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Abstract. An important aim in bilateral negotiations is to achieve a win-win solution for both parties; therefore, a critical aspect of a negotiating agent's success is its ability to take the opponent's preferences into account. Every year, new negotiation agents are introduced with better learning techniques to model the opponent. Our main goal in this work is to evaluate and compare the performance of a selection of state-of-the-art online opponent modeling techniques in negotiation, and to determine under which circumstances they are beneficial in a real-time, online negotiation setting. Towards this end, we provide an overview of the factors influencing the quality of a model and we analyze how the performance of opponent models depends on the negotiation setting. This results in better insight into the performance of opponent models, and allows us to pinpoint well-performing opponent modeling techniques that did not receive much previous attention in literature.

Keywords: Negotiation, Opponent Model Performance, Quality Measures.

1 Introduction

A negotiation between two agents is a game in which both agents try to reach an agreement better than their status quo. To avoid exploitation, agents often keep their preferences private during the negotiation [6]; however, if an agent has no knowledge about its opponent's preferences, then this can result in a suboptimal outcome [10]. A common technique to counter this is *learning* the opponent's preference profile during the negotiation, which aids in increasing the quality of the negotiation outcome by identifying bids that are more likely to be accepted by the opponent [6,10,21].

If there have been previous negotiations with a similar opponent, the opponent model can be prepared *before* the start of the negotiation; we will refer to these models as *offline* models (for example [6]). Contrastingly, if the agent has to learn the preferences *during* the negotiation it performs *online* modeling (for example [8,10,14]).

In this work we focus on *online* opponent models in a *single-shot* negotiation with *private* preference profiles; i.e., a setting in which an agent has no knowledge about the opponent's preference profile and no history of previous negotiations is available. There has been recent interest in opponent modeling for such settings, for example in the Automated Negotiating Agents Competition (ANAC) [1,4]. Despite ongoing research in this area, it is not yet clear how different approaches compare, and empirical evidence

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has raised the question whether using an opponent model is beneficial at all in such a setting. To illustrate: state-of-the-art agents, such as the top three agents of both ANAC 2010 [4] and ANAC 2011 [1], do not model the opponent, yet outperformed agents that do. One reason that opponent modeling does not guarantee a better outcome for an agent is that the model can be a poor representation of the opponent's preferences. If the model consistently suggests unattractive bids for the opponent, it may even be preferable to not employ one at all. Secondly, a time-based deadline introduces an additional challenge for online opponent modeling, as learning the model can be computationally expensive and can therefore influence the amount of bids that can be explored. More precisely, the gain in using the model should be higher than the loss in utility due to decreased exploration of the outcome space. We will refer to this as the *time/exploration trade-off*.

Apart from the inherent trade-off in opponent modeling, we are interested whether opponent models are accurate enough to provide gains at all, even when ignoring computational costs. To this end, we evaluate opponent models in two settings: a time-based and round-based negotiation protocol. This paper compares a large set of opponent modeling techniques, which were isolated from state-of-the-art negotiation strategies. We measure their performance in various negotiation settings, and we provide a detailed overview of how the different factors influence the final negotiation outcome.

After discussing related work in Section 2, we introduce the negotiation setting and consider the difficulties in evaluating opponent models in Section 3. In Section 4 we introduce a method to quantify opponent model performance, after which we apply it to a set of models in Section 5. We formulate hypotheses and analyze the results in Section 6; and finally, in Section 7 we provide directions for future work.

2 Related Work

Opponent modeling has received a lot of attention in automated negotiation. There are three groups of related work when considering opponent model evaluation. The first category consists of work that details an agent strategy in which the opponent model is introduced, but the performance is not evaluated. Examples of this type are [8] and [20].

The second category compares a single novel model with a set of baseline strategies. The approaches usually differ in how they define performance. In [10] for example, a model is introduced for the same time-based protocol discussed in this work. The performance of the opponent model is estimated by embedding it in a strategy and comparing the average utility against two baseline strategies. The modeling technique discussed by [16] introduces a model for a similar protocol, but in this case the baseline is set by humans. Zeng and Sycara measure performance in terms of social welfare, but focus on single-issue negotiations in which they compare the performance of three settings: both learn, neither learn, and only the buyer learns [21]. Finally, [5] evaluates the accuracy of a model against simple baseline strategies in terms of the likelihood that the correct class is estimated to which the opponent's preference profile belongs.

The last category is most similar to our work, and consists of literature comparing the performance of a model against other models or against a theoretical lower or upper bound. For example, Coehoorn and Jennings [6] evaluate the performance of their opponent model using a standard bidding strategy that can be used both with and without a model. The performance of the strategy is evaluated in three settings: without knowledge, with perfect knowledge, and when using an offline opponent model. This work is similar to our work, however, it differs in the fact that we focus on *online* opponent modeling. Our setting is especially challenging as it involves the time/exploration trade-off. Another example is the work by [13], which introduces two opponent models for e-recommendation in a multi-object negotiation. Compared to our work, we focus on the more general type of multi-issue negotiations. Finally, [11] defines two accuracy measures and uses these measures to analyze the accuracy of two opponent models. The main differences are that we focus on a larger set of performance measures, and pay more attention to the factors that influence the performance of the model.

Furthermore, as far as we know, our work is the first to compare and analyze such a large set of state-of-the art models of the opponent's preference profile.

3 Evaluating Opponent Models

The main goal of this work is to answer the following research question: "*Under what circumstances is it beneficial to use an online opponent model in a real-time negotiation setting?*". An answer is not straightforward due to the time/exploration trade-off and potentially poor accuracy of a model. In particular, we want to answer the following:

1. Assuming *perfect* knowledge about the opponent's preferences, is there a significant performance gain in using this information compared with ignoring it?
2. Is there a significant performance gain from using an *online opponent model* in comparison to *not using a model*, assuming no prior knowledge is available?

The main difficulty in finding a conclusive answer to these questions, is that the performance of an opponent model depends on the negotiation setting. Therefore, we study an third, overarching research question:

3. How does the performance of using an opponent model depend on the setting?

3.1 Preliminaries

In this work we focus on a bilateral automated negotiation in which two agents try to reach an agreement while maximizing their own utility. Agents use the widely-employed alternating-offers protocol for bilateral negotiations [17], in which the negotiating parties take turns in exchanging offers. A negotiation scenario consists of the negotiation domain, which specifies the setting and all possible bids, together with a privately-known preference profile for each party. A preference profile is described by a utility function $u(x)$, which maps each possible outcome x in the negotiation domain to a utility in the range $[0, 1]$. In this work we discuss opponent models that attempt to estimate the opponent's utility function $u'(x)$ during the negotiation.

3.2 Influence of the Agent's Strategy

Different agents apply their opponent model in different ways. There are two main factors in which the application of an opponent model by a bidding strategy can differ:

- *Type of information gained from the opponent model.* A bidding strategy can employ an opponent model for different reasons: for example, it can be employed to select the best bid for the opponent out of a set of similarly preferred bids [3,20]; to select a bid that optimizes a weighted combination of both utility functions [8]; or to help estimate the utility of a specific outcome, such as the Nash-point [3].
- *Selecting a bid using an opponent model.* When a model is used to select a bid from a set of similarly preferred bids, the question still remains which one to choose. One can select the *best* bid for the opponent, but this may be suboptimal, as models may be inaccurate. An alternative is to select a bid from the set of n best bids [3].

Even when the factors above are taken into account, still care has to be taken to properly compare different models. Opponent models can only be fairly compared if the other components, such as bidding strategy and acceptance strategy [2] are fixed.

3.3 Influence of the Opponent's Strategy

All opponent modeling techniques make certain assumptions about the opponent, so as to assign meaning to the observed behavior. If the opponent does not adhere to these assumptions, the model may not reflect reality well. The set of strategies against which a model is tested is a decisive factor when measuring its performance. Therefore, a set of opponents should contain both agents that fulfill the model's assumptions to determine its efficacy in optimal conditions; and agents that test the model's robustness by violating its assumptions.

The following assumptions were found by analyzing the models in Section 5.2:

1. *The concession of the opponent follows a particular function.* Some opponent modeling techniques assume that the opponent uses a given time-based bidding strategy. Modeling the opponent then reduces to estimating all issue weights such that the predicted utility by the modeled preference profile is close to the assumed utility.
2. *The first bid made by the opponent is the most preferred bid.* The best bid is the selection of the most preferred value for each issue, and thereby immediately reveals which values are the best for each issue. Many agents start with the best bid.
3. *There is a direct relation between the preference of an issue and the times its value is significantly changed.* To learn the issue weights, some models assume that the amount of times the value of an issue is changed is an indicator for the importance of the issue. The validity of this assumption depends on the distribution of the issue and value weights of the opponent's preference profile and its bidding strategy.
4. *There is a direct relation between the preference of a value and the frequency it is offered.* A common assumption to learn the value weights is to assume that values that are more preferred are offered more often. Similar to the issue weights assumption, this assumption strongly depends on the agent's strategy and domain.

3.4 Influence of the Negotiation Scenario

Three main factors of a scenario influence the quality of an opponent model:

1. *Domain size.* In general, the larger the domain, the less likely a bid is a Pareto-bid. Furthermore, domains with more bids are likely more computationally expensive to model. Therefore, the influence of the time/exploration trade-off is higher.

2. *Bid distribution*. The bid distribution quantifies how bids are distributed. We define bid distribution as the average distance of all bids to the nearest Pareto-bid. The bid distribution directly influences the performance gain attainable by a model.
3. *Opposition*. We define opposition as the distance from the Kalai-point to complete satisfaction $(1, 1)$. The opposition of a domain influences the number of possible agreements, and opponent models may be help in locating them more easily.

4 Measuring the Performance of Opponent Models

As we noted in the previous section, the effectiveness of an agent's opponent model is heavily influenced by the negotiation setting. This work proposes a careful measurement method of opponent modeling performance, and can be interpreted as a first step towards creating a generic performance benchmark for the type of opponent models that we study here. The following sections discuss the four components of the method.

4.1 Negotiation Strategies of the Agents

For the negotiation strategies of the agents in which the opponent models are embedded, we elected a variant of the standard time-dependent tactic [7]. This strategy is chosen for its simple behavior, which elicits regular behavior from its opponents; furthermore, adding a model may significantly increase its performance. Given a target utility, the adapted agent generates a set of similarly preferred bids and then selects a bid using the opponent model. We focus on selecting a bid from a set of similarly preferred bids, as this usage is commonly applied, for example in [20] and [14]. We embedded the models in four time-dependent agents ($e = 0.1; 0.2; 1.0; 2.0$). We opted for multiple agents as we believed that the concession speed can influence the performance gain.

The remaining issue in using an opponent model is which bid to select for the opponent given a set of similarly preferred bids. Given the approaches in Section 3.2, we opted to have the models select the best bid for the opponent, as this approach is most differentiating: it leads to better performance of the more accurate opponent models.

4.2 Negotiation Strategies of the Opponents

This section discusses the opponents selected using the guidelines outlined in Section 3.3. The set of opponent strategies consists of three cooperative agents, which should be easy to model as their concession speed is high, and five competitive agents. The set of conceding agents consists of two *time-dependent agents* with high concession speeds $e \in \{1, 2\}$, and the *offer decreasing* agent, which offers the set of all possible bids in decreasing order of utility. The set of competitive agents contains two *time-dependent agents* with low concession speeds $e \in \{0.0, 0.2\}$, and the ANAC agents *Gahboninho*, *HardHeaded*, and *IAMcrazyHaggler*.

Given the five opponent modeling assumptions introduced in Section 3.3, the first assumption about the opponent's decision function fails in general, as an opponent in practice never completely adheres to the assumed decision function. The second assumption holds for all agents except *IAMcrazyHaggler*, whose first bid is randomly picked. The other three assumptions are typical for the frequency models. It is not possible to adhere to or violate these assumptions completely, as they depend both on the negotiation scenario structure and opponents.

4.3 Negotiation Scenarios

As we explored in Section 3.4, the *domain size*, *bid distribution*, and *opposition* of a negotiation scenario are all expected to influence an opponent model's performance, and therefore we aimed for a large spread of the characteristics of the scenarios, as visualized in Table 1. In total seven negotiation scenarios were selected.

Table 1. Characteristics of the negotiation scenarios

Scenario name	**Size**		**Bid distrib.**		**Opposition**	
ADG [1]	15625	(*med.*)	0.136	(*low*)	0.095	(*low*)
Grocery [1]	1600	(*med.*)	0.492	(*high*)	0.191	(*med.*)
IS BT Acquisition [1]	384	(*low*)	0.121	(*low*)	0.125	(*low*)
Itex–Cypress [12]	180	(*low*)	0.222	(*med.*)	0.431	(*high*)
Laptop [1]	27	(*low*)	0.295	(*med.*)	0.178	(*med.*)
Employment contract [19]	3125	(*med.*)	0.267	(*med.*)	0.325	(*high*)
Travel [4]	188160	(*high*)	0.416	(*high*)	0.230	(*med.*)

4.4 Quality Measures for Opponent Models

The quality of an opponent model can be measured in two ways: a black box approach, in which *performance measures* evaluate the quality of the outcome; and a white box view, which uses *accuracy measures* capable of considering the internal design of a strategy and revealing the accuracy of the estimation of the opponent's preferences.

This work focuses on the performance measures shown in Table 2, as [11] has already compared models using a white box approach, albeit in a more limited setting.

Table 2. Overview of the performance measures

Performance measure	**Description**
Avg. utility [1,13,10]	Average score of the agents against selected opponents on all negotiation scenarios.
Avg. time of agr. [2]	Average time required to reach an agreement.
Avg. rounds [13,21]	Average rounds a negotiation lasts. In a rounds-based setting, less means more accurate.
Avg. Pareto dist. of agr. [1,9]	Average minimal distance to the Pareto-frontier. Lower is better.
Avg. Kalai dist. of agr. [9]	Average distance to the Kalai-point. Lower means more fair.
Avg. Nash dist. of agr. [9]	Average distance to the Nash-point. Lower means more fair.

5 Experiments

We applied the method described in the previous section to our experimental setup below in order to answer the research questions introduced in Section 3.

5.1 Experimental Setup

To analyze the performance of different opponent models, we employed GENIUS [15], which is an environment that facilitates the design and evaluation of automated negotiators' strategies and their components. The experiments are subdivided into two categories: we use a standard *time-based protocol*, as well as a *round-based protocol*. In total, we ran 17920 matches, which on a single computer takes nearly two months.

Our main interest goes out to the real-time setting, as this protocol features the time/exploration trade-off. We applied our benchmark to the set of models using the time-based protocol. Each match features a real-time deadline set at three minutes.

In the round-based protocol the same approach is applied, but in this case, time does not pass within a round, giving the agent infinite time to update its model. This provides valuable insights into the best *theoretical* result an opponent model can achieve.

5.2 Opponent Models

We compare the performance of the opponent models used in ANAC [1,4], which is a yearly international competition in which negotiating agents compete on multiple domains. Each year, the competition leads to the introduction of new negotiation strategies with novel opponent models. While the domain (i.e., the set of outcomes) is common knowledge to all agents, the utility function of each player is private information and hence has to be learned. The utility functions of the agents are *linearly additive*; that is, the overall utility consists of a weighted sum of the utility for each individual issue. The setting of ANAC is consistent with the preliminaries in this paper.

We specifically opted to use agents that participated in ANAC for the following reasons: the agents are designed for one consistent negotiation setting, which makes it possible to compare them fairly; their implementation is publicly available; and finally, we believe that the agents and opponent models represent the current state-of-the-art. We used modeling techniques from ANAC 2010 [4], ANAC 2011 [1], and a selection of opponent models designed for ANAC 2012. We isolated the opponent models from the agents and reimplemented them as separate generic components to be compatible with all other agents (as in [2]). As discussed in Section 3.2, this setup allows us to equip a single negotiation strategy with various opponent models, which makes it straightforward to fairly compare the different modeling techniques.

Table 3 provides a summary of the online opponent models used in our experiments, with references to the papers in which they are described. We did not include the *Bayesian Model* from [10] and the *FSEGA Bayesian Model* [18], even though they fitted our setup, as both models were not designed to handle domains containing more than a 1000 bids. We are aware that many alternative opponent modeling techniques exist [5,10,16,21]; however, for our negotiation setting, this is currently the largest set available of comparable opponent modeling techniques.

Based on our analysis, we found that in our selection two approaches to opponent modeling are prominent: *Bayesian opponent models* and *Frequency models*.

Bayesian opponent models generate hypotheses about the opponent's preferences [10]. The models presuppose that the opponent's strategy adheres to a specific decision function; for example a time-dependent strategy with a linear concession speed. This is then used to update the hypotheses using Bayesian learning.

Table 3. Overview of the online opponent models and their modeling assumptions (M)

Model	Description	M
No Model	No knowledge about the preference profile.	-
Perfect Model	Perfect knowledge about the preference profile.	-
Bayesian Scalable Model [10]	This model learns the issue and value weights separately using Bayesian learning. Each round, the hypotheses about the preference profile are updated based assuming that the opponent conceded a constant amount.	1
IAMhaggler Bay. Model [20]	Efficient implementation of the *Bayesian Scalable Model* in which the opponent is assumed to use a particular time-dependent decision function.	1
HardHeaded Freq. Model [14]	This model learns the issue weights based on how often the value of an issue changes between turns. The value weights are determined based on the frequency in which they have been offered.	3 4
Smith Freq. Model [8]	Similar to the *HardHeaded Frequency Model*, but less efficient. The issue weights depends on the relative frequency of the most offered values.	3 5
Agent X Freq. Model	This model is a more complex variant of the *HardHeaded Frequency Model* that also takes the opponent's tendency to repeat bids into account.	3 4
N.A.S.H. Freq. Model	In contrast to *HardHeaded Frequency Model*, this model learns the issue weights based on the frequency that the assumed best value is offered.	2 4

Frequency models learn the issue and value weights separately. The issue weights are usually calculated based on the frequency that an issue *changes* between two offers. The value weights are oten calculated based on the frequency of *appearance* in offers.

Both modeling approaches are prone to failure as they rely on a subset of the assumptions introduced in Section 3.3. More specifically, Bayesian models make strong assumptions about the opponent's strategy, whereas frequency models assume knowledge about the value distribution of the issues of a preference profile and place weak restrictions on the opponent's negotiation strategy. Generally, the Bayesian models are far more computationally expensive; however, it is unknown if they are more accurate.

6 Results

Below we analyze the outcomes of the experiment to provide an answer to the research questions in the form of hypotheses **H1–H6**. We first discuss the overall gain in performance when using perfect knowledge versus online opponent modeling. Section 6.2 provides an answer to the final research question on how the negotiation setting influences the performance of an opponent model.

6.1 Overall Performance of Opponent Models

Our experimental results for a selection of the quality measures described in Section 4.4 are shown in Table 4 for both the time-based and round-based protocol. Before we analyze the performance gain of online opponent models, we first answer the question whether perfect knowledge aids in improving the negotiation outcome at all:

H1. *Usage of the perfect model by a negotiation strategy leads to a significant performance gain in comparison to not using an opponent model.*

We expected that perfect knowledge about the opponent's preferences would significantly improve performance of an agent. Our main aim here was not to reconfirm the already widely acknowledged benefits of integrative bargaining, but to analyze whether our experimental setup is a valid instrument for measuring the learning effect in other types of settings. Our expectation is confirmed by the experiment, as the *Perfect Model* yields a significant performance increase on all quality measures (except average rounds) for both protocols. For the real-time protocol, the difference between the best online opponent model (*HardHeaded Frequency Model*) and *No Model* is 0.0135; for the round-based protocol it is 0.0144 (*Smith Frequency Model*). Note that while the gains are small, there are three small domains where opponent modeling does not result in significant gains. If we solely focus on the large *Travel* negotiation scenario, then the gain relative to *No Model* becomes 0.0413 for the *Perfect Model*. Especially note the improvement in distance between the outcome and Pareto-frontier, and the earlier agreements, in Table 4. This leads us to conclude that using an opponent model leads to better performance as it aids in increasing the quality of the outcome.

H2. *Usage of an online opponent model leads to a significant performance gain when time is not an issue. Online opponent modeling does not yield the same benefit in a real-time setting because of the time/exploration trade-off.*

We noted previously that in some cases, ANAC agents that do not model the opponent can outperform agents that do, and such agents have even won the competition. This led us to believe that online modeling does not benefit the agents, either because it misrepresents the preferences, or by taking too much time in a time-sensitive setting.

This is why it came as a surprise that in *both* the time- and round-based protocol, online opponent models performed significantly better on all quality measures. For the time-based protocol the best online opponent models are the frequency models, except for the *Smith Frequency Model* who scores badly in this case. However, for the round-based protocol, the *Smith Frequency Model* is actually best. This is caused by the time/exploration trade-off, because the model is computationally expensive as indicated by the small amount of bids offered in the time-based protocol.

Surprisingly the worst performance on a quality measure is not always made by using *No Model*. For example in the time-based experiment the *Bayesian Scalable Model* has the worst performance. The Bayesian model of *IAMhaggler* however, performs much better, but disappoints in the round-based protocol. We believe this can be attributed to its updating mechanism: only unique bids are used to update the model, which speeds-up updating but can result in poor performance against slowly conceding agents that offer the same bid multiple times.

In conclusion, online opponent model can result in significant gains and surprisingly, frequency models lead to the largest gains, outperforming the Bayesian models. We believe that the winners of ANAC could have performed even better by learning the opponent's preferences with a frequency model. The success of the frequency model can be attributed to its simplicity and hence faster performance, and to the fact that it is more robust by making weaker assumptions about the strategy of the opponent in comparison to the Bayesian modeling approaches.

6.2 Influence of the Negotiation Setting

We will now discuss the influence of each of the three components of the negotiation setting on the quality of an opponent model, following the structure of Section 3.

Table 4. Performance of all models on a set of quality measures for both protocols

Quality Measures	Perfect	HH. FM	Agent X FM	Nash FM	IAH. BM	Smith FM	None	Scal. BM
Time-based								
Avg. utility	.7285	.7260	.7257	.7257	.7178	.7156	.7125	**.7077**
Avg. time of agr.	**.4834**	.4865	.4867	.4865	.4958	.4937	.5022	.5055
Avg. rounds	7220	7218	7231	7198	7004	**4745**	7352	4836
Avg. Pareto dist. of agr.	**.0007**	.0017	.0015	.0018	.0069	.0068	.0059	.0071
Avg. Kalai dist. of agr.	**.2408**	.2434	.2447	.2428	.2515	.2474	.2683	.2561
Avg. Nash dist. of agr.	**.2442**	.2471	.2481	.2483	.2541	.2500	.2721	.2594
Rounds-based								
Avg. utility	.7235	.7196	.7191	.7192	.7111	.7199	**.7050**	.7124
Avg. time of agr.	**.4928**	.4975	.4978	.4977	.5058	.4974	.5136	.5038
Avg. rounds	**2508**	2531	2533	2533	2572	2531	2567	2562
Avg. Pareto dist. of agr.	**.0010**	.0029	.0023	.0028	.0073	.0026	.0066	.0063
Avg. Kalai dist. of agr.	**.2332**	.2380	.2395	.2380	.2456	.2369	.2614	.2445
Avg. Nash dist. of agr.	**.2370**	.2403	.2437	.2404	.2516	.2403	.2644	.2472

Influence of the Agent's Strategy. The performance gain of using an opponent model necessarily depends on the strategy in which it is embedded. Table 5 provides an overview of the relative gain in comparison to *No Model* for all opponent models in the time-based experiment. Based on the results, we have tested the following hypothesis:

H3. *The more competitive an agent, the more it benefits from using an opponent model.*

At each turn of a negotiation session, a set of possible agreements can be defined. This is the intersection of two sets: the set of bids that an agent considers for offering, and the set of all bids acceptable to the opponent. The more competitive the agent, the smaller the intersection between the two sets. When an agent concedes, the number of possible agreements increases at the cost of utility. An opponent model can help in finding possible agreements, preventing concession and therefore loss in utility. We therefore expected the gain for competitive agents to be higher, as the set of possible agreements each turn is smaller, and therefore an optimal bid is more easily missed by an agent not employing an opponent model. This is especially decisive in the last few seconds of the negotiation, when many agents concede rapidly to avoid non-agreement.

The hypothesis is confirmed by our experiments. In Table 5 there is a negative correlation between the concession speed and relative gain in performance. If we ignore the results of the three worst performing models, a small – albeit statistically significant – negative correlation of -0.508 is found.

Influence of the Opponent's Strategy. The opponent's behavior also has an important impact on the performance of an opponent model. Based on the results shown in Table 6, we test the three hypotheses below.

H4. *An agent benefits more from an opponent model against competitive agents.*

Intuitively, the more competitive the opponent, the more useful the opponent model as the set of possible agreements is smaller, analogous to hypothesis **H3**. Therefore, we expected the highest gain against the competitive agents *Gahboninho V3*, *HardHeaded*,

Table 5. Utility of each opponent model relative to using *No Model* for each agent

Agents	$e = 0.1$	$e = 0.2$	$e = 1$	$e = 2$
Perfect Model	0.0180	0.0164	0.0152	0.0144
HardHeaded Freq. Model	0.0156	0.0137	0.0118	0.0128
Agent X Freq. Model	0.0161	0.0137	0.0116	0.0113
N.A.S.H. Freq. Model	0.0166	0.0129	0.0108	0.0121
IAMhaggler Bay. Model	0.0084	0.0055	0.0033	0.0039
Smith Freq. Model	-0.0031	0.0020	0.0071	0.0063
Bayesian Scalable Model	**-0.0050**	**-0.0058**	**-0.0032**	**-0.0053**

and *IAMcrazyHaggler*. However, in Table 6 only the gain for *Gahboninho V3* and *IAMcrazyHaggler* is very high.

For *HardHeaded*, we believe this can be attributed to the agent using an opponent model itself. If the opponent uses a well-performing opponent model, then the performance gain of an opponent model can be expected to be lower, as the opponent is already able to make Pareto-optimal bids. Our experiment appears to the confirm this hypothesis in the case of playing against *HardHeaded*, whose well-performing opponent model seems to diminish the effect of opponent modeling by the other side.

Concluding, given the results of our experiment, we believe that the hypothesis holds, at least for consistently competitive opponents without an opponent model.

H5. *Frequency models are more robust against opponents employing a random tactic than the Bayesian models.*

In order to estimate the opponent's utility of a certain bid, both types of models make certain assumptions about the opponent. The Bayesian opponent models assume that the opponent follows a particular decision function through time (cf. modeling assumption 1 in Section 3.3), while the frequency models assume higher valued bids are offered more often (cf. modeling assumptions 3 and 4). Many opponent strategies do not adhere to these assumptions, which causes the learning models to make wrong predictions when playing against them. For example, opponents such as *IAMcrazyHaggler* who employ a random negotiation strategy, explicitly violate the assumptions of both models. For the Bayesian learning models, this means the opponent preferences will be estimated incorrectly, and more so through time. The frequency models however, are much more robust, not only in the sense that a negotiation tactic has a greater chance to satisfy its assumptions, but more significantly: it is less sensitive to a tactic violating its assumptions. For instance, in the case of *IAMcrazyHaggler*, it will deduce that it equally prefers any bid it has offered so far – which, in this case, is exactly right.

We therefore expected relatively poor performance from the Bayesian models. This hypothesis is confirmed by our experiment: the frequency models have a high performance gain against *IAMcrazyHaggler*, whereas using the Bayesian models is even worse than not using an opponent model at all.

Influence of the Negotiation Scenario. The performance of an opponent model is influenced by the characteristics of the negotiation scenario, such as amount of bids, distribution of the bids, and the opposition of the domain. Table 7 provides an overview of the relative gain of all opponent models in comparison to *No Model* for in the time-based experiment. Based on these results, we formulate the following hypothesis:

Table 6. Utility of each opponent model relative to using *No Model* for each opponent

Opponents	**TDT 0**	**TDT 0.2**	**TDT 1.0**	**TDT 2.0**	**OD**	**Gah.**	**HH.**	**IcH.**
Perfect	<u>.0085</u>	.0015	<u>.0008</u>	.0022	.0060	<u>.0676</u>	.0015	<u>.0399</u>
HH. Freq. Model	<u>.0085</u>	.0013	-.0002	.0019	.0060	.0515	.0000	.0388
Agent X Freq. Model	<u>.0085</u>	<u>.0019</u>	.0002	<u>.0036</u>	.0058	.0561	.0009	.0285
N.A.S.H. Freq. Model	<u>.0085</u>	.0005	-.0005	.0020	<u>.0065</u>	.0507	.0037	.0336
IAH. Bay. Model	**.0000**	.0003	-.0021	-.0001	-.0046	.0511	<u>.0039</u>	**-.0066**
Smith Frequency	-.0038	-.0023	-.0019	.0007	-.0113	**.0357**	**-.0224**	.0297
Bay. Scalable Model	**.0000**	**-.0033**	**-.0055**	**-.0058**	**-.0535**	.0458	-.0128	-.0036

H6. *The higher the amount of bids, bid distribution, or opposition of a scenario, the more an agent benefits from using an opponent model.*

We anticipated the bid distribution to be the major factor determining the performance gain of an opponent model. If the bid distribution is high, then the Pareto-frontier is more sparse. This means a higher gain can be expected of utilizing an opponent model to locate bids close to the Pareto-frontier. This hypothesis is confirmed by our experiments, as we found a strong Pearson correlation of 0.778 between the bid distribution and the performance gain of the best four models, and 0.701 if we solely focus on the perfect opponent model. Therefore we confirm this sub-hypothesis.

Another factor is the size of the negotiation domain. If a domain contains more bids, then there are relatively less bids that are Pareto-optimal, so an opponent model can aid more in identifying them. On the other hand, opponent models are more computationally expensive on the larger domains. Despite this effect, we found a strong Pearson correlation between the amount of bids and the performance gain: 0.631 for the best four models, and 0.596 when using the perfect model.

The final factor is the opposition of the scenario. Intuitively, if the opposition is higher, then there are less possible agreements. Opponent models can aid in identifying these rare acceptable bids, thereby preventing break-offs and unnecessary concessions. Nevertheless, if the opposition is high, then the bids are also relatively closer to the Pareto-optimal frontier, which renders it more difficult for an opponent model to make a significant impact on the negotiation outcome. Despite this effect, we expected that higher opposition would lead to higher performance gain. However, in our experiments we noted only a small positive Pearson correlation of 0.256 for the best four models and 0.262 for the perfect model. Based on these results we are unable to draw a conclusion, which leads us to believe the two mentioned effects cancel each other out, making the other two characteristics of the scenario decisive in the effectiveness of a model.

Table 7. Gain of each model relative to using *No Model* for each scenario parameter

	Model	**Low**	**Medium**	**High**
Size	*Perfect*	0.001	0.022	0.041
	Best 4	0.002	0.018	0.039
Bid Distribution	*Perfect*	0.001	0.013	0.035
	Best 4	-0.001	0.010	0.034
Opposition	*Perfect*	0.001	0.023	0.020
	Best 4	-0.001	0.022	0.016

7 Conclusion and Future Work

This paper evaluates and compares the performance of a selection of state-of-the-art online opponent models. The main goal of this work is to evaluate if, and under what circumstances, opponent modeling is beneficial.

Measuring the performance of an opponent model is not trivial, as the details of the negotiation setting affects the effectiveness of the model. Furthermore, while we know an opponent model improves the negotiation outcome in general, the role of time should be taken into account when considering *online* opponent modeling in a real-time negotiation because of the time/exploration trade-off: a computationally expensive model may produce predictions of better quality, but in a real-time setting it may lead to less bids being explored, which may harm the outcome of the negotiation.

Based on an analysis of the contributing factors to the quality of an opponent model, we formulated a measurement method to quantify the performance of online opponent models and applied it to a large set of state-of-the-art opponent models. We analyzed two main types of opponent models: frequency models and Bayesian models. We noted that the time/exploration trade-off is indeed an important factor to consider in opponent model design of both types. However, we found that the best performing models did not suffer from the trade-off, and that most – but not all – online opponent models result in a significant improvement in performance compared with not using a model; not only because the deals are made faster, but also because the outcomes are on average significantly closer to the Pareto-frontier. A main conclusion of our work is that we noted that frequency models consistently outperform Bayesian models. This is not only because they are faster, because the effect remains in a round-based setting. This suggests that frequency models combine the best of both worlds. Surprisingly, despite their performance, frequency models have not received much attention in literature.

Our other main conclusion concerns the effects of the negotiation setting on an opponent model's effectiveness. We found that the more competitive an agent, or its opponent, the more benefit an opponent model provides. In addition, we found that the higher the size or the bid distribution of a scenario, the higher the gain of using a model.

For future work, it would be interesting to examine other uses of opponent modeling, such as opponent prediction. Another direction of future work is to investigate the interaction between opponent model performance and its accuracy through time. We also plan to test a larger set of models derived from literature and ANAC 2012.

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