on the Gaussian utility function they are equipped with.

In multi-issue negotiations, the agents apply linear-additive utility functions to calculate the relative utility of a bid [43]. Accordingly, every issue has an evaluation function and a weight that shows its relative importance. All issue weights must add up to 1. In more detail, for every bid, we denote the set of weights as λ_i, the evaluation function of each issue value ω_i as $eval_i(\omega_i)$, and $1 \le i \le n$. As such, the linear-additive utility function is calculated as illustrated in the literature as follows [44, 45]:

$$U(\vec{w}) = \sum_{i=1}^{n} \lambda_i \cdot eval_i(\omega_i). \quad (1)$$

4- Benchmark Gaussian Bidder Agents

In the experimental analysis of studies in opponent modeling of automated negotiating agents, researchers need benchmark agents that either bid (Fig. 2a) or bid and decide to accept a bid (Fig. 2b), to assess the performance and accuracy of their models.

Here, we provide specific types of these two benchmark agents, with single-peaked utility functions using Gaussian instances of the Skew Normal Distribution function,

$$f(x,\omega,p,\alpha) =$$

$$\frac{1}{\omega\pi} e^{\frac{(x-p)^2}{2\omega^2}} \int_{-\infty}^{\left(\alpha\left(\frac{x-p}{\omega}\right)\right)} e^{\frac{-t^2}{2}} dt \quad (2)$$

where, ω refers to scale, and p and α denote location (of peak) and skewness (or shape), respectively. This function (Eq. 2) can produce both symmetric and asymmetric shapes based on three major parameters by changing the value of α. Positive and negative values for α respectively cause right-skewness and left-skewness while for $\alpha = 0$, we will have a (normal) Gaussian shape. In the present research, we utilize symmetric shapes produced by the Gaussian function.

Here, when there is more than one issue, we utilize the single-peaked utility function on all issue values to determine their utility and make all issues single-peaked. This Gaussian utility function is embedded in the Bidding and Acceptance strategies of B and BA Gaussian Benchmark bidding agents (cf. Fig. 2a and 2b).

4- 1- Single-Peaked Bidding Strategy of B and BA Agents

We need to train the agents under the fair and same conditions to make sure that the results and comparisons we get from their opponent models' evaluation regarding performance measures are fair and reliable. To this end, the benchmark agents must be armed with non-adaptive bidding strategies in performance as well as accuracy experiments, or else their bidding strategy changes according to the strategy of the opponent agents and hence, produces incongruous training data.

We have used three types of bidding strategies from three general strategy families as follows:

Concession strategies: In such strategies, a target utility is calculated by Eq. (3) [46]:

$$U_t = P_{max} \cdot \left(1 - t^{1/E}\right) \quad (3)$$

According to concession strategies, the agent commences the negotiation with a high-utility bid and gradually concedes to its reservation value (which refers to the least favorable point at which the agent will accept an agreement). Here, E is the concession rate that determines the speed of concession, and P_{max} refers to the highest utility bid in the agent's preference profile. When $E \geq 1$, the agent concedes quickly to the reservation value (also called a Concede bidding strategy), while for $0 < E < 1$, the agent concedes at the final rounds of the negotiation (Boulware bidding strategy in other words) [1].

Concession strategies with an offset: They resemble concession strategies, but differ in one case which is starting the negotiation with a bid whose utility is lower than the best bid.

Non-concession strategies: These strategies start the negotiation with a low-utility bid and gradually increase it to the highest-utility bid $P_{max} = 1$. The target utility in such strategies is calculated according to Eq. (4) [46].

$$U_t = P_{min} + (1 - P_{min}).t \quad (4)$$

4- 2- Single-peaked acceptance strategy of BA agents

In the performance experiment (cf. Section 6.1), agents must reach an agreement. In that case, we will be capable of analyzing the agreement in terms of performance measures. To do so, agents must be armed with an acceptance strategy. Instead of more complex acceptance strategies [47], like ANAC experiments, a simple strategy entitled AC_{next} has been utilized for the Benchmark single-peaked bidding agents. This is done to make sure the negotiations will finish. According to AC_{next}, an agent accepts the opponent's offer if its utility is equal to or greater than the bid the agent is currently going to offer. Instead of AC_{next}, any other rational acceptance strategy is permitted. Rationality means that agents ought to prefer more utility to less.

4- 3- No model single-peaked B and BA agents

Again as was described in Section 4-1, the benchmark agents are devoid of opponent models to make sure the sequence of bids an agent offers remains unchanged. Therefore, to assure fairness in both performance and accuracy experiments, Benchmark single-peaked bidding agents do not contain opponent models.

5- Experiment Setting

This section describes the benchmark bidder agents, opponent agents, negotiation domains, and evaluation metrics we used in the experiments.

5- 1- Gaussian benchmark bidders

Using $\alpha = 0$ in Eq. (2), we will have 3 distinct symmetric groups of benchmark agents. The combination of these agents with 9 bidding strategies (cf. Section 4), engenders 27 Gaussian benchmark agents (Table 1). We utilize E = 0.1, 1, 2, P_{max} = 0.7, 0.8, 0.9, and P_{min} = 0.25, 0.5, 0.75 for Conceder (Eq. 3, $P_{max} = 1$), Offset-based (Eq. 3, $E = 1$) and Non-Conceder (Eq. 4, $P_{max} = 1$) bidding strategies, respectively. They are depicted in Fig. 3.

5- 2- Opponent Agents

We need some agents to confront our single-peaked Gaussian agents and assess their opponent models' capability in terms of performance and accuracy. In order to do so, we

Table 1. Gaussian bidder agents

Type		1	2	3
Name		Left_Half	Right_Half	Middle
Parameters	w	0.01	0.04	0.005
	p	first value	last value	median
Bidding Strategy		conceder with E = 0.1, 1, 2 offset-based with P_{max} = 0.7, 0.8, 0.9 non-conceder with P_{min}= 0.25, 0.5, 0.75		
Acceptance Strategy		AC_{next}		

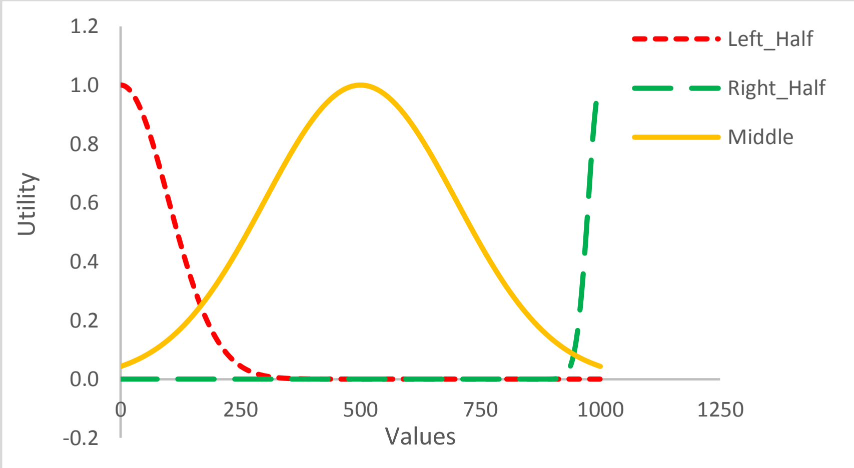

Fig. 3. Gaussian utility functions benchmarked in this study (per a sample issue).

utilized six first superior agents who attended ANAC during 2010-2019. All of these agents' opponent models can estimate the preferences of their opponents. Needless to say, opponent models may predict other attributes of an opponent, but since the present study is concerned about preferences, we only extracted the ones that have this capability. All agents with this capability (14 agents) are listed in Table 2. They utilize either frequency-based or Bayesian (cf. Introduction) opponent models. They are as follows:

IAMHaggler [29]: It is an efficient implementation of Scalable model so that, unlike the Scalable model, it has access to the utility of bids from the opponent's viewpoint

Hardheaded [30]: It assesses the value of evaluation functions and issue weights according to the number of times they appear in the opponent's bids and their value changes, respectively.

CUHKAgent [31]: This model assesses the value of evaluation functions based on the number of times they appear in the opponent's consecutive bids. it utilizes the first 100 unique bids in its estimations and considers the issue weights to be uniform.

AgentLG [28]: It assesses the value of evaluation functions based on the number of times they appear in the opponent's consecutive bids. Like CUHKAgent, this model also considers the issue weights to be uniform.

Negotiator [32]: It is similar to IAMHaggler, but it utilizes different parameters for the opponent's concession function.

The Fawkes [28]: This model assesses the value of evaluation functions based on their incidence in the opponent's bids as many other frequency models. In the case of the issue weights estimation, it considers the number of times each issue's value changes in the consecutive bids. This model resembles InoxAgent's opponent model in many facets. However unlike InoxAgent, in the current opponent model, the last received bid is compared with the first received bid from the opponent to evaluate an issue's change.

InoxAgent [28]: Just as in many other frequency opponent models, this model assesses the value of evaluation functions based on their incidence in the opponent's bids. Accordingly, the more important an issue is, the less probable its value would change. This model compares the two last received bids from the opponent to evaluate an issue's change.

RandomDance [33]: This model doesn't estimate issue weights and solely focuses on each value's incidence to estimate the opponent's preference profile.

AgentBuyogV2 [34]: This model surmises that the older and more frequent values are of a higher evaluation. In this regard, all of the issues are assigned the same weight. Then the number of unchanged values during multiple bids is calculated and a predefined constant is added to their issue weights. Consequently, to reduce this predefined constant, it is multiplied by the remaining time of the negotiation.

AgreeableAgent2018 [35]: Every evaluation value is calculated according to its incidence in the opponent's bids. In the case of each issue weight, the standard deviation of each issue is calculated.

Group Y: The number of times each value recurs in the received bids is considered to estimate the opponent's preference profile.

FSEGA2019 [36]: This opponent model is the improved version of the Scalable model so that it regards the time limitations of ANAC and therefore, ameliorates the learning process.

HardDealer: It creates a hypothesis space of different permutations of negotiation issues. Afterward, the probability of every hypothesis is calculated according to the distance between the target utility and the computed utility by the opponent model. After at least two bids are received from the opponent, the opponent model is updated.

Group1 BOA: This model has been inspired by HardHeaded, but has a main difference which is the way of increasing issue weights. In the current opponent model, the possible range of change for every issue is calculated and normalized to be considered as the issue's weight.

Table 2. List of superior agents who attended ANAC 2010-2019

Number	Agent Name	Opponent Model	Year	Rank
1	IAMHaggler [49]	Bayesian	2010	4
2	Hardheaded [50]	Frequency	2011	1
3	CUHKAgent [51]	Frequency	2012	1
4	AgentLG [48]	Frequency	2012	2
5	Negotiator [52]	Bayesian	2012	3
6	TheFawkes [48]	Frequency	2013	1
7	InoxAgent [48]	Frequency	2013	4-5
8	RandomDance [53]	Frequency	2015	3
9	AgentBuyogV2 [54]	Frequency	2015	5
10	AgreeableAgent2018 [17]	Frequency	2018	1
11	Group Y *	Frequency	2018	6
12	FSEGA2019 [55]	Bayesian	2019	2
13	HardDealer *	Bayesian	2019	5
14	Group1 BOA *	Frequency	2019	6

* It has not been explained in any other papers.

All of the experiments have been conducted at the latest version of Genius (a Java-based General Environment for Negotiation with Intelligent multi-purpose Usage Simulation) [48]. These agents utilize the predefined embedded utility function as well as the reservation value (RV) that exists in the domain. Needless to say, as the RV increases, the utility space of the agent tends to shrink. As a result, the agent becomes more and more greedy; as defined below Eq. (3), RV describes the minimum possible utility that the agent accepts.

In the performance assessment, these agents boast all BOA components, while the single-peaked agents are devoid of the opponent model (Fig. 4a). What these agents bid or accept is not of concern. Since these agents also must bid or accept when it is their turn, we simply arm them with the AC_{next} acceptance strategy and conceder bidding strategy with $E = 0.1, 1, 2,$ and $P_{max} = 1$ and as ascribed in Eq. (3).

As regards the accuracy assessment, we need an equal number of exchanged offers in all negotiation sessions (Fig. 4b). As such, we drop the existing agents' acceptance strategy in the experiments. Since these agents' bidding strategy has no effect on the process of opponent modeling, we can choose any arbitrary bidding strategy for them.

5- 3- Negotiation Domains

The single-peaked agents utilize the Gaussian function to rate the negotiation items. Therefore, we need monotonic domains to correspond with our purpose. In this regard, we extracted six monotonic domains from the Genius repository. These domains differ in size (Table 3), are devoid of discount, and their RV is set to 0. They are as follows:

Barter: This small domain concerns exchanging a certain amount of three products. Every product has four, five, and four values respectively. Therefore, the aggregate number of possible bids is 80 [56].

Itex vs Cypress: It is a small domain that concerns the negotiation between representatives of Itex (manufacturer of

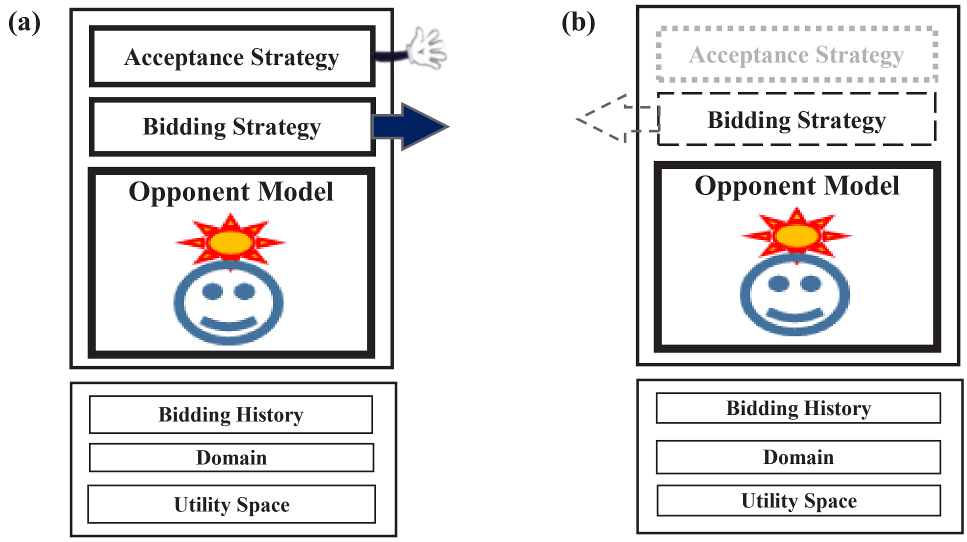

Fig. 4. The architecture of the agents whose opponent model is evaluated regarding: a) performance, b) accuracy (adapted from [1]).

Table 3. List of domains used in experiments

Domain Name	Domain Size (issues, outcomes)
Barter	Small (3, 80)
Itex vs Cypress	Small (4, 180)
Airport Site Selection	Medium (3, 420)
Smart Energy Grid	Medium (4, 625)
Energy Small	Large (6, 15625)
Energy	Large (8, 390625)

bicycle components) a seller and Cypress (manufacturer of bicycles) a buyer. It has four issues such that they have five, four, three, and three values respectively. This produces 180 possible bids in total [57].

Airport Site Selection: It is a medium-sized domain that is about deciding where to erect an airport site based upon three issues that respectively have ten, seven, and six values. In this regard, the aggregate number of feasible bids is 420 [56].

Smart Energy Grid: It is a medium-sized domain that concerns energy producers, consumers, and brokers that negotiate over four issues. Every issue has five values and hence, the aggregate number of possible bids is 625 [58].

Energy Small: It concerns diminishing electricity consumption in peak hours so that a representative of an electricity distribution company negotiates with a representative of a major customer. Energy Small has six issues and each issue has five values which produce 15625 possible bids in total [56].

Energy: This domain is a bigger version of the Energy Small domain. Energy has eight issues and each issue has five values which produce 390625 possible bids in total [56].

5- 4- Evaluation Measures

Here, we apply evaluation measures that also have been frequently used in ANAC for several years. The performance of each agent is evaluated using two factors: 1) individual utility and 2) social welfare. The individual utility is measured as Equation (5) [59].

$$AvgUtility_A = \frac{\sum_{i=1}^{N} utility_A^i}{N}, \tag{5}$$

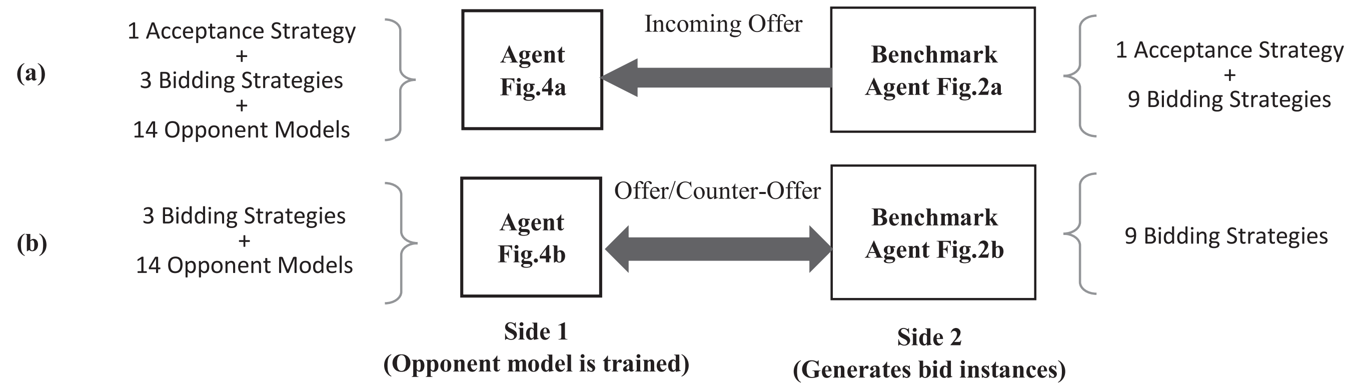

Fig. 5. Interactions of existing ANAC agents (side A) with benchmark Gaussian agents (side B) in a) performance experiment, b) accuracy experiment (adapted from [1]).

Here, N and $AvgUtility_A$ respectively refer to the aggregate number of negotiation sessions, and the average utility agent A obtains during N sessions. $utility_A^i$ shows the utility of agent A in session i.

As for evaluating social welfare, we utilize Equation (6) [1]:

$$AvgJointUtility_{A,B} = \frac{\sum_{i=1}^{N} utility_A^i + utility_B^i}{2N} \tag{6}$$

so that, N and $AvgJointUtility_{A,B}$ respectively refer to the aggregate number of negotiation sessions, and the average social welfare for agents A, B obtained during N sessions. $utility_A^i$ and $utility_B^i$ respectively show the utility of agents A and B in session i.

And eventually, to evaluate the accuracy of each opponent model, the Pearson correlation is used (Eq. 7) [1]:

$$d_p(u_{OP}, \acute{u}_{OP}) = \frac{\sum_{\vec{\omega}\in\Omega}(u_{OP}(\vec{\omega}) - \overline{u_{OP}})(\acute{u}_{OP}(\vec{\omega}) - \overline{\acute{u}_{OP}})}{\sqrt{\sum_{\vec{\omega}\in\Omega}(u_{OP}(\vec{\omega}) - \overline{u_{OP}})^2 \sum_{\vec{\omega}\in\Omega}(\acute{u}_{OP}(\vec{\omega}) - \overline{\acute{u}_{OP}})^2}} \tag{7}$$

where u_{OP} refers to the real preference profile of the opponent, and $\acute{u}_{OP}$ shows the estimated preference profile from the opponent model's point of view. $u_{OP}(\vec{\omega})$ and $\acute{u}_{OP}(\vec{\omega})$ ‹ refer to the real utility of a bid and the estimated utility of a bid $\vec{\omega}$ in the opponent's preference profile respectively.

6- Experiment Interactions and Results

We evaluate opponent agents confronting benchmark Gaussian bidders in two distinct experiments. They negotiate in different domains that differ in size and issues. Each experiment is elucidated in the following.

6- 1- Interactions in Experiment for Assessing Performance

According to Section 5-2, to assess the performance of the opponent models regarding individual utility (Eq. 5) as well as social welfare (Eq. 6), we need to arm every opponent model with 3 sorts of bidding strategy and 1 acceptance strategy (Table 2, placed at Side 2 in Fig. 5a). Furthermore, each model negotiates over 6 domains (Table 3) with 27 benchmark agents in Side 1 (Table 1) in 1000 rounds, and for both sides. Therefore, for every opponent model, there exist $27 \times 6 \times 2 = 324$ sessions. Having 14 opponents available, the aggregate number of negotiation sessions is $324 \times 14 \times 3 = 13608$. For every opponent model, the average of both individual utility and social welfare in all negotiation sessions has been calculated as can be seen in Fig. 6.

6- 2- Interactions in Experiment for Assessing Accuracy

In the accuracy assessment, there are 14 agents (Table

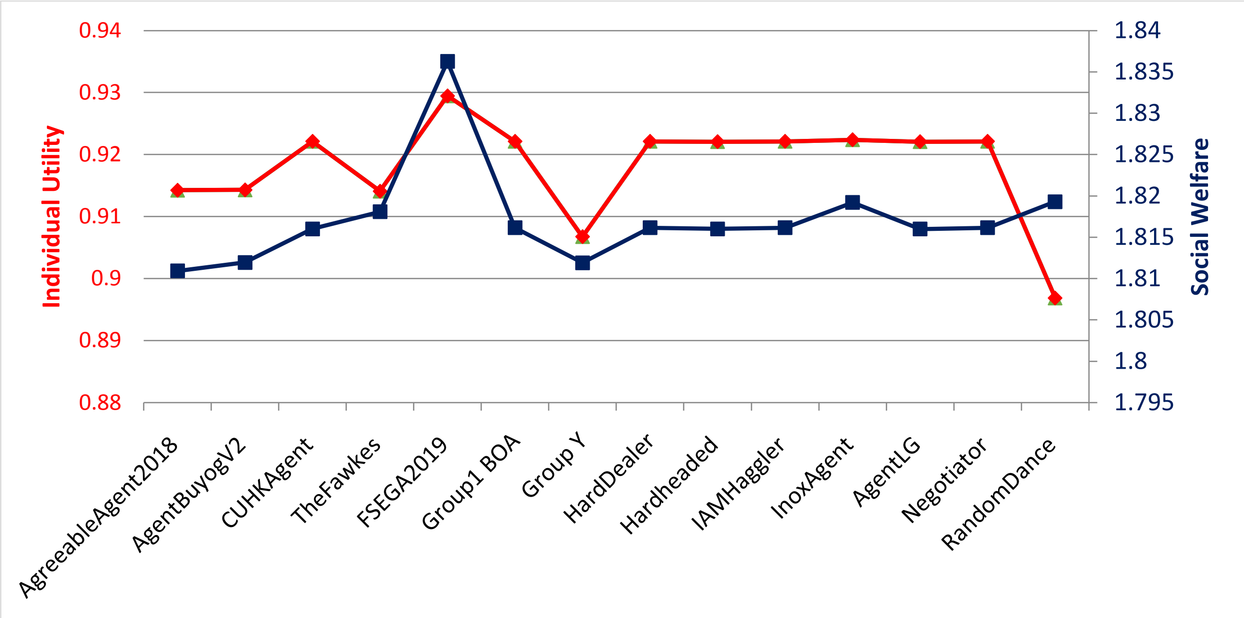

Fig. 6. Agents' individual utility and social welfare (cf. Table 2) confronting Gaussian bidders

2) on side B of Fig. 5b that negotiate over 6 domains (Table 3) with 27 single-peaked agents (Table 1) on side A per 5000 rounds. Hence, for each opponent model, there are $27 \times 6 = 162$ sessions and the number of bids used as training data is $162 \times 5000 = 810000$. Fig. 7 shows the Pearson correlation at 11 points in time (with equal intervals) for each opponent model and in all sessions. This figure shows how every model's accuracy changes over time.

6- 3- Experiment Results

In the present study, we do not assume any hypothesis. Furthermore, we conduct our experiments with a non-random dataset such that all encounters in all domains are fairly considered. As a result, the statistical significance of the results is certain (Also, cf. Sections 4-1 and 5-2, Fig. 2, and Fig. 4). All negotiations (cf. Sections 5-1 and 5-2) are bilateral and they are executed in the Genius 9.1.13. According to Fig. 6, Inox and Randomdance outdo their peers in individual utility and social welfare (respectively) when they confront all Gaussian bidders in all domains. As regards accuracy, IAmHaggler outperforms other agents (as shown in Fig. 7). However, the results are not satisfactory. The accuracy of the opponent models in each of the domains is also depicted in Fig. 8. This figure shows that the opponents' accuracies in medium-sized domains are better than in large and small domains. Moreover, their accuracies in large domains are better than in small domains. Amongst the agents, Fsega was not executed in the Energy domain in both experiments and the available results are related to 5 domains. The ranks for each opponent model regarding individual utility as well as social welfare are listed in Table 4.

7- Conclusion

Single-peaked preferences are common in many real-world scenarios including competitive negotiations among self-interested parties to reach mutually beneficial agreements. Automated negotiations facilitate the complexities in making decisions about what is the best alternative to bid and when is the best time and offer to accept in negotiations over large combinatorial domains. To decrease the risk of negotiation failure and reach the best win-win agreement, the automated negotiating strategies also include a component to model opponents. The present research, as a pioneer one is dedicated to evaluating automated negotiating agents' opponent modeling components in modeling single-peaked bidding agents. It implements single-peaked preferences in 27 Gaussian negotiating bidder agents. Despite ANAC experiments in which the agents employ their private negotiation strategies but the same utility function embedded in the negotiation domain, in this study, the preferences of any bidding agent utilize an individual single-peaked utility function rather than a general one. We analyzed the capability of ANAC agents in fair bilateral negotiation experiments. As a result, two frequency-based opponent models, one from ANAC 2015 and one from ANAC 2019, outdid others in performance measures. As for the accuracy measure, a Bayesian opponent

Table 4. List of opponent models' rank in performance experiment' measures

Number	Agent Name	Individual Utility Rank	Social Welfare Rank
1	IAMHaggler	3	5
2	Hardheaded	5	7
3	CUHKAgent	3	6
4	AgentLG	4	8
5	Negotiator	3	5
6	TheFawkes	9	4
7	InoxAgent	1	3
8	RandomDance	11	1
9	AgentBuyogV2	6	9
10	AgreeableAgent2018	7	11
11	Group Y	10	10
12	FSEGA2019	2	2
13	HardDealer	3	5
14	Group1 BOA	3	5

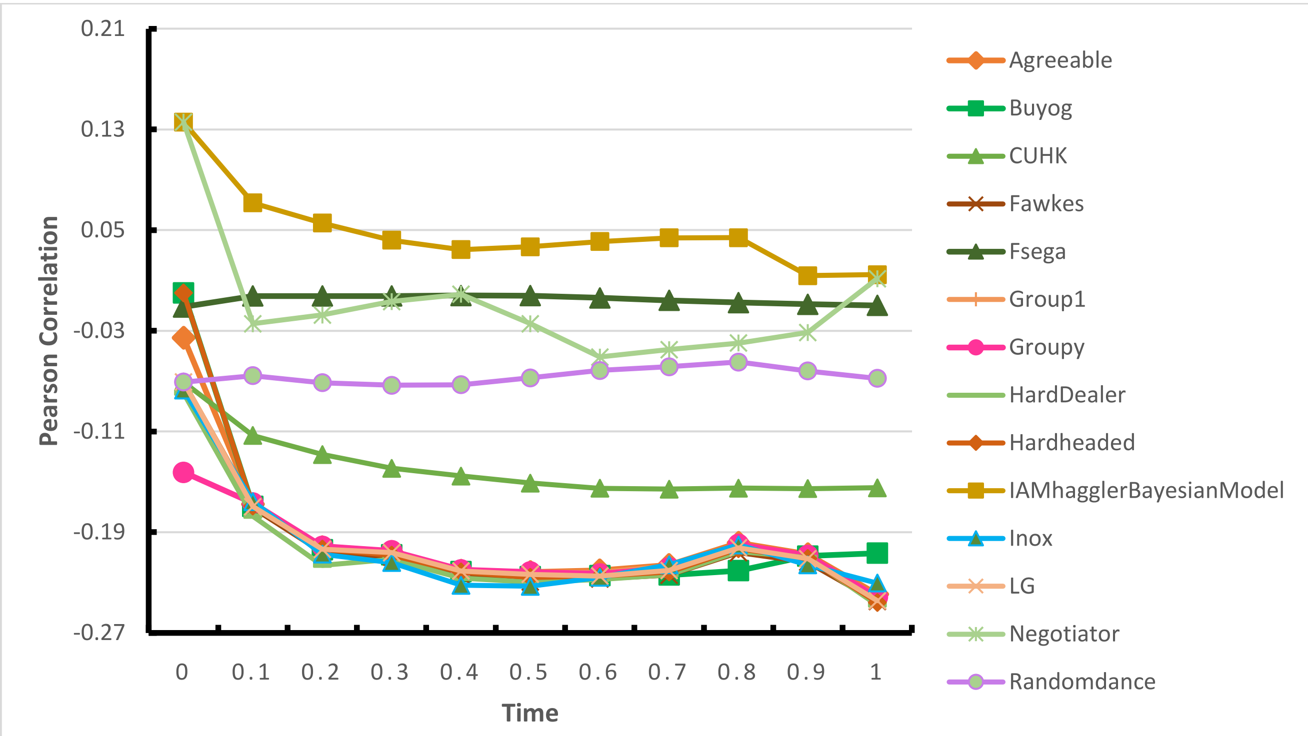

Fig. 7. Agents accuracy (cf. Table 2) in modeling Gaussian bidders

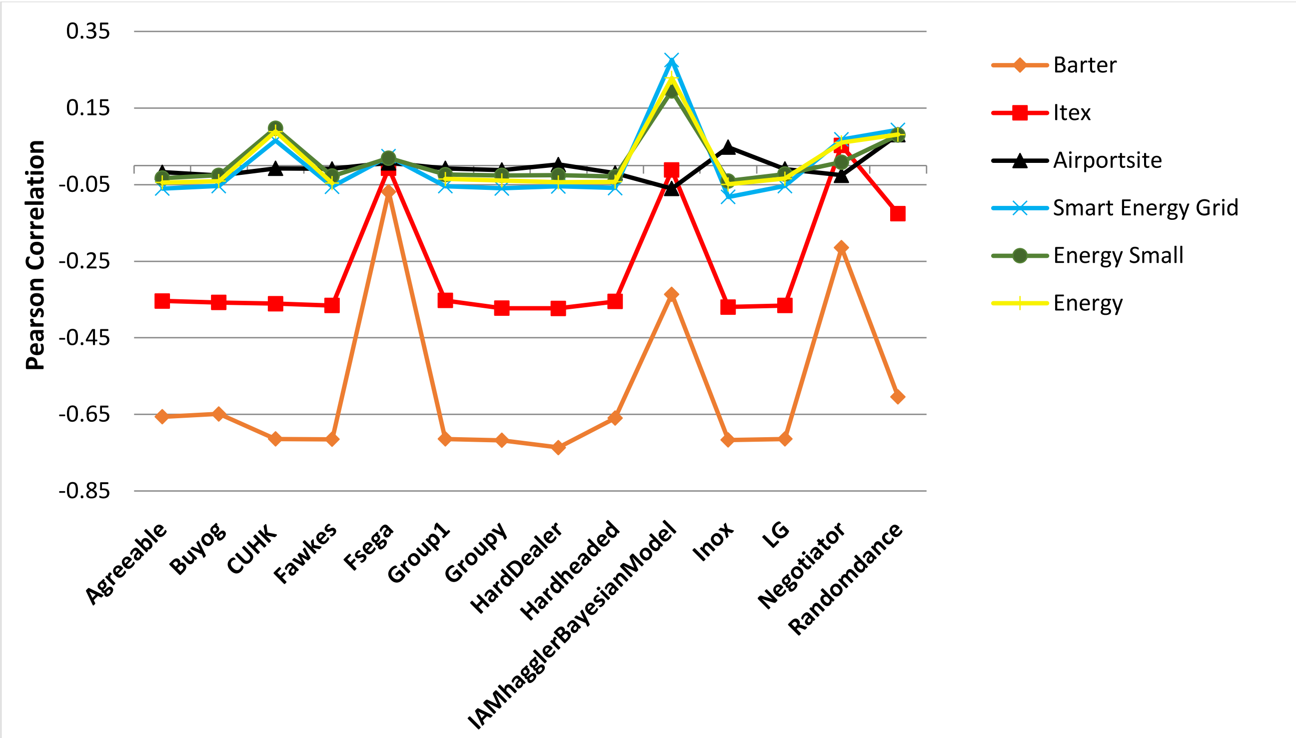

Fig. 8. Agents accuracy (cf. Table 2) in front of Gaussian bidders in each domain

model from ANAC 2019 showed better results. The results of our experiments revealed that the most accurate opponent does not necessarily lead to higher performance, since the tested opponent models did not show satisfactory results for accuracy but showed acceptable results for performance measures. Especially, the most accurate opponent models do not necessarily lead to higher performance. Therefore, the design and implementation of a more efficient and accurate opponent model are recommended.

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