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Whom should I persuade during a negotiation? An approach based on social influence maximization

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ABSTRACT

During a negotiation, an agent must make several key decisions in order to achieve a profitable agreement. When the negotiation is carried out in a social context, agents can use persuasion, besides the traditional exchange of concessions. To carry out the persuasion and make concessions, the agents must employ resources that are usually scarce. For this reason, the agents should carefully decide which opponent they should persuade to maximise their profit, especially when the negotiation involves multiple parties. To make this decision, we propose that the agents should persuade the opponents with a high influence on the other agents involved in the negotiation. Therefore, we represent a negotiation context as a social influence maximization problem and solve it under a model that learns how influence flows in a network by analyzing historical information. This allows an agent to determine what opponents exert the highest influence. Finally, the agent uses this information to decide which opponent to persuade during the negotiation. Experimental results showed that the agreement rate increased when agents applied this approach.

1. Introduction

In multi-agent systems, negotiation is a fundamental tool to reach an agreement among agents with conflicting goals. Negotiation is a form of interaction in which a group of agents, with conflicting interests and a desire to cooperate, try to come to a mutually acceptable agreement on the division of scarce resources [1]. The essence of the negotiation process is the exchange of proposals. Agents make proposals and respond to proposals in order to make concessions and converge on a mutually acceptable agreement. However, not all approaches are restricted to an exchange of proposals. In argumentation-based approaches [2–4,1,5,6], agents are allowed to exchange some additional information as arguments, besides the information uttered on the proposals, where social factors play an important role. Thus, in the context of the negotiation, an argument is seen as a piece of information that supports a proposal and allows an agent (a) to justify its position of negotiation, or (b) to influence the position of negotiation of other agents [7].

In some scenarios, the negotiation includes multiple parties (for example, a group of personal agents that should negotiate date, place and topics of a meeting on behalf of users). In these scenarios, agents make proposals, present arguments to persuade other agents, and accept or reject other proposals. In general, when an agent persuades another agent, some scarce resources are affected by the succeeding concessions that it must carry out during this process. Particularly, this fact is further reinforced when agents exchange rewards and threats as a form of rhetorical arguments [8,9]. In other words, persuading an opponent and making concessions have additional costs to the act of simply uttering an argument or a proposal [8,10]. In this context, it is necessary for the agent to manage the concessions that it can offer, in order to ensure maximum influence on the rest of the participants. For example, once an agent is persuaded to accept a proposal, this agent is expected to continue participating in the negotiation in favour of such proposal. Thus, if the agent succeeds in persuading an influential participant, then this participant is expected to be able to persuade a great number of participants on its own account. In contrast, if the agent persuades a participant with little influence, the possibility of propagating the proposal will be smaller. For this reason, deciding which participant to persuade is a key task, due to the fact that the proposal spread will be higher if the influence of the persuadee is also higher.

Moreover, the agents of a multilateral negotiation usually form (implicitly or explicitly) a social network in which several social factors affect the negotiation result directly or indirectly. For example, these factors are the trust among participants [4], their reputation [11], and authority roles [3], among others. Additionally, these factors are related to the spread of influence through a social network. The study of the spread of influence exerted by users of a social network on other users has received great attention in the last years. A key problem in this area is the influence maximization problem. The influence maximization problem involves finding a set of users in a social network, such

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that by targeting this set, one maximises the expected spread of influence in the network [12,13].

In this context, we propose an approach that allows an agent to decide which opponent to persuade by observing the degree of influence that the agents exert during the negotiations, and assuming that the resources available during the negotiation are scarce. To do this, we adapt the traditional influence maximization problem to the negotiation context and apply a data-based approach to social influence maximization that learns how influence flows in a network by directly leveraging available propagation traces, named *Credit Distribution Model* [12].

On the other hand, the feasibility and benefits of using autonomous agents in negotiations with humans have been shown in several works [14–16]. For this reason, although we present our approach from a perspective of autonomous agents, we claim that our approach can also be applied to assist human negotiators by guiding them to make decisions, which increases their benefits, during a negotiation.

The experiments were carried out under several configurations, taking into account the number of agents involved in the negotiation, the number of previous negotiation traces used to train the model, the social network density (graph density), the average trust level among the agents, and the trust update rate (we took into account that trust among agents can change during the negotiations). Experimental results showed that the agreement rate increases when an agent decide, and is able, to persuade the opponent that maximises the expected influence spread according to the Credit Distribution model. Moreover, the results showed that the increase of the agreement rate is high in some configuration (e.g., when the social network density is low and the trust level is high) and low in others (e.g., when both the social network density and the trust level is high).

In short, we highlight two main contributions of this work. First, this work presents an approach that allows an agent to improve the agreement rate during multilateral negotiations by indicating which opponent to persuade. Moreover, we present an experimental analysis that shows in which scenarios the social influence plays an important role during the selection of an opponent to persuade.

The article is organised as follows. Section 2 introduces basic concepts about negotiation and social influence maximization. Section 3 presents the approach to decide which opponent to persuade according to its influence. Section 4 shows the results obtained from the experiments. Finally, Section 5, states our conclusions and suggests future work.

2. Backgrounds

In this section, we review two relevant fields for our work, namely, negotiation among intelligent agents and social influence maximization. Thus, in the next section, we review some concepts about negotiation. Next, we introduce the main concepts on social influence maximization, propagation models and algorithms.

2.1. Negotiation among intelligent agents

Negotiation is a form of interaction in which a group of agents, with conflicting interests and a desire to cooperate, try to come to a mutually acceptable agreement on the division of scarce resources [1]. Much work on negotiation is either concerned with bilateral (one-to-one) negotiation [17] or with auctions [18]. However, in many real negotiation scenarios groups of more than just two agents can freely come together and agree on a deal [19]. For this reason, several multilateral negotiation protocols have been proposed. In these protocols, a multilateral agreement is defined as an agreement that is reached iff one agent makes a proposal that is at least as good for each other agent as their own current proposal [19]. Obviously, as the number of agents increases, reaching a multilateral agreement is more difficult than reaching a bilateral one. Despite the fact that the multilateral negotiation protocols define the rules to guide the agents to an agreement, the agents must usually take some key decisions to reach a profitable agreement.

As stated previously, the agents can exchange proposals and arguments during a negotiation. To carry out this exchange, the agent must possess a set of resources over which the concessions are made. For example, from the point of view of the proposal exchange, when a seller reduces the price of a good in order to reach a deal with a buyer, the seller is also reducing her/his revenue in exchange for an agreement. Moreover, when the agents exchange rhetorical arguments, the use of a reward to persuade an opponent to accept a deal implies that the agent must concede some resources as a reward in exchange for the acceptance [8,9]. As a result, it is important that the agent carefully select the target of its concessions.

On the other hand, in addition to the utility of a proposal, there are other factors that determine whether an agreement will be reached or not. These factors participate actively during the persuasion process.

Mainly, the trust among the agents is a crucial factor. In the most abstract manner, trust is a relation between a trustor and a trustee in a context [20]. There are several kinds of trust. For example, we can distinguish between *human trust* and *computational trust*. Human trust refers to a mental state of humans. However, computational trust describes representations of trust used in trust management systems. Moreover, computational trust is usually processed in a manner that aims to replicate how humans reason about human trust. In addition, without explicitly making the distinction between human and computational trust, we can found more detailed definitions of trust. *Expectancy trust* is a subjective, context-dependent expectation that the trustee will choose a specific action in an encounter. Furthermore, *dependency trust* can be defined as the subjective, context-dependent extent to which the trustor is willing to depend on the trustee in a situation of uncertainty [20].

Particularly, in our work, we understand trust as expectancy trust, since this definition is widely adopted in the field of negotiation among intelligence agents [21]. Thus, trust is seen as a relation between two entities such that one entity (trustor) believes, expects and accepts that a trusted entity (trustee) will act or intend to act beneficially [22]. Trust is an especially important issue from the perspective of autonomous agents and multi-agent systems [21]. Agents usually maintain a trust network of their acquaintances, which includes ratings of how much those acquaintances are trusted, and how much those acquaintances trust their acquaintances, and so on [23]. Agents compute this trust from different information sources. Direct experiences (the experience based on the direct interaction with the acquaintance) and witness information (the information that comes from other members of the community) are the traditional information sources used by computational trust [21].

When agents use argumentation to persuade other agents during a negotiation, trust is used to determine which kind of argument they should utter as well as to evaluate the proposals and arguments that they receive. In agreement with this idea, Ramchurn et al. [4] proposed an approach for persuasive negotiation and defined rules for argument selection by observing the trust in the opponent and the expected utility of the proposal. For example, if the trust is low and the utility is high then the agent should send a strong argument, but if the trust is high and the utility low, then it should utter a weak one. The authors also proposed specific evaluation functions that agents can use whenever a proposal, whether or not supported by an argument, is received. These functions incorporate the notion of trust as the confidence in the opponent to fully carry out a proposed action (be it a proposal or an argument). For example, the agent evaluates a received proposal by calculating the expected utility of moving into the proposed state weighted by the trust in the sender, added to the expected utility of remaining in the present state weighted by the amount of distrust in the other party. Similarly, trust is applied in several negotiation-related scenarios: auctions [24,25], argumentation [23], multi-agent cooperation [26], and e-commerce [27], among others. Moreover, other social factors, such as authority roles, have been taken into account to generate and evaluate arguments during argumentation-based negotiations [3].

Taking decisions early during the planning stage of the negotiation allows the agent to reach better agreements [28]. Some works [28,29] have shown the importance of making negotiation decisions in a planning stage, though these approaches did not take into account the social influence to make decisions. Additionally, the design of negotiation strategies has been studied from several perspectives [30–33]. Particularly, Rahwan et al. [34] determine that a negotiation strategy may be defined as a rule or algorithm which specifies what the agent should utter and when, in a particular negotiation interaction. In that direction, Rahwan et al. identify some factors that *may* influence the design of the strategy. These factors include goals (what goals the agent wants to achieve by undertaking a negotiation), opponents (the nature of the other participants), and resources (the time and the resources available for the agent), among others. In this context, deciding which opponents to persuade can be seen as the first step of the negotiation strategy. As mentioned above, making this decision includes taking into account the characteristics of the opponents (in this work, the social influence exerted by the opponent) and the resources with which the agent can make concessions.

2.2. Social influence maximization

Social influence is defined as change in an individual's thoughts, feelings, attitudes, or behaviours that results from interaction with another individual or a group [35]. Social influence occurs when one's actions are affected by others and can be seen in conformity, socialization, peer pressure, obedience, leadership, persuasion, sales, and marketing [36]. Many applications exploit the social influence. In the field of data mining, some applications include viral marketing [37], recommender systems [38], analysis of information diffusion in Facebook and Twitter [39], expert finding [40], link prediction [41] and ranking of feeds [42]. In this context, the propagation of influence that users of a social network exert on other users has been widely studied in recent years. However, it has not been applied to support decisions during a negotiation process.

One of the key problems in this area is the identification of influential users [12]. Kempe et al. [13] formalized this as the influence maximization problem: *given a directed graph* $G = (V, E, p)$*, where nodes are users and edges are labelled with influence probabilities among users, the influence maximization problem looks for a set of seeds (users) that maximises the expected spread of influence in the social network under a given propagation model.* A propagation model indicates how influence propagates through the network. Two propagation models were proposed by Kempe et al.: the *Independent Cascade* (IC) and the *Linear Threshold* (LT) models. In both models, each node can be either active or inactive at a given moment. Moreover, the tendency of each node to become active increases monotonically as more of its neighbours become active.

Given a propagation model m (for example, IC or LT) and an initial seed set $S \subseteq V$, the expected number of active nodes at the end of the process is the *expected (influence) spread*, denoted by $\sigma_m(S)$ [12]. Then, the influence maximization problem is defined as follows: *given a directed and edge-weighted social graph* $G = (V, E, p)$*, a propagation model m, and a number* $k \leq |V|$*, find a set* $S \subseteq V$*,* $|S| = k$*, such that* $\sigma_m(S)$ *is maximum*. Several approaches have been developed to solve this problem. Despite the fact that this problem is NP-hard under both the IC and LT propagation models, some characteristics of the function $\sigma_m(S)$ (monotonicity and submodularity, see [13] for further details) made it possible to develop a greedy algorithm to solve the problem.

One of the limitations of the *IC* and *LT* propagation models is that the edge-weighted social graph is assumed as input to the problem, without addressing the question of how the probabilities are obtained [43]. For this reason, Goyal et al. [12] proposed the *Credit Distribution* (*CD*) model, which directly estimates influence spread by exploiting historical data. In this context, the influence maximization problem to be solved under the *CD* model is reformulated as follows: *given a directed social graph* $G = (V, E)$*, an action log* $\mathbb{L}$*, and a integer* $k \leq |V|$*, find a set* $S \subseteq V$*,* $|S| = k$*, such that* $\sigma_{cd}(S)$ *is maximum*. To solve this problem, Goyal et al. developed an algorithm for influence maximization under the *CD* model. This algorithm initially scans the action log $\mathbb{L}$ to learn the influence probabilities in the social network, computing the influenceability scores for the users. Then, the seed set is selected under de *CD* model by using a greedy algorithm with *CELF* optimization [44]. Finally, the true influence spread is computed. See [12] for further details on algorithm implementation.

3. Modelling the process of deciding which opponent to persuade as an influence maximization problem

To carry out concessions and persuasion during a negotiation, the agent must employ resources that are usually scarce. For this reason, agents should carefully decide which opponent they should persuade to maximise their profit, especially when the number of agents involved in the negotiation is large. To make this decision, we propose that the agent persuade the opponents with a high influence on other agents also involved in the negotiation. This influence is particularly interesting to observe, since there are several factors related to the social relations of the agents that influence the acceptance or rejection of a proposal. Among these factors, we can distinguish the trust in the opponents, their reputations and authority roles, among others.

As introduced in Section 2.2, an algorithm for influence maximization allows us to find the set of users in a social network, such that by targeting this set, one maximises the expected spread of influence in the network. For this reason, we propose to model the process of deciding which opponent to persuade as an influence maximization problem. Particularly, we use the *CD* model [12], since it allows us to use historical data of past negotiation to estimate the influence spread. To do this, we adapt the influence maximization problem to the negotiation context indicating how to define the problem inputs: a directed social graph $G = (V, E)$, an action log $\mathbb{L}$, and an integer $k \leq |V|$.

First, we will define the characteristics of the negotiation context in which our approach can be applied. Clearly, as we stated previously, the negotiation contexts must be multilateral. Otherwise, it would be impossible to analyze any influence spread. As we show in Section 4 below, the number of agents involved in the negotiation affects the benefits of our approach.

Moreover, the decision functions of the negotiation protocol, especially the proposal and argument evaluation mechanisms, must consider social factors (e.g., trust), besides the proposal utility. In this point, the argumentation-based negotiation approaches, such as the one proposed by Ramchurn et al. [4], meet this requirement. One of the benefits is that the social factors have a low variation from one negotiation to another, as occurs with the influence in social networks, allowing an algorithm to learn patterns that could be applied for decision making. In contrast, the utility rarely bears relation to the influence exerted by one agent on another one. In addition, the utility can have a high variation among negotiations. Finally, we assume that agents have scarce resources to employ during the negotiations.

In this context, we define the directed social graph $G_{neg} = (V_{neg}, E_{neg})$, where V_{neg} is the set of agents that are participating in the negotiation and E_{neg} is the set of directed edges corresponding to social relations among the agents. Each edge is linked to a set of social factors *sf*, and each factor is represented by a name and a value (between 0 and 1). For example, given two agents a_1 and a_2, an edge $e_{1,2}$, representing a relation between a_1 and a_2, is linked to a set of social factors $sf_{1,2} = \{(trust, 0.8)\}$ indicating that a_1 has a high trust in a_2. It is worth noticing that the social relations are not reciprocal. Thus, an edge $e_{2,1}$, representing a relation between a_2 and a_1, can be linked to $sf_{2,1} = \{(trust, 0.2)\}$. That is, although a_1 has a high trust in a_2, a_2 has a

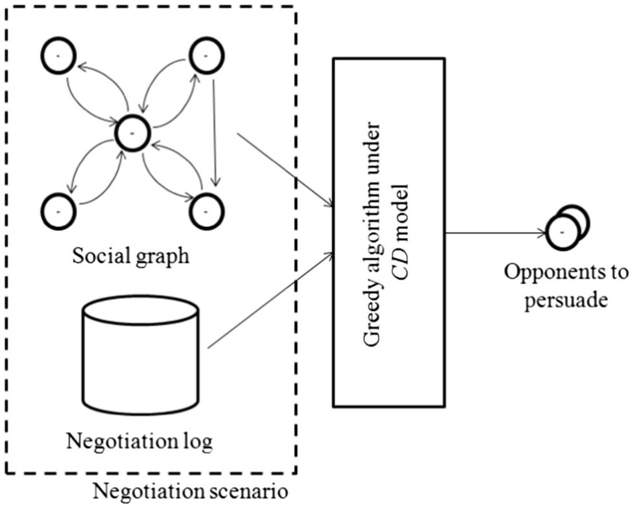

Fig. 1. Graphical representation of our approach.

low trust in a_1. Moreover, we assume that not all agents are related to each other. Therefore, G_{neg} is not complete. However, the graph can be dense (in which the number of edges is close to the maximal number of edges) or sparse (a graph with only a few edges). The experiments (Section 4) show how this fact has a repercussion on the agreement rate obtained by the agents.

Moreover, we define a negotiation log $\mathbb{L}_{neg}$ where the proposals accepted by the agents are recorded. That is, a tuple $(a, p, t) \in \mathbb{L}_{neg}$ indicates that agent a accepts proposal p at time t. It is worth noticing that we need to record only the acceptance of the proposal, allowing the agents to keep any other interaction private. Finally, we define an integer $k_{neg} \leq |V_{neg}|$ depending on the number of resources that the agent has to make concessions and persuade opponents. From a pragmatic point of view, k_{neg} represents the number of concessions or persuasions that the agent managed to achieve during the negotiation.

Then, we adapt the influence maximization problem to the negotiation context as follows: *given a directed social graph* $G_{neg} = (V_{neg}, E_{neg})$, *a negotiation log* $\mathbb{L}_{neg}$, *and a integer* $k_{neg} \leq |V_{neg}|$, *find a set* $S_{neg} \subseteq V_{neg}$, $|S_{neg}| = k_{neg}$, *such that* $\sigma_{cd}(S_{neg})$ *is maximum*. Finally, we run the algorithm[1] for influence maximization defined in [12] and obtain S_{neg}. Notice that, intuitively, set S_{neg} contains the opponents that the agent should persuade during the negotiation. Fig. 1 shows a graphical representation of our approach.

4. Experimental evaluations

4.1. Experimental settings

To evaluate our approach, we ran experiments in several negotiation scenarios. The experiments were implemented by using the multi-agent platform JADE [45]. Moreover, each negotiation scenario was described by the following dimensions:

- Number of agents involved in the negotiation (n): since the negotiation is multilateral, several agents were involved in each negotiation. We ran experiments with a small group of agents ($|V_{neg}| = 10$) and a large one ($|V_{neg}| = 100$).
- Graph density (gd): the graph density represents the rate between the real number of edges of a graph and the maximal number of edges that the graph could have. As stated previously, we assume that not all agents are socially related to each other. Thus, each agent is related to a set of agents (acquaintances). That is, for each agent $a_i \in V_{neg}$, there exists a set $Q_i = \{q_i^j \in V_{neg} | e_{i,j} \in E_{neg} \wedge q_i^j \neq a_i\}$. Moreover, we assume that agent a_i can only persuade agent a_j iff $a_j \in Q_i$. This is because if $a_j \notin Q_i$ there is not a social relation between the agents, which is equivalent, for example, to saying that $sf_{i,j} = sf_{j,i} = \{(trust, 0.0)\}$. In such a case, we assume that any proposal of a_i will be rejected by a_j (see function $EV_a(p, b)$ below). For the scenarios where $|V_{neg}| = 10$, we defined a graph density of 0.2, 0.5 and 0.8, and for the scenarios where $|V_{neg}| = 100$, we defined a density of 0.02, 0.05 and 0.08. Thus, the average number of acquaintances for each agent is 2, 5 and 8. Experiments showed that when the number of acquaintances exceeded 8 the results did not change. In short, we use random networks, in which the structure of the social network in each scenario was determined by the number of agents involved in the negotiation (V_{neg}) and the number of social relations (E_{neg}) of each agent given by the graph density value (gd) using a uniform distribution (see Section 4.2 for further details).
- Trust level among agents: we selected the trust as social factor among the agents, since this is a crucial factor in most of the negotiation approaches. Depending on how the trust level it is initialized, we defined four scenarios. In the first three scenarios, we applied a normal distribution with a mean of 0.2, 0.5 and 0.8, taking into account that a trust level is between 0 and 1, and the standard deviation is 0.2. We chose this distribution and these mean values to model scenarios in which the overall trust of the agents is low (mean = 0.2), intermediate (mean = 0.5) and high (mean = 0.8). Experiments showed that the behaviour of our approach is different in these scenarios. In addition, we applied a uniform distribution in the fourth scenario.
- Trust update: since the trust among agents can be influenced during the course of the negotiations, we modelled in the experiments the updates of the trust levels during the training stage. We based these updates on the direct experience of the agents, since it is the most relevant and reliable information source for a trust model [21,46]. Thus, during a negotiation, an agent a_j can break a deal and refuses a proposal of agent a_i. In such a case, agent a_i reduces the trust in agent a_j, otherwise, the trust is increased. For this reason, we included two dimensions in order to model different grades of change in the trust levels. These dimensions are the *break rate* (br) and the *value of trust update* (δ). The break rate indicates how often an agent breaks a deal. We adopted three values for this dimension: 0.05 (a low value that indicates that agents rarely break a deal); 0.2 (an intermediate value); and 0.5 (a high value, taking into account that breaking deals should not be frequent in negotiation contexts). These values have two different effects in the overall trust of the agents. When br is low the overall trust tends to increase, since there are less deals break. In contrast, when br is high the overall trust tends to decrease. In addition, δ represents how much the trust in an agent is modified after each direct experience. Thus, the trust in the opponent is increased or decreased according to δ after a positive (the opponent did not break the deal) or negative (the opponent broke the deal) experience, respectively. We also adopted three values for this dimension: 0.01 (a low value, indicating that the trust varies slightly after each direct experience), 0.05 (an intermediate value); and 0.1 (a high value, taking into account that the level of trust varies from 0 to 1).

During a negotiation, each agent makes proposals that can be observed for all agents but persuades only its acquaintances. When the agents receive a proposal p, they evaluate it. To carry out this evaluation, an agent takes into account the utility of the proposal and the trust in its sender, where both values are between 0 and 1. In these experiments, we defined an evaluation function, inspired by the

[1] It is worth noticing that any algorithm that solves the influence maximization problem under de *CD* model can be applied in our approach.

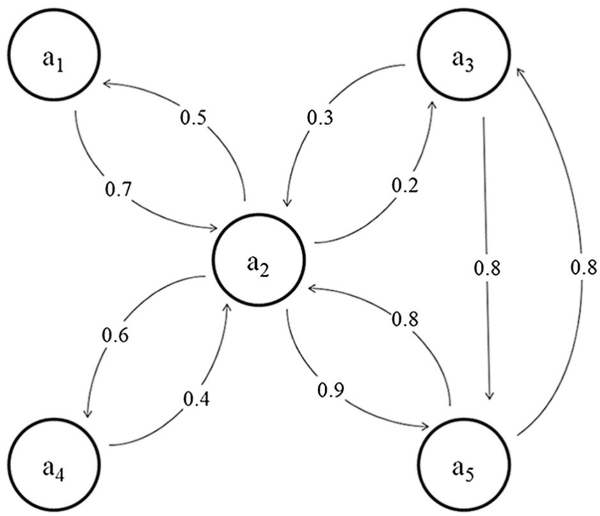

Fig. 2. Example graph G_{neg}.

evaluation function defined in [4], where the agent evaluates the received proposal by calculating the expected utility of accepting the proposal weighted by the trust in the sender. Thus, the evaluation function is: $EV_a(p, b) = U_a(p) \cdot Trust(a, b)$, where $U_a(p)$ is the utility of proposal p for agent a and $Trust(a, b)$ represents the trust level that a has about b. Then, if the evaluation of the received proposal is higher than the evaluation of the own proposal, the agent accepts it; otherwise, the agent rejects it. To simplify the experiments, the agents did not exchange arguments. However, the persuasion was exerted through the trust among the agents. Finally, if the agent accepts a proposal of an acquaintance, the agent will continue participating in the negotiation in favour of such a proposal, since this proposal obtained a better evaluation (*EV* value) that its own alternative.

Let's see an example. Fig. 2 shows a graph $G_{neg} = (V_{neg}, E_{neg})$, where $V_{neg} = \{a_1, a_2, a_3, a_4, a_5\}$ and $E_{neg} = \{e_{1,2}, e_{2,1}, e_{3,2}, e_{2,3}, e_{3,5}, e_{5,3}, e_{2,5}, e_{5,2}, e_{4,2}, e_{2,4}\}$. Moreover, each edge has an associated trust value. For example, the set of social factor associated with $e_{1,2}$ is $sf_{1,2} = \{(trust, 0.7)\}$ representing the trust level that a_1 has about a_2. In addition, we assume that each agent a_i has a proposal p_i to utter during the negotiation. Table 1 shows the agents' utility given each proposal. In this example, agent a_3 must support proposal p_3 and $Q_{a_3} = \{a_2, a_5\}$. If a_3 tries to persuade a_2 to accept p_3, a_2 will reject it since $EV_{a_2}(p_3, a_3) = U_{a_2}(p_3) \cdot Trust(a_2, a_3) = 0.7 \cdot 0.2 = 0.14$ is smaller than $U_{a_2}(p_2) = 0.6$. In contrast, if a_3 tries to persuade a_5 to accept p_3, a_5 will accept it since $EV_{a_5}(p_3, a_3) = 0.65 \cdot 0.8 = 0.52$ is higher than $U_{a_5}(p_5) = 0.5$. Then, since a_5 accepted p_3, it will, expectably, try to persuade a_2 to accept p_3. Now, $EV_{a_2}(p_3, a_5) = 0.7 \cdot 0.9 = 0.63$. Therefore, a_2 accepts p_3. Finally, a_2 tries to persuade a_1 and a_3. In that case, a_1 will accept p_3 since $EV_{a_1}(p_3, a_2) = 0.7 \cdot 0.7 = 0.49$ is higher than $U_{a_1}(p_1) = 0.45$. However, a_4 will reject p_3 since $EV_{a_4}(p_3, a_2) = 0.6 \cdot 0.4 = 0.24$ is smaller than $U_{a_4}(p_4) = 0.4$.

Table 1
Example of agents' utilities by proposal.

Agents	Proposals				
	p_1	p_2	p_3	p_4	p_5
a_1	0.45	0.5	0.7	0.2	0.8
a_2	0.35	0.6	0.7	0.8	0.7
a_3	0.3	0.7	0.8	0.7	0.4
a_4	0.2	0.4	0.6	0.4	0.55
a_5	0.2	0.2	0.65	0.2	0.5

4.2. Procedure

We ran experiments in several negotiation scenarios, described as $ns = (n, gd, t, br, \delta)$, taking into account five dimensions: agents ($N = \{10, 100\}$); graph density ($GD = \{0.2, 0.5, 0.8\}$ for $n = 10$ and $GD = \{0.02, 0.05, 0.08\}$ for $n = 100$); trust ($T = \{0.2, 0.5, 0.8, u\}$, where the first three values represent a normal distribution with mean 0.2, 0.5 and 0.8, and u represents a uniform distribution); break rate ($BR = \{0.01, 0.2, 0.5\}$); value of trust update ($\Delta = \{0.01, 0.05, 0.1\}$); where $n \in N$, $dg \in DG$, $t \in T$, $br \in BR$, and $\delta \in \Delta$. Each experiment consisted of three stages: *setup*, *training* and *testing*. The setup stage consisted in generating the negotiation scenarios according to the dimensions described above. Basically, during this stage, we built the directed social graph G_{neg}. To do this, we first generated n agents. Then, for each pair of agents a_i and a_j, we randomly determined if a social relation existed between them according to the gd dimension. To do this, we generated a random number r using a uniform distribution between 0 and 1, then if $r \leq gd$ we added the edges $e_{i,j}$ and $e_{j,i}$ to E_{neg}. In addition, for each edge, we simulated a trust level using a normal distribution with mean t and standard deviation 0.2 or an uniform distribution when $t = u$.

The training part consisted in generating the negotiation traces stored in the negotiation log $\mathbb{L}_{neg}$. To do this, we randomly selected an agent $a_{ini} \in V_{neg}$ to make an initial proposal, which started the negotiation. A proposal consists of an action that can be accepted or rejected by an agent. For example, in the context of agents that are scheduling a meeting, a proposal could be to arrange to meet in a given place. Once agent a_{ini} has been selected, this agent tried to persuade the agents with which it had a social relation (i.e., there was an edge that linked them). Then, each agent that accepted the proposal continued propagating it. Each time that the proposal was accepted, a new tuple (a, p, t) was added to $\mathbb{L}_{neg}$, where a was the agent that accepted proposal p at time t. Finally, when all agents uttered an opinion about the initial proposal, the negotiation finished. This process was carried out n_{train} times. The variable n_{train} determined how much historical information (negotiation traces) was processed to determine the set S_{neg}. Then, for each scenario, we ran experiments with three values of n_{train}: 10, 50 and 100. Since our goal is minimise the amount of information needed for train the model, we set a maximum n_{train} of 100. Thus, we added a new dimension to the negotiation scenario: $ns' = (n, gd, t, br, \delta, n_{train})$. As a result, we actually carried out experiments in 648 scenarios. Last, for each scenario, we ran the algorithm for influence maximization under the *CD* model with G_{neg}, $\mathbb{L}_{neg}$, and $k_{neg} = 1$ assuming that during the testing stage an agent had resources to persuade only one opponent.

The testing stage consisted in comparing the agreement rate reached by an agent a_{im}, which is using our approach to decide whom to persuade, and the agreement rate reached by a base agent a_r, which decides randomly whom to persuade. As the goal of an agent, which is participating of a multilateral negotiation, is to maximise the number of acceptances of its proposals [19], we define the agreement rate ar as follow:

$$ar_x = \frac{|Ag_x|}{|V_{neg}|}.100 \tag{1}$$

where Ag_x is the set of agents participating in the negotiation that accepted the proposal of agent $a_x \in \{a_{im}, a_r\}$. Following the example presented in Section 4.1, the agreement rate of a_3 is $ar_{a_3} = (4/5) \cdot 100 = 80\%$. Taking into account Eq. (1), we define two metrics, named *real improvement* (*RI*) and *improvement rate* (*IR*), which allow us to compare the agreement rate of both a_{im} and a_r. Metric *RI* is defined as follows:

$$RI = ar_{im} - ar_r. \tag{2}$$

Intuitively, this metric indicates the rate of agents that were persuaded by a_{im} but not by a_r. On the other hand, metric *IR* is defined as follows:

$$IR = \frac{ar_{im} - ar_r}{ar_r}. \quad (3)$$

The rationale behind this metric is to indicate the rate of improvement of the agreement rate obtained by a_{im} in relation to a_r. For instance, if $|V_{neg}| = 10$, $|Ag_{im}| = 6$, and $|Ag_r| = 3$, $RI = (6/10).100 - (3/10).100 \cong 33.33$ % and $IR = ((6/10).100 - (3/10).100)/(3/10).100 = 100$ %. Notice that both metrics are calculated comparing the agreement rate of agents a_r (ar_r) and a_{im} (ar_{im}). Thus, if ar_{im} is higher than ar_r, *IR* and *RI* are positive, otherwise, they are negative.

4.3. Results

The experiments showed that the agreement rate achieved by agent a_{im} was higher than that achieved by agent a_r in most of the scenarios. Tables A.2–A.10 show the agreement rate (ar) obtained by agents a_{im} and a_r in each scenario. Notice that each table represents a different combination of δ and *br*. To obtain these values, we ran the testing stage 10,000 times in each scenario and then we computed the average of the agreement rate and its standard deviation. Once we obtained the average agreement rate, we calculated metrics *RI* and *IR*. Figs. A.3–A.8 compare the results of metrics *IR* and *RI* in each scenario. Particularly, Figs. A.3–A.5 represent the results of metric *IR* in scenarios with different *br* values. Similarly, Figs. A.6–A.8 represent the results of metric *RI*. Notice that we zoom in the scale of the charts between 0 and 1 to improve the readability of small values. To make easy the discussion of the results, we divide it in subsections according to the dimensions to analyze.

4.3.1. Number of agents involved in the negotiation

Comparing the results obtained with $n = 10$ and $n = 100$ (i.e., $|V_{neg}|$ value), we can observe some similarities and differences. First, the *IR* values obtained when $n = 100$ were considerably higher than the same obtained when $n = 10$. Whereas *IR* values did not exceed 40% when $n = 10$, the same value in scenarios where $n = 100$ reached 120% (Figs. A.3–A.5). However, the tendency of metric *IR* when other dimensions changed seemed to be the same when $n = 10$ and $n = 100$. For example, as n_{train} increased, metric *IR* also increased when $t = 0.2$, $br = 0.05$ and *gd* was low, and decreased when $t = 0.8$ in scenarios where $n = 10$ as well as in scenarios where $n = 100$. However, last tendency reversed in both scenarios of *n* when *br* was 0.2. Similar situations occurred when δ increased, despite some exceptions can be seen when n_{train} was high, $t = 0.2$ and *gd* was low. In these scenarios, if *br* was low, metric *IR* decreased as δ increased when $n = 10$, but it increased when $n = 100$ (Fig. A.3). In contrast, if *br* was high, metric *IR* keep almost constant as δ increased when $n = 10$, but it decreased when $n = 100$ (Fig. A.3). The first cause of this fact was that the agreement rate in such scenarios when $n = 100$ was considerably lower than when $n = 10$. The second cause was that when δ increased the changes of the trust levels among the agents was more significant, then a low *br* and a high n_{train} produced a strong increase in the overall trust of the agents during the training stage. However, when $n = 10$ the increases were focused on 10 agents instead of 100. This fact produced that when δ increased, the increases of the agreement rate when $n = 10$ were higher (given the increase in the overall trust) than when $n = 100$. However, the difference between ar_{im} and ar_r kept constant, consequently, metric *IR* decreased. In regard to metric *RI,* the values obtained in scenarios with $n = 100$ were generally higher than with $n = 10$ (Figs. A.6–A.8). We think that it is because when *n* increased the decision alternatives also increased. For these reason, our approach, applied by a_{im}, obtained better agreement rates. An exception can be seen when *dg* and *t* is low. In these scenarios, metric *RI* when $n = 100$ was lower than when $n = 10$, because the agreement rates obtained by a_{im} and a_r were very low (around 3% and 1.5% respectively).

4.3.2. Graph density

In general, the best results (in both metrics) were obtained when *gd* was low. This was because when *gd* increased the number of good alternatives to achieve agreements also increased. In consequence, agent a_r could also obtain a high agreement rate, especially, in scenarios when trust was high. However, when trust was low, metric *RI* increased as *gd* also increased, mainly in scenarios where $n = 100$ and δ is low. This was because, although *gd* increased, a low value in the overall trust maintained low the number of good alternatives to achieve agreements.

4.3.3. Trust level among agents

Since the effects of this dimensions on the values of metrics *IR* and *RI* depended on the other dimensions, it is not possible to do an isolate analysis of the trust dimension. For example, when *gd* was low the best value of metric *IR* was mostly obtained when $t = 0.5$ or $t = u$ and the best value of metric *RI*, when $t = 0.8$. However, when *gd* was intermediate and high the best value of metric *IR* was obtained when trust was low. In contrast, the analysis of metric *RI* in such scenarios is not so simple. In these scenarios, when $n = 10$, the best value of metric *RI* was also obtained when trust was low.

Nevertheless, when $n = 100$, others dimensions affected the results. For example, when δ was low and *br* was low or intermediate (Figs. A.6 and A.7), the best value of metric *RI* when $n_{train} = 10$ was obtained with a intermediate value of trust, but as n_{train} increased, the best value was obtained with a low trust. Moreover, in the scenarios with $\delta = 0.05$ and $\delta = 0.1$ the best *RI,* when *gd* was intermediate and high, was obtained when trust was low. This was because, as n_{train} and δ increased, the changes in the overall trust of the agents produced that the agreement rate also increased in scenarios with intermediate or high values of *t*. As a consequence, the difference between ar_{im} and ar_r was reduced.

In contrast, when *br* was high the changes in the overall trust of the agents were balanced (Fig. A.8). That was, the number of broken and fulfilled deals was similar. In consequence, after the training stage, the overall trust of the agents did not suffer drastic changes. In these scenarios, the best value of metric *RI* was obtained when $t = 0.5$ or $t = u$ in scenarios with a intermediate value of *gd*, and when $t = 0.8$ in scenarios with a high *gd*.

Moreover, Fig. A.8 clearly shows the relationship between *dg* and *t* dimensions when *n* and *br* were high (independently of δ value). In these scenarios, as *gd* increased, metric *IR* increased in scenarios with low trust and decreased in scenarios with high trust.

Finally, it is worth noticing that the results obtained with the trust initiated with a normal distribution with mean 0.5 ($t = 0.5$) and a uniform distribution ($t = u$) were equivalent in all the scenarios.

4.3.4. Trust update

In previous subsections, we have been discussing the role of δ and *br* in the performance of our approach. As stated above, the combination of δ and *br* determines how much the overall trust of the agents changes during the training stage. In this context, when δ was high and *br* was low the overall trust tended to increase, also increasing the agreement rates. For these reason, for example, metric *RI* decrease markedly as δ increased when *br* and *t* was low and *gd* was high (Fig. A.6). It is also worth noticing that this decrease was more significant when n_{train} was high. Intuitively, this was because an increase in n_{train} emphasized the changes in the overall trust.

In general, the best values of metric *IR* and *RI* were obtained when *br* was high, due to the fact that in these scenarios the changes in the overall trust of the agents were balanced.

4.3.5. Training/historical information

Intuitively, we could think that when n_{train} increased, metrics *IR* and *RI* also should increase, since our approach should have more information to train the model. However, as stated above, since δ and *br* determine the level of change in the overall trust of the agent, increasing n_{train} does not assure an improvement of such metrics. For this reason, when *gd* was low and as n_{train} increased, both metrics increased when *t* was low, but decrease when *t* was high. Other example of this effect could be seen in scenarios where *gd* was low and trust was high. In these scenarios, metric *RI* increased as n_{train} increased when *br* was low (Fig. A.6), but metric *RI* decreased as n_{train} increased when *br* was high (Fig. A.8).

4.3.6. General discussion

The experimental results showed in which scenarios our approach (a_{im}) exhibited the best improvements regarding to the agreement rate obtained by a base agent (a_r). In general, our approach considerably improved the agreement rate in scenarios where the number of decision alternatives was high, but only a reduced number of such alternatives allowed the agent to achieve wide agreements. For example, this fact could be seen in scenarios where graph density was low and trust was high, and vice versa. Intuitively, this effect was more relevant when the number of agents involved in the negotiation (n) was high. In contrast, in scenarios where there were no alternatives to achieve wide agreements (low graph density and trust) or there were multiple alternatives (high graph density and trust) the improvements of our approach was minimum.

The experiments also showed how the trust update affected the performance of our approach. Particularly, the performance of our approach decreased in the scenarios where the overall trust tended to increase markedly (low break rate and high δ). In such scenarios, the role of n_{train} was also important. Since the trust update was carried out during the training stage, the effect of this process was more significant in scenarios where n_{train} was high. In contrast, in scenarios where the overall trust did not change drastically ($br = 0.5$ and low δ), metrics *IR* and *RI* increased as n_{train} increased. However, it is worth noticing that our approach performed well when the number of actions for training was low. This is a good aspect of our approach, since in some scenarios it could be hard to find a great amount of historical information to train the model. Moreover, since a little information is needed to train the model, the computational cost of running the influence maximization algorithm is minimum. For example, in the scenarios with most volume of information ($n = 100$ and $n_{train} = 100$) the average time to find the seed set was 1309 ms ($\pm$ 86.6 ms).

5. Conclusions and future work

In this work, we have proposed a novel approach to assist a negotiator (an autonomous agent or a human negotiator) to decide which opponent to persuade during a negotiation by taking into account the social influence of the negotiation participants. To do this, we reformulated the influence maximization problem to be solved under the *CD* model in negotiation contexts. Moreover, we have defined some characteristics of the negotiation context in which our approach can be applied and we have tested our approach in several scenarios. From these experiments, we observed that the agreement rate increases when an agent decides and is able to persuade the opponent that maximises the expected influence spread according to the *CD* model.

Moreover, the results showed that the increase of the agreement rate is high in some scenarios and low in others. These variations are directly related to the dimensions of each negotiation scenario (i.e., $ns = (n, gd, t, br, \delta, n_{train})$). As stated above, our approach allows a negotiator to improve the agreement rate, especially in scenarios where the number of decisions is high but not all alternatives lead to good agreements. In addition, a little historical information is needed to train the model and obtain good results. This fact is also important since a high variation in the overall trust of the agents during the training stage can reduce the performance of our approach. It is also worth noticing that this information is easily accessible, since the proposals accepted by the agents during a multilateral negotiation are public. On the other hand, a limitation of our approach is that in scenarios where there are no alternatives to achieve wide agreements or there are multiple alternatives the improvements of our approach are minimum.

Future work will focus on exploring other negotiation configurations and other social factors such as reputation and authority roles. Moreover, we will analyze the effects of social influence in other key decisions that agents must make during a negotiation. Particularly, we will explore how social influence maximization can be applied to improve the process of coalition formation. Further future research may also focus on doing additional experiments with human negotiators.

Appendix A. Experimental results: tables and figures

Table A.2
Agreement rates in the negotiation scenarios when $\delta = 0.01$ and $br = 0.05$.

n_{train}	gd	a_x	t: 0.2	t: 0.5	t: 0.8	t: u
***n* = 10**						
10	0.2	*im*	19.41% ± 5.63	40.62% ± 13.35	64.48% ± 20.64	41.15% ± 15.77
		r	15.78% ± 2.58	32.03% ± 11.79	53.20% ± 21.78	31.32% ± 12.64
	0.5	*im*	39.83% ± 11.22	85.82% ± 9.19	98.50% ± 3.01	87.50% ± 11.32
		r	32.88% ± 8.62	82.67% ± 9.73	97.82% ± 4.00	84.46% ± 11.63
	0.8	*im*	62.65% ± 10.40	98.51% ± 1.59	99.99% ± 0.03	98.50% ± 1.54
		r	59.72% ± 9.25	98.37% ± 1.45	99.99% ± 0.04	98.12% ± 2.14
50	0.2	*im*	22.72% ± 5.70	43.11% ± 15.28	66.07% ± 20.52	47.17% ± 14.38
		r	17.03% ± 3.82	33.70% ± 13.80	56.99% ± 23.17	35.60% ± 12.88
	0.5	*im*	43.30% ± 11.45	91.74% ± 6.66	98.92% ± 2.64	90.64% ± 7.37
		r	36.56% ± 9.14	90.13% ± 7.83	98.54% ± 4.06	87.64% ± 9.23
	0.8	*im*	70.57% ± 9.26	99.18% ± 1.16	99.99% ± 0.04	99.32% ± 0.95
		r	67.15% ± 9.41	99.16% ± 1.20	100.00% ± 0.01	99.21% ± 1.14
100	0.2	*im*	22.48% ± 5.82	47.73% ± 15.98	71.76% ± 18.28	48.88% ± 16.11
		r	16.61% ± 3.33	38.28% ± 16.25	62.64% ± 22.90	38.34% ± 17.06
	0.5	*im*	48.22% ± 12.52	95.35% ± 4.38	99.54% ± 0.87	94.38% ± 5.66
		r	40.86% ± 12.13	94.73% ± 5.15	99.50% ± 1.04	93.13% ± 7.03
	0.8	*im*	79.45% ± 7.57	99.69% ± 0.46	100.00% ± 0.01	99.65% ± 0.58
		r	76.64% ± 7.33	99.59% ± 0.54	100.00% ± 0.01	99.66% ± 0.51

(continued on next page)

Table A.2 (*continued*)

n_{train}	gd	a_x	t			
			0.2	0.5	0.8	u
n = 100						
10	0.02	*im*	2.46% ± 0.80	15.25% ± 6.92	57.62% ± 11.32	15.63% ± 7.26
		r	1.75% ± 0.20	7.77% ± 3.39	38.28% ± 10.75	7.64% ± 3.45
	0.05	*im*	16.12% ± 5.56	88.31% ± 3.55	98.02% ± 1.10	88.38% ± 4.03
		r	10.39% ± 2.87	80.80% ± 4.96	96.52% ± 2.15	80.52% ± 5.02
	0.08	*im*	62.27% ± 8.34	97.83% ± 1.46	99.77% ± 0.34	98.03% ± 1.01
		r	51.97% ± 7.48	96.78% ± 1.85	99.56% ± 0.81	96.65% ± 1.70
50	0.02	*im*	2.93% ± 0.96	17.74% ± 6.77	61.23% ± 10.82	17.97% ± 7.75
		r	1.72% ± 0.22	8.36% ± 3.43	45.26% ± 12.42	8.73% ± 4.34
	0.05	*im*	19.17% ± 6.56	91.60% ± 2.16	98.21% ± 0.95	91.12% ± 2.39
		r	11.24% ± 4.10	87.50% ± 3.84	97.41% ± 2.06	86.57% ± 4.24
	0.08	*im*	70.94% ± 6.35	98.60% ± 0.61	99.87% ± 0.18	98.46% ± 0.70
		r	60.18% ± 6.66	97.99% ± 1.09	99.85% ± 0.25	97.84% ± 1.12
100	0.02	*im*	3.05% ± 0.82	20.95% ± 8.85	65.92% ± 10.52	19.49% ± 7.75
		r	1.74% ± 0.20	10.26% ± 5.88	52.18% ± 13.37	9.09% ± 4.65
	0.05	*im*	22.80% ± 7.89	93.60% ± 1.69	98.30% ± 1.05	92.60% ± 2.38
		r	13.69% ± 5.40	91.65% ± 2.61	97.55% ± 2.04	89.99% ± 3.95
	0.08	*im*	79.65% ± 5.22	98.99% ± 0.45	99.81% ± 0.28	98.85% ± 0.67
		r	69.99% ± 6.86	98.69% ± 0.84	99.75% ± 0.48	98.63% ± 0.94

Table A.3
Agreement rates in the negotiation scenarios when $\delta = 0.01$ and $br = 0.2$.

n_{train}	gd	a_x	t			
			0.2	0.5	0.8	u
n = 10						
10	0.2	*im*	19.21% ± 5.12	41.20% ± 13.12	64.33% ± 18.15	42.27% ± 15.05
		r	15.70% ± 2.43	31.21% ± 10.51	52.89% ± 18.95	31.82% ± 13.08
	0.5	*im*	39.02% ± 9.69	87.63% ± 7.11	98.84% ± 1.79	87.16% ± 10.50
		r	34.22% ± 7.81	84.28% ± 8.47	98.23% ± 2.55	83.90% ± 10.73
	0.8	*im*	61.35% ± 9.29	98.32% ± 1.61	99.98% ± 0.10	98.56% ± 2.03
		r	58.01% ± 8.67	98.24% ± 1.53	99.97% ± 0.15	98.32% ± 1.79
50	0.2	*im*	20.78% ± 6.32	42.08% ± 13.50	65.09% ± 19.96	42.85% ± 15.23
		r	15.75% ± 3.18	31.56% ± 11.89	54.75% ± 22.78	32.44% ± 14.07
	0.5	*im*	43.10% ± 10.40	89.38% ± 8.33	98.94% ± 2.00	90.39% ± 8.29
		r	35.71% ± 9.10	86.67% ± 9.33	98.52% ± 3.08	87.57% ± 9.79
	0.8	*im*	68.63% ± 9.77	98.73% ± 1.35	100.00% ± 0.02	99.09% ± 1.05
		r	64.68% ± 9.28	98.54% ± 1.62	99.98% ± 0.13	98.88% ± 1.21
100	0.2	*im*	21.15% ± 5.13	44.86% ± 13.49	71.41% ± 20.03	45.39% ± 17.46
		r	16.07% ± 3.30	35.49% ± 13.67	63.06% ± 24.16	34.27% ± 16.56
	0.5	*im*	47.26% ± 10.08	92.61% ± 7.09	98.93% ± 2.03	91.69% ± 7.94
		r	39.59% ± 10.27	90.87% ± 8.10	98.70% ± 3.01	90.03% ± 8.28
	0.8	*im*	72.83% ± 9.21	99.48% ± 0.52	99.99% ± 0.04	99.43% ± 0.70
		r	70.64% ± 9.15	99.35% ± 0.70	99.99% ± 0.03	99.19% ± 0.90
n = 100						
10	0.02	*im*	2.70% ± 1.06	13.89% ± 5.94	60.34% ± 12.87	15.87% ± 8.05
		r	1.73% ± 0.23	7.08% ± 2.64	41.66% ± 13.44	7.87% ± 3.78
	0.05	*im*	16.10% ± 5.74	88.03% ± 3.36	97.80% ± 1.15	89.02% ± 3.17
		r	10.41% ± 3.17	79.92% ± 5.29	95.87% ± 2.56	81.21% ± 4.96
	0.08	*im*	59.75% ± 8.76	97.86% ± 1.17	99.81% ± 0.27	97.98% ± 1.45
		r	50.13% ± 8.08	96.76% ± 1.52	99.69% ± 0.68	96.60% ± 1.58
50	0.02	*im*	2.95% ± 0.91	17.16% ± 7.48	59.92% ± 10.64	17.87% ± 7.83
		r	1.72% ± 0.20	8.03% ± 4.07	42.55% ± 11.88	8.56% ± 4.77
	0.05	*im*	16.83% ± 5.98	90.75% ± 2.49	98.10% ± 1.00	90.33% ± 2.96
		r	10.48% ± 3.93	84.76% ± 4.64	97.00% ± 2.04	84.02% ± 4.26
	0.08	*im*	67.67% ± 7.64	98.36% ± 0.64	99.83% ± 0.26	98.35% ± 0.75
		r	56.36% ± 7.21	97.39% ± 1.32	99.78% ± 0.46	97.20% ± 1.36
100	0.02	*im*	3.06% ± 0.92	18.18% ± 6.95	64.65% ± 10.91	19.36% ± 8.08
		r	1.77% ± 0.22	8.22% ± 4.01	50.00% ± 12.98	8.98% ± 5.25
	0.05	*im*	19.94% ± 6.51	92.13% ± 2.16	98.27% ± 0.96	92.00% ± 2.32
		r	11.47% ± 4.73	88.43% ± 3.38	97.50% ± 1.92	88.09% ± 4.17
	0.08	*im*	76.36% ± 5.71	98.61% ± 0.55	99.86% ± 0.26	98.69% ± 0.66
		r	66.00% ± 6.88	98.09% ± 1.02	99.84% ± 0.41	98.13% ± 1.20

Table A.4
Agreement rates in the negotiation scenarios when $\delta = 0.01$ and $br = 0.5$.

n_{train}	gd	a_x	t			
			0.2	0.5	0.8	u
***n* = 10**						
10	0.2	*im*	19.27% ± 5.59	39.11% ± 13.42	63.50% ± 17.90	40.44% ± 14.59
		r	15.41% ± 2.73	29.40% ± 11.45	52.38% ± 19.47	29.54% ± 10.57
	0.5	*im*	38.46% ± 10.23	85.31% ± 9.61	98.68% ± 2.94	86.86% ± 10.43
		r	32.71% ± 7.02	81.75% ± 10.50	98.07% ± 4.71	81.88% ± 11.99
	0.8	*im*	60.18% ± 9.74	98.37% ± 1.66	99.99% ± 0.02	98.58% ± 1.51
		r	57.93% ± 8.59	98.09% ± 1.65	99.97% ± 0.16	97.87% ± 2.46
50	0.2	*im*	20.70% ± 5.64	41.32% ± 13.70	64.34% ± 19.29	41.56% ± 14.40
		r	15.82% ± 3.39	30.63% ± 11.16	52.57% ± 20.24	29.10% ± 11.38
	0.5	*im*	41.88% ± 8.91	87.08% ± 8.60	98.79% ± 1.98	86.93% ± 8.78
		r	33.83% ± 7.33	83.16% ± 9.64	98.26% ± 3.17	81.68% ± 10.34
	0.8	*im*	63.08% ± 10.89	98.31% ± 1.47	99.98% ± 0.06	98.46% ± 1.65
		r	58.79% ± 8.35	97.73% ± 1.89	99.98% ± 0.10	97.89% ± 2.06
100	0.2	*im*	22.08% ± 6.06	40.32% ± 12.75	65.49% ± 18.65	41.04% ± 14.42
		r	16.17% ± 2.92	28.92% ± 10.28	53.97% ± 20.50	29.77% ± 11.84
	0.5	*im*	43.50% ± 10.07	87.65% ± 8.06	98.55% ± 2.59	88.20% ± 8.91
		r	34.74% ± 8.63	82.91% ± 9.31	97.62% ± 4.00	83.13% ± 11.00
	0.8	*im*	63.10% ± 8.67	98.44% ± 1.19	99.99% ± 0.08	98.81% ± 1.19
		r	58.09% ± 8.70	97.90% ± 1.65	99.97% ± 0.25	98.19% ± 1.50
***n* = 100**						
10	0.02	*im*	2.42% ± 0.89	13.53% ± 5.95	55.77% ± 12.14	15.74% ± 7.34
		r	1.73% ± 0.23	7.01% ± 2.77	36.45% ± 11.29	7.48% ± 2.97
	0.05	*im*	16.65% ± 6.56	87.80% ± 4.50	97.75% ± 1.78	88.02% ± 4.54
		r	10.56% ± 3.57	80.31% ± 4.59	95.99% ± 2.90	79.79% ± 5.83
	0.08	*im*	58.35% ± 8.32	97.58% ± 1.72	99.81% ± 0.31	97.86% ± 1.06
		r	48.84% ± 6.59	96.61% ± 2.01	99.67% ± 0.57	96.37% ± 1.75
50	0.02	*im*	2.92% ± 0.96	15.96% ± 6.86	57.18% ± 10.64	16.52% ± 7.34
		r	1.74% ± 0.24	7.38% ± 3.22	36.64% ± 10.59	7.19% ± 3.51
	0.05	*im*	16.75% ± 5.55	88.75% ± 3.11	97.81% ± 1.06	88.56% ± 3.35
		r	9.90% ± 2.76	79.33% ± 5.28	95.60% ± 2.46	79.51% ± 5.39
	0.08	*im*	60.64% ± 7.33	97.88% ± 0.86	99.84% ± 0.23	97.84% ± 1.00
		r	48.48% ± 6.58	96.14% ± 1.85	99.64% ± 0.69	95.95% ± 2.16
100	0.02	*im*	3.17% ± 0.96	16.45% ± 6.02	59.97% ± 12.08	17.31% ± 6.71
		r	1.71% ± 0.20	7.28% ± 3.05	39.20% ± 11.27	7.36% ± 3.29
	0.05	*im*	17.97% ± 5.73	88.55% ± 2.92	97.88% ± 1.10	89.23% ± 3.02
		r	10.07% ± 2.79	78.49% ± 6.03	95.64% ± 2.44	79.68% ± 5.57
	0.08	*im*	62.05% ± 6.47	98.13% ± 0.59	99.84% ± 0.20	97.97% ± 0.85
		r	49.42% ± 6.92	96.28% ± 1.79	99.70% ± 0.44	95.95% ± 1.98

Table A.5
Agreement rates in the negotiation scenarios when $\delta = 0.05$ and $br = 0.05$.

n_{train}	gd	a_x	t			
			0.2	0.5	0.8	u
***n* = 10**						
10	0.2	*im*	19.86% ± 5.64	44.62% ± 15.73	66.88% ± 19.85	41.65% ± 16.83
		r	15.82% ± 2.89	36.11% ± 14.92	57.62% ± 23.02	33.67% ± 13.71
	0.5	*im*	40.88% ± 10.57	90.82% ± 6.26	99.14% ± 1.79	90.05% ± 8.28
		r	36.90% ± 8.50	89.21% ± 7.30	99.05% ± 1.74	87.00% ± 10.41
	0.8	*im*	69.23% ± 9.01	99.09% ± 0.95	100.00% ± 0.02	99.05% ± 1.18
		r	67.20% ± 8.59	98.88% ± 1.04	100.00% ± 0.02	98.78% ± 1.37
50	0.2	*im*	24.56% ± 8.13	61.02% ± 20.08	74.48% ± 18.40	59.40% ± 19.89
		r	18.60% ± 6.51	53.25% ± 22.49	63.96% ± 22.60	50.83% ± 22.96
	0.5	*im*	70.13% ± 14.04	98.39% ± 3.06	99.67% ± 1.46	97.68% ± 3.38
		r	66.65% ± 15.37	98.24% ± 4.33	99.51% ± 2.64	97.58% ± 4.14
	0.8	*im*	93.59% ± 4.46	99.94% ± 0.15	100.00% ± 0.00	99.89% ± 0.53
		r	93.47% ± 4.98	99.95% ± 0.14	100.00% ± 0.00	99.90% ± 0.50
100	0.2	*im*	35.94% ± 15.74	71.87% ± 21.42	78.14% ± 18.83	67.35% ± 21.94
		r	27.77% ± 15.18	63.83% ± 24.86	68.27% ± 24.21	58.82% ± 24.90
	0.5	*im*	90.47% ± 10.56	99.53% ± 1.52	99.85% ± 1.04	98.29% ± 3.92
		r	89.64% ± 12.16	99.52% ± 1.94	99.81% ± 1.49	97.89% ± 5.89
	0.8	*im*	99.39% ± 0.96	100.00% ± 0.01	100.00% ± 0.00	99.99% ± 0.08
		r	99.42% ± 1.06	100.00% ± 0.02	100.00% ± 0.00	99.99% ± 0.05

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Table A.5 (*continued*)

n_{train}	gd	a_x	t			
			0.2	0.5	0.8	u
***n* = 100**						
10	0.02	*im*	2.60% ± 0.90	17.01% ± 7.23	61.42% ± 13.26	15.84% ± 9.11
		r	1.73% ± 0.20	8.69% ± 3.70	45.88% ± 14.01	8.24% ± 4.35
	0.05	*im*	17.04% ± 6.45	91.29% ± 2.35	98.14% ± 1.03	90.74% ± 2.68
		r	11.23% ± 3.78	87.65% ± 3.30	97.48% ± 1.87	86.77% ± 4.20
	0.08	*im*	68.37% ± 8.71	98.33% ± 1.00	99.86% ± 0.22	98.13% ± 2.28
		r	60.06% ± 7.41	97.76% ± 1.04	99.83% ± 0.33	97.63% ± 1.35
50	0.02	*im*	3.28% ± 1.05	31.28% ± 15.19	68.50% ± 9.30	27.03% ± 13.78
		r	1.78% ± 0.21	19.96% ± 13.47	54.06% ± 11.90	15.98% ± 11.14
	0.05	*im*	34.56% ± 15.80	95.96% ± 1.52	98.60% ± 0.78	94.93% ± 1.82
		r	24.27% ± 13.26	95.19% ± 2.30	98.08% ± 1.51	94.07% ± 2.41
	0.08	*im*	91.90% ± 2.23	99.45% ± 0.43	99.93% ± 0.15	99.30% ± 0.48
		r	90.43% ± 3.03	99.47% ± 0.42	99.92% ± 0.23	99.27% ± 0.58
100	0.02	*im*	3.81% ± 1.22	43.24% ± 16.24	71.44% ± 7.82	43.68% ± 14.40
		r	1.88% ± 0.25	31.76% ± 16.22	57.41% ± 10.36	30.93% ± 13.30
	0.05	*im*	71.44% ± 14.48	96.98% ± 1.53	98.72% ± 0.92	96.26% ± 1.85
		r	64.40% ± 17.36	96.26% ± 2.52	98.35% ± 1.49	95.43% ± 2.49
	0.08	*im*	96.71% ± 1.37	99.70% ± 0.35	99.89% ± 0.26	99.49% ± 0.49
		r	96.49% ± 1.75	99.68% ± 0.42	99.84% ± 0.53	99.49% ± 0.53

Table A.6
Agreement rates in the negotiation scenarios when $\delta = 0.05$ and $br = 0.2$.

n_{train}	gd	a_x	t			
			0.2	0.5	0.8	u
***n* = 10**						
10	0.2	*im*	19.34% ± 5.71	43.43% ± 14.73	67.08% ± 18.56	41.85% ± 15.54
		r	15.74% ± 3.17	34.83% ± 13.04	58.46% ± 21.09	32.37% ± 13.32
	0.5	*im*	42.34% ± 10.81	90.31% ± 7.02	98.98% ± 2.50	90.40% ± 8.15
		r	38.14% ± 9.90	87.75% ± 8.30	98.64% ± 3.96	88.33% ± 9.62
	0.8	*im*	67.11% ± 10.67	98.53% ± 2.11	99.97% ± 0.20	99.03% ± 1.40
		r	64.63% ± 8.82	98.48% ± 1.39	99.97% ± 0.17	99.07% ± 1.06
50	0.2	*im*	23.11% ± 7.61	55.51% ± 18.38	74.37% ± 20.70	50.67% ± 17.23
		r	17.67% ± 4.96	46.75% ± 20.47	66.55% ± 24.78	40.18% ± 17.59
	0.5	*im*	56.25% ± 14.62	97.63% ± 2.56	99.53% ± 1.76	96.22% ± 5.97
		r	50.66% ± 14.94	97.54% ± 3.22	99.30% ± 3.28	95.94% ± 6.43
	0.8	*im*	87.66% ± ± 7.73	99.88% ± 0.23	100.00% ± 0.03	99.76% ± 0.43
		r	86.80% ± 7.78	99.90% ± 0.19	100.00% ± 0.03	99.74% ± 0.46
100	0.2	*im*	27.47% ± 9.98	64.14% ± 20.71	73.52% ± 17.93	63.62% ± 19.55
		r	21.16% ± 9.22	57.61% ± 23.29	63.04% ± 22.04	55.04% ± 22.65
	0.5	*im*	77.62% ± 15.33	98.52% ± 2.74	99.98% ± 0.09	98.43% ± 2.89
		r	73.62% ± 18.70	98.22% ± 4.12	99.98% ± 0.08	98.43% ± 3.06
	0.8	*im*	97.77% ± 2.45	99.99% ± 0.05	100.00% ± 0.00	99.97% ± 0.12
		r	97.71% ± 2.77	99.99% ± 0.05	100.00% ± 0.00	99.96% ± 0.14
***n* = 100**						
10	0.02	*im*	2.51% ± 0.90	15.67% ± 7.83	62.32% ± 9.72	15.58% ± 8.45
		r	1.77% ± 0.22	8.08% ± 3.93	45.12% ± 11.40	7.86% ± 4.08
	0.05	*im*	14.99% ± 6.66	90.23% ± 3.73	97.99% ± 1.08	89.97% ± 4.49
		r	10.01% ± 3.98	85.43% ± 4.25	96.70% ± 2.38	84.79% ± 4.42
	0.08	*im*	66.17% ± 7.48	98.00% ± 2.11	99.89% ± 0.16	98.32% ± 0.78
		r	56.60% ± 6.55	97.27% ± 1.50	99.85% ± 0.27	97.48% ± 1.50
50	0.02	*im*	3.18% ± 0.97	24.51% ± 11.84	65.17% ± 9.45	21.67% ± 10.45
		r	1.75% ± 0.22	13.71% ± 8.97	50.10% ± 11.08	11.23% ± 8.02
	0.05	*im*	27.86% ± 10.53	94.94% ± 1.96	98.42% ± 0.91	94.12% ± 1.81
		r	17.95% ± 8.45	93.89% ± 2.84	97.71% ± 1.79	92.61% ± 2.66
	0.08	*im*	87.36% ± 3.80	99.24% ± 0.40	99.90% ± 0.17	99.15% ± 0.52
		r	82.96% ± 6.03	99.15% ± 0.56	99.87% ± 0.43	99.05% ± 0.76
100	0.02	*im*	3.29% ± 0.93	32.54% ± 15.91	68.22% ± 9.45	31.69% ± 14.81
		r	1.80% ± 0.23	21.36% ± 14.19	53.68% ± 11.65	19.57% ± 12.57
	0.05	*im*	51.81% ± 17.42	96.61% ± 1.39	98.48% ± 1.05	95.67% ± 2.02
		r	40.60% ± 17.92	96.05% ± 2.08	97.69% ± 2.05	94.74% ± 2.82
	0.08	*im*	94.74% ± 1.73	99.54% ± 0.42	99.92% ± 0.21	99.40% ± 0.51
		r	94.06% ± 2.18	99.52% ± 0.48	99.88% ± 0.42	99.35% ± 0.67

Table A.7
Agreement rates in the negotiation scenarios when $\delta = 0.05$ and $br = 0.5$.

n_{train}	gd	a_x	t			
			0.2	0.5	0.8	u
***n* = 10**						
10	0.2	*im*	19.29% ± 5.45	36.67% ± 13.39	65.86% ± 18.10	42.26% ± 15.86
		r	15.68% ± 2.69	28.17% ± 10.53	54.27% ± 18.80	31.22% ± 11.39
	0.5	*im*	38.10% ± 10.56	85.19% ± 9.38	98.59% ± 2.54	85.69% ± 10.05
		r	32.87% ± 8.13	82.30% ± 9.55	97.51% ± 4.73	80.73% ± 11.42
	0.8	*im*	59.50% ± 12.15	98.43% ± 1.63	99.99% ± 0.04	98.72% ± 1.02
		r	56.51% ± 10.03	98.04% ± 1.45	99.96% ± 0.15	98.28% ± 1.45
50	0.2	*im*	20.59% ± 5.35	42.10% ± 13.13	63.76% ± 17.03	40.36% ± 13.77
		r	15.66% ± 2.78	32.10% ± 12.77	50.21% ± 18.47	29.75% ± 10.50
	0.5	*im*	41.18% ± 11.43	86.61% ± 9.69	98.79% ± 1.69	87.98% ± 8.33
		r	32.68% ± 8.49	81.49% ± 10.95	97.74% ± 3.19	82.30% ± 11.86
	0.8	*im*	65.46% ± 11.00	98.56% ± 1.42	99.99% ± 0.03	98.39% ± 1.76
		r	60.88% ± 9.42	98.00% ± 1.67	99.97% ± 0.11	97.99% ± 1.93
100	0.2	*im*	22.17% ± 7.61	42.05% ± 12.26	61.25% ± 18.19	40.76% ± 13.09
		r	15.87% ± 4.45	31.36% ± 10.22	46.68% ± 18.09	28.79% ± 10.73
	0.5	*im*	44.79% ± 10.96	85.80% ± 9.69	97.97% ± 3.10	85.00% ± 12.00
		r	36.35% ± 8.95	81.10% ± 11.79	96.15% ± 5.64	79.40% ± 13.76
	0.8	*im*	68.92% ± 9.71	98.61% ± 1.31	99.97% ± 0.08	98.63% ± 1.53
		r	64.32% ± 10.01	98.33% ± 1.36	99.87% ± 0.35	98.07% ± 2.01
***n* = 100**						
10	0.02	*im*	2.63% ± 0.88	14.41% ± 6.71	58.31% ± 12.22	16.29% ± 7.97
		r	1.76% ± 0.23	7.39% ± 3.06	38.78% ± 12.40	7.78% ± 3.79
	0.05	*im*	15.04% ± 5.43	88.00% ± 4.41	97.63% ± 1.05	88.00% ± 3.66
		r	9.42% ± 2.77	79.76% ± 4.83	95.47% ± 2.63	79.19% ± 4.92
	0.08	*im*	58.47% ± 9.96	97.50% ± 2.23	99.84% ± 0.21	97.91% ± 0.87
		r	48.90% ± 7.35	96.44% ± 1.47	99.67% ± 0.53	96.58% ± 1.57
50	0.02	*im*	2.86% ± 0.97	16.54% ± 6.14	56.63% ± 11.13	16.47% ± 7.50
		r	1.74% ± 0.18	7.44% ± 2.81	33.98% ± 10.00	7.42% ± 3.67
	0.05	*im*	17.82% ± 6.45	88.46% ± 3.21	97.68% ± 1.04	88.84% ± 2.76
		r	10.17% ± 3.28	79.50% ± 5.44	94.43% ± 3.00	79.36% ± 4.88
	0.08	*im*	64.73% ± 6.49	97.96% ± 0.72	99.77% ± 0.30	98.03% ± 0.67
		r	51.65% ± 6.41	96.18% ± 1.79	99.61% ± 0.58	96.27% ± 1.69
100	0.02	*im*	3.00% ± 0.87	17.31% ± 6.36	50.94% ± 12.38	17.51% ± 6.87
		r	1.71% ± 0.23	7.57% ± 3.11	28.81% ± 10.53	7.65% ± 3.75
	0.05	*im*	18.74% ± 5.49	88.41% ± 3.23	97.39% ± 1.26	88.97% ± 2.82
		r	10.38% ± 3.02	79.48% ± 5.32	93.73% ± 3.53	80.23% ± 5.14
	0.08	*im*	69.84% ± 6.43	98.01% ± 0.74	99.79% ± 0.24	98.01% ± 0.83
		r	58.14% ± 7.49	96.07% ± 2.01	99.54% ± 0.59	96.10% ± 1.89

Table A.8
Agreement rates in the negotiation scenarios when $\delta = 0.1$ and $br = 0.05$.

n_{train}	gd	a_x	t			
			0.2	0.5	0.8	u
***n* = 10**						
10	0.2	*im*	19.82% ± 5.30	43.20% ± 17.15	72.03% ± 18.88	46.85% ± 18.63
		r	16.76% ± 3.18	35.97% ± 16.53	65.51% ± 22.11	38.83% ± 17.92
	0.5	*im*	45.84% ± 12.59	94.94% ± 4.98	99.33% ± 1.15	93.32% ± 6.50
		r	42.16% ± 11.56	94.44% ± 6.33	99.46% ± 0.96	93.17% ± 7.13
	0.8	*im*	76.80% ± 10.21	99.38% ± 1.04	99.99% ± 0.06	99.44% ± 0.92
		r	76.78% ± 8.26	99.43% ± 0.97	99.99% ± 0.03	99.44% ± 0.81
50	0.2	*im*	36.18% ± 18.08	67.20% ± 21.93	75.72% ± 19.70	66.23% ± 22.15
		r	29.14% ± 18.42	58.59% ± 24.38	66.04% ± 23.73	57.71% ± 24.87
	0.5	*im*	89.09% ± 12.12	99.36% ± 1.61	99.86% ± 1.04	98.83% ± 2.42
		r	88.32% ± 13.69	99.36% ± 1.84	99.77% ± 1.96	98.69% ± 3.12
	0.8	*im*	98.94% ± 1.64	100.00% ± 0.04	100.00% ± 0.00	99.99% ± 0.06
		r	98.92% ± 1.79	100.00% ± 0.01	100.00% ± 0.00	99.99% ± 0.04
100	0.2	*im*	54.46% ± 21.20	72.95% ± 21.41	72.56% ± 22.46	77.07% ± 20.82
		r	44.78% ± 22.63	63.46% ± 25.34	62.33% ± 26.19	68.41% ± 24.92
	0.5	*im*	98.09% ± 3.80	99.68% ± 2.98	99.90% ± 0.99	99.54% ± 2.65
		r	97.62% ± 5.21	99.49% ± 4.36	99.82% ± 1.71	99.38% ± 3.59
	0.8	*im*	99.90% ± 0.64	100.00% ± 0.00	100.00% ± 0.00	100.00% ± 0.00
		r	99.91% ± 0.58	100.00% ± 0.00	100.00% ± 0.00	100.00% ± 0.00

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Table A.8 (*continued*)

n_{train}	gd	a_x	t			
			0.2	0.5	0.8	u
***n* = 100**						
10	0.02	*im*	2.75% ± 0.91	18.83% ± 9.79	62.80% ± 13.08	18.90% ± 10.35
		r	1.77% ± 0.23	10.35% ± 5.97	48.89% ± 13.92	10.44% ± 6.09
	0.05	*im*	20.66% ± 9.88	93.28% ± 2.14	98.43% ± 1.05	92.55% ± 2.33
		r	14.12% ± 6.56	91.06% ± 3.41	97.79% ± 2.09	89.82% ± 3.58
	0.08	*im*	78.56% ± 5.31	98.93% ± 0.52	99.88% ± 0.21	98.70% ± 0.73
		r	70.88% ± 6.72	98.73% ± 0.69	99.85% ± 0.32	98.52% ± 0.92
50	0.02	*im*	3.26% ± 0.98	41.69% ± 15.83	72.04% ± 7.42	35.15% ± 14.76
		r	1.82% ± 0.27	30.08% ± 14.61	58.22% ± 10.46	23.23% ± 13.19
	0.05	*im*	69.14% ± 14.37	97.17% ± 1.22	98.67% ± 1.06	96.37% ± 1.65
		r	61.51% ± 17.51	96.67% ± 1.70	97.95% ± 1.98	95.61% ± 2.35
	0.08	*im*	96.47% ± 1.21	99.60% ± 0.46	99.90% ± 0.19	99.55% ± 0.48
		r	96.23% ± 1.51	99.58% ± 0.51	99.89% ± 0.25	99.51% ± 0.65
100	0.02	*im*	4.12% ± 2.11	56.66% ± 12.80	73.41% ± 8.43	53.25% ± 13.98
		r	2.05% ± 0.63	44.23% ± 13.94	59.67% ± 11.48	40.39% ± 14.49
	0.05	*im*	87.98% ± 6.48	97.59% ± 1.21	98.69% ± 1.05	97.28% ± 1.37
		r	85.84% ± 8.48	96.98% ± 1.92	97.93% ± 2.10	96.45% ± 2.26
	0.08	*im*	98.11% ± 1.07	99.77% ± 0.38	99.94% ± 0.17	99.74% ± 0.40
		r	97.92% ± 1.29	99.71% ± 0.64	99.94% ± 0.24	99.71% ± 0.52

Table A.9
Agreement rates in the negotiation scenarios when $\delta = 0.1$ and $br = 0.2$.

n_{train}	gd	a_x	t			
			0.2	0.5	0.8	u
***n* = 10**						
10	0.2	*im*	20.29% ± 6.73	44.55% ± 17.04	66.75% ± 20.61	43.14% ± 16.98
		r	16.67% ± 5.17	38.28% ± 17.12	58.28% ± 22.94	34.81% ± 16.01
	0.5	*im*	45.40% ± 12.15	92.09% ± 6.54	99.43% ± 1.28	93.10% ± 7.32
		r	40.20% ± 12.10	90.53% ± 7.20	99.33% ± 1.95	91.61% ± 7.33
	0.8	*im*	68.80% ± 9.82	99.35% ± 0.66	99.99% ± 0.03	99.38% ± 0.80
		r	67.49% ± 8.79	99.19% ± 0.81	100.00% ± 0.02	99.30% ± 0.80
50	0.2	*im*	26.52% ± 11.05	61.86% ± 19.80	74.60% ± 18.60	60.47% ± 22.39
		r	21.42% ± 9.51	53.78% ± 22.05	65.31% ± 22.23	52.94% ± 24.00
	0.5	*im*	77.62% ± 15.33	98.68% ± 2.19	99.73% ± 1.12	98.26% ± 2.73
		r	75.44% ± 17.08	98.48% ± 3.06	99.65% ± 1.51	97.88% ± 3.78
	0.8	*im*	97.57% ± 2.68	99.92% ± 0.36	100.00% ± 0.01	99.95% ± 0.15
		r	97.50% ± 2.79	99.93% ± 0.35	100.00% ± 0.00	99.94% ± 0.23
100	0.2	*im*	42.00% ± 19.87	70.77% ± 20.96	75.61% ± 19.84	66.41% ± 23.10
		r	33.41% ± 19.83	61.42% ± 25.17	65.39% ± 23.70	57.74% ± 25.41
	0.5	*im*	94.59% ± 7.82	99.52% ± 2.30	99.53% ± 2.40	99.54% ± 1.21
		r	94.21% ± 8.81	99.35% ± 3.32	99.28% ± 3.71	99.49% ± 1.26
	0.8	*im*	99.67% ± 0.80	100.00% ± 0.01	100.00% ± 0.00	100.00% ± 0.02
		r	99.68% ± 0.76	100.00% ± 0.00	100.00% ± 0.00	99.99% ± 0.10
***n* = 100**						
10	0.02	*im*	2.55% ± 0.91	16.69% ± 7.63	62.64% ± 11.68	15.53% ± 8.30
		r	1.73% ± 0.19	8.94% ± 3.77	46.53% ± 12.77	7.83% ± 4.38
	0.05	*im*	18.42% ± 8.24	92.04% ± 2.77	98.03% ± 1.13	91.39% ± 2.71
		r	12.01% ± 4.85	88.98% ± 3.71	96.89% ± 2.12	87.16% ± 4.36
	0.08	*im*	72.65% ± 7.39	98.70% ± 0.64	99.85% ± 0.26	98.37% ± 1.15
		r	65.02% ± 7.11	98.26% ± 1.07	99.81% ± 0.37	97.99% ± 0.99
50	0.02	*im*	3.08% ± 1.10	34.42% ± 15.59	68.42% ± 7.71	30.21% ± 14.43
		r	1.81% ± ± 0.28	22.45% ± 13.76	54.27% ± 10.55	18.61% ± 12.01
	0.05	*im*	50.25% ± 19.24	96.30% ± 1.53	98.36% ± 1.06	95.30% ± 1.84
		r	39.82% ± 19.27	95.41% ± 2.46	97.56% ± 1.85	94.05% ± 2.76
	0.08	*im*	94.44% ± 1.95	99.50% ± 0.41	99.90% ± 0.15	99.27% ± 0.60
		r	93.64% ± 2.55	99.49% ± 0.50	99.90% ± 0.18	99.21% ± 0.76
100	0.02	*im*	3.44% ± 1.27	48.60% ± 15.25	69.85% ± 9.63	46.23% ± 15.83
		r	1.86% ± 0.31	35.28% ± 14.58	54.25% ± 11.60	33.26% ± 15.47
	0.05	*im*	77.84% ± 10.57	96.97% ± 1.32	98.76% ± 0.98	96.54% ± 1.74
		r	72.17% ± 13.76	96.15% ± 2.19	98.14% ± 1.85	95.86% ± 2.37
	0.08	*im*	97.26% ± 1.27	99.71% ± 0.33	99.90% ± 0.20	99.69% ± 0.36
		r	97.10% ± 1.39	99.71% ± 0.35	99.88% ± 0.28	99.65% ± 0.49

Table A.10
Agreement rates in the negotiation scenarios when $\delta = 0.1$ and $br = 0.5$.

n_{train}	gd	a_x	t			
			0.2	0.5	0.8	u
n = 10						
10	0.2	*im*	19.54% ± 5.22	38.81% ± 12.05	59.97% ± 21.05	39.78% ± 15.42
		r	15.67% ± 2.66	29.53% ± 9.86	48.16% ± 21.13	30.37% ± 12.09
	0.5	*im*	39.50% ± 11.09	86.84% ± 8.08	98.70% ± 2.14	87.69% ± 8.99
		r	33.67% ± 8.57	82.88% ± 9.10	97.72% ± 3.63	82.43% ± 10.95
	0.8	*im*	63.60% ± 10.98	98.27% ± 1.85	99.97% ± 0.14	98.56% ± 1.81
		r	61.67% ± 9.43	97.93% ± 1.54	99.96% ± 0.15	98.18% ± 1.92
50	0.2	*im*	21.70% ± 6.00	39.30% ± 12.02	59.19% ± 16.28	40.85% ± 14.73
		r	16.30% ± 3.87	29.11% ± 9.67	44.79% ± 15.15	29.95% ± 12.50
	0.5	*im*	43.41% ± 11.25	86.92% ± 9.43	97.60% ± 3.42	85.23% ± 11.94
		r	36.30% ± 10.14	81.87% ± 11.46	95.24% ± 5.49	80.61% ± 11.69
	0.8	*im*	71.22% ± 10.49	98.33% ± 2.20	99.97% ± 0.13	98.05% ± 3.93
		r	66.87% ± 10.36	98.24% ± 1.70	99.91% ± 0.26	98.12% ± 2.01
100	0.2	*im*	22.23% ± 5.53	40.71% ± 12.49	59.17% ± 19.42	40.87% ± 13.62
		r	16.17% ± 3.77	30.02% ± 10.38	43.29% ± 17.55	29.43% ± 9.65
	0.5	*im*	50.73% ± 11.98	87.43% ± 8.69	96.10% ± 4.89	87.24% ± 10.65
		r	43.17% ± 11.38	81.57% ± 11.66	92.82% ± 7.52	81.86% ± 12.98
	0.8	*im*	78.31% ± 9.10	98.23% ± 2.42	99.93% ± 0.20	98.36% ± 2.10
		r	74.59% ± 9.72	97.40% ± 2.95	99.80% ± 0.51	97.74% ± 2.34
n = 100						
10	0.02	*im*	2.68% ± 0.90	15.37% ± 7.06	55.71% ± 12.98	14.82% ± 7.17
		r	1.77% ± 0.25	7.76% ± 3.33	35.22% ± 11.14	7.16% ± 2.90
	0.05	*im*	16.31% ± 5.13	87.29% ± 4.12	97.69% ± 1.20	87.98% ± 4.28
		r	10.24% ± 3.08	79.66% ± 5.69	95.22% ± 2.63	79.94% ± 5.50
	0.08	*im*	59.90% ± 9.10	97.77% ± 1.28	99.81% ± 0.27	97.69% ± 1.70
		r	51.06% ± 7.22	96.29% ± 1.72	99.56% ± 0.88	96.59% ± 1.78
50	0.02	*im*	3.16% ± 0.88	16.47% ± 6.79	51.65% ± 10.62	16.93% ± 6.81
		r	1.79% ± 0.22	7.53% ± 3.14	28.35% ± 8.63	7.35% ± 3.81
	0.05	*im*	18.66% ± 6.22	88.56% ± 2.58	97.49% ± 1.04	88.27% ± 3.18
		r	11.23% ± 3.91	79.60% ± 5.54	93.10% ± 2.93	79.10% ± 5.37
	0.08	*im*	71.82% ± 5.72	98.03% ± 0.70	99.81% ± 0.22	97.91% ± 0.89
		r	60.36% ± 6.64	96.18% ± 1.84	99.35% ± 0.84	96.21% ± 1.80
100	0.02	*im*	3.02% ± 0.95	16.31% ± 5.85	46.33% ± 12.50	17.17% ± 6.72
		r	1.74% ± 0.21	7.48% ± 3.08	23.56% ± 8.45	7.48% ± 3.44
	0.05	*im*	21.80% ± 7.06	88.93% ± 2.69	96.92% ± 1.28	88.39% ± 2.96
		r	12.77% ± 4.52	79.64% ± 5.05	91.68% ± 3.74	79.35% ± 4.96
	0.08	*im*	78.99% ± 4.88	98.02% ± 0.75	99.75% ± 0.23	98.07% ± 0.91
		r	69.14% ± 5.93	96.16% ± 1.90	99.06% ± 1.07	96.26% ± 1.91

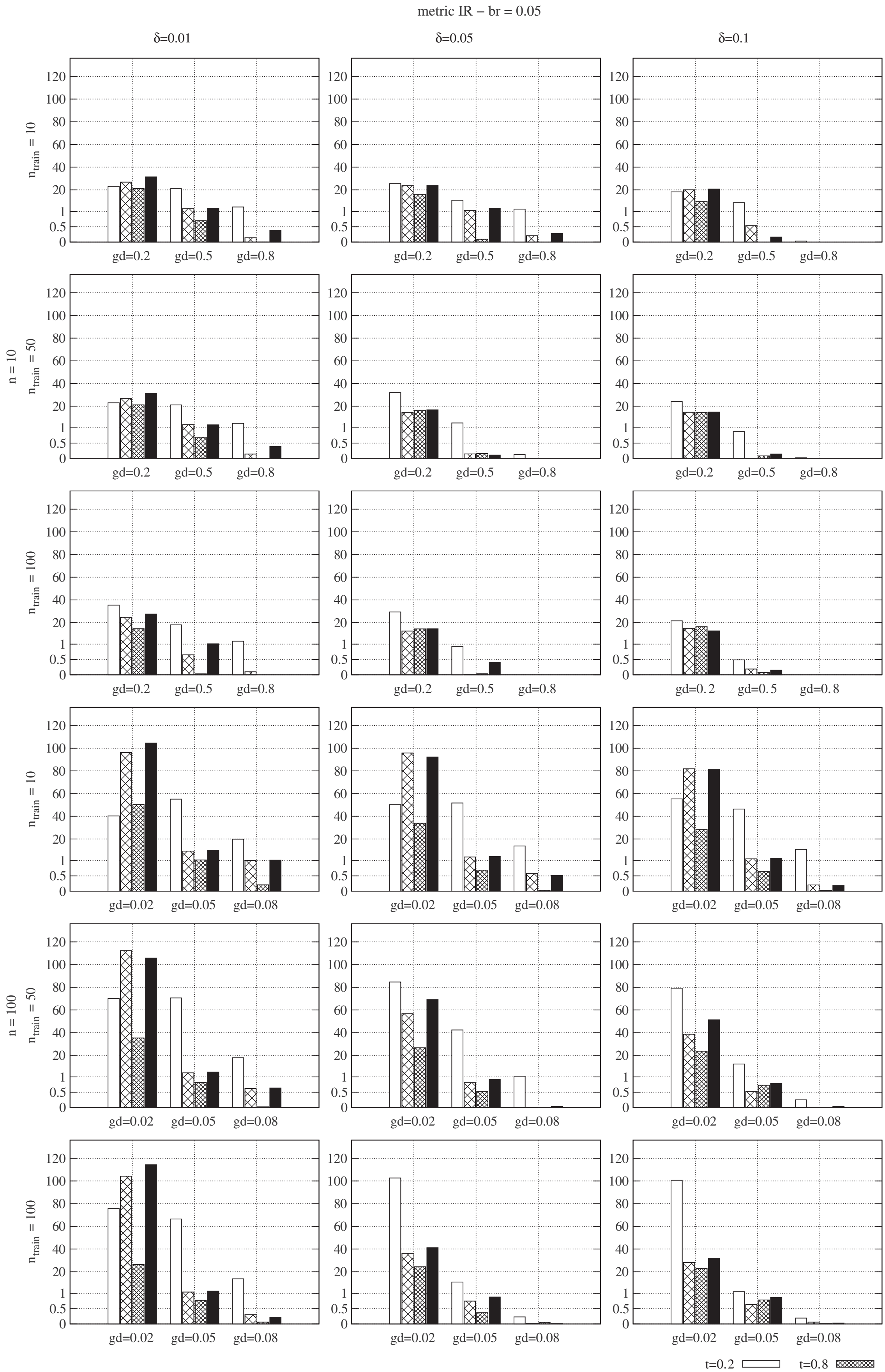

Fig. A.3. Comparison of metric *IR* with $br = 0.05$.

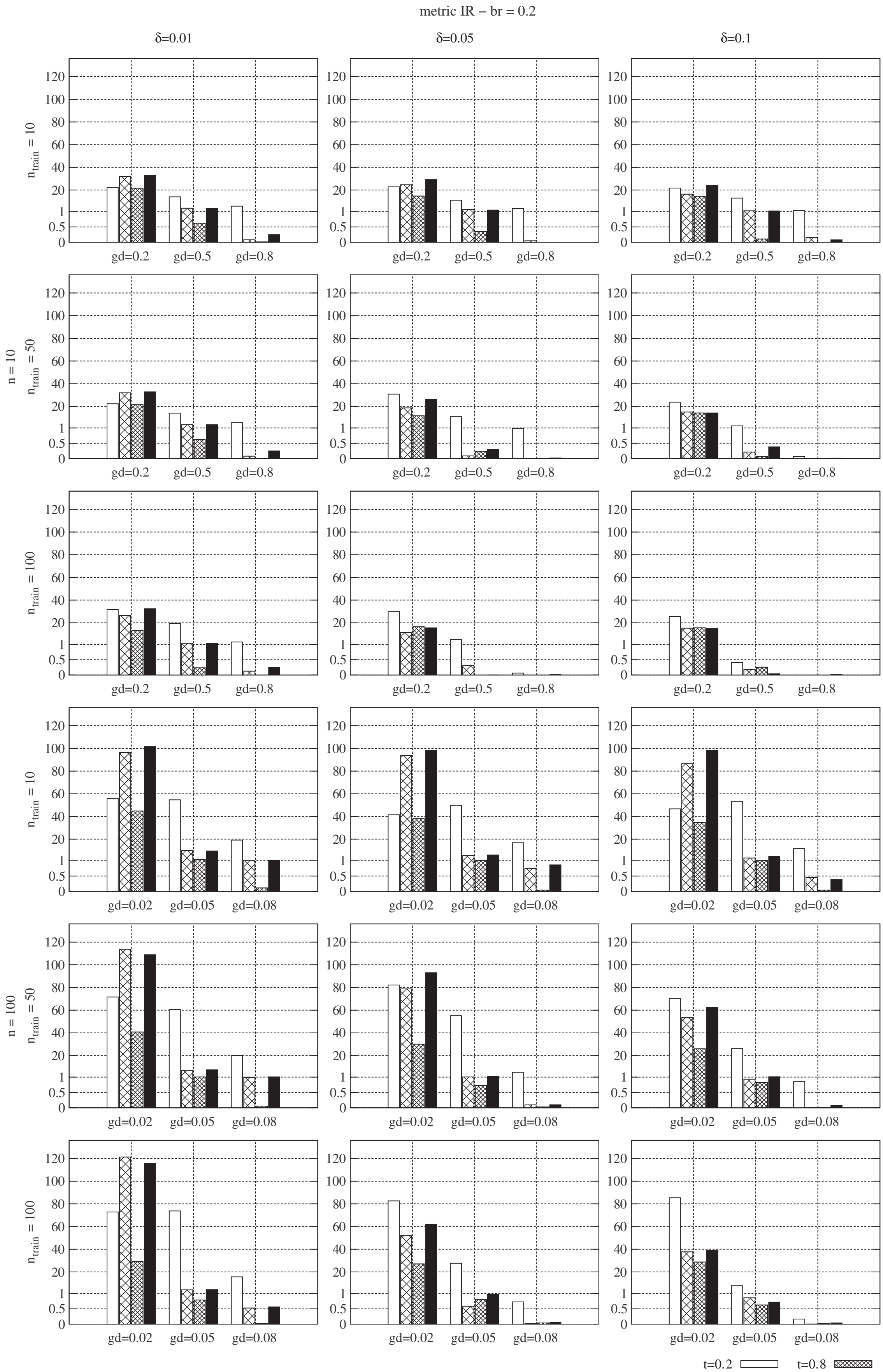

Fig. A.4. Comparison of metric *IR* with $br = 0.2$.

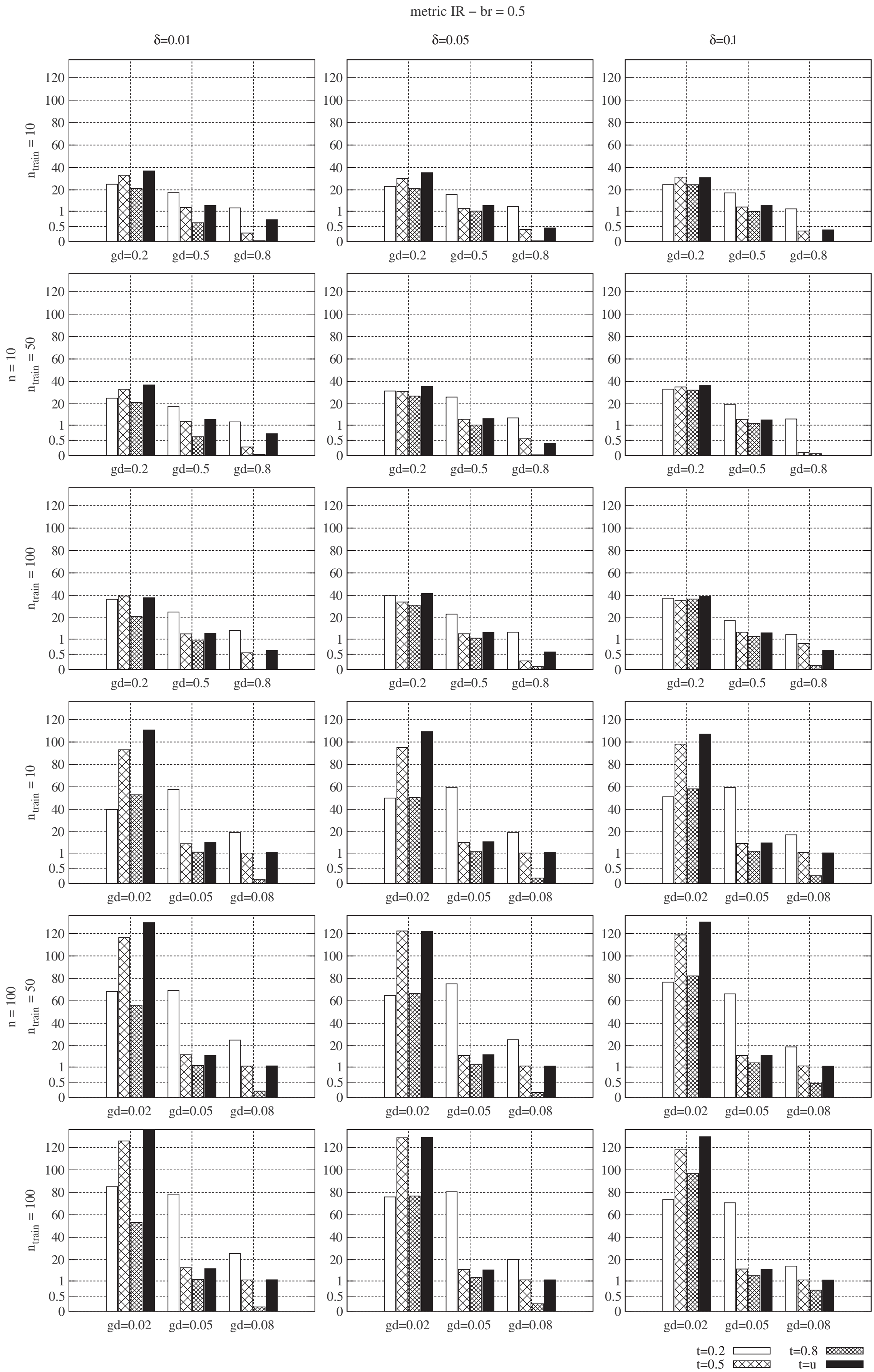

Fig. A.5. Comparison of metric *IR* with $br = 0.5$.

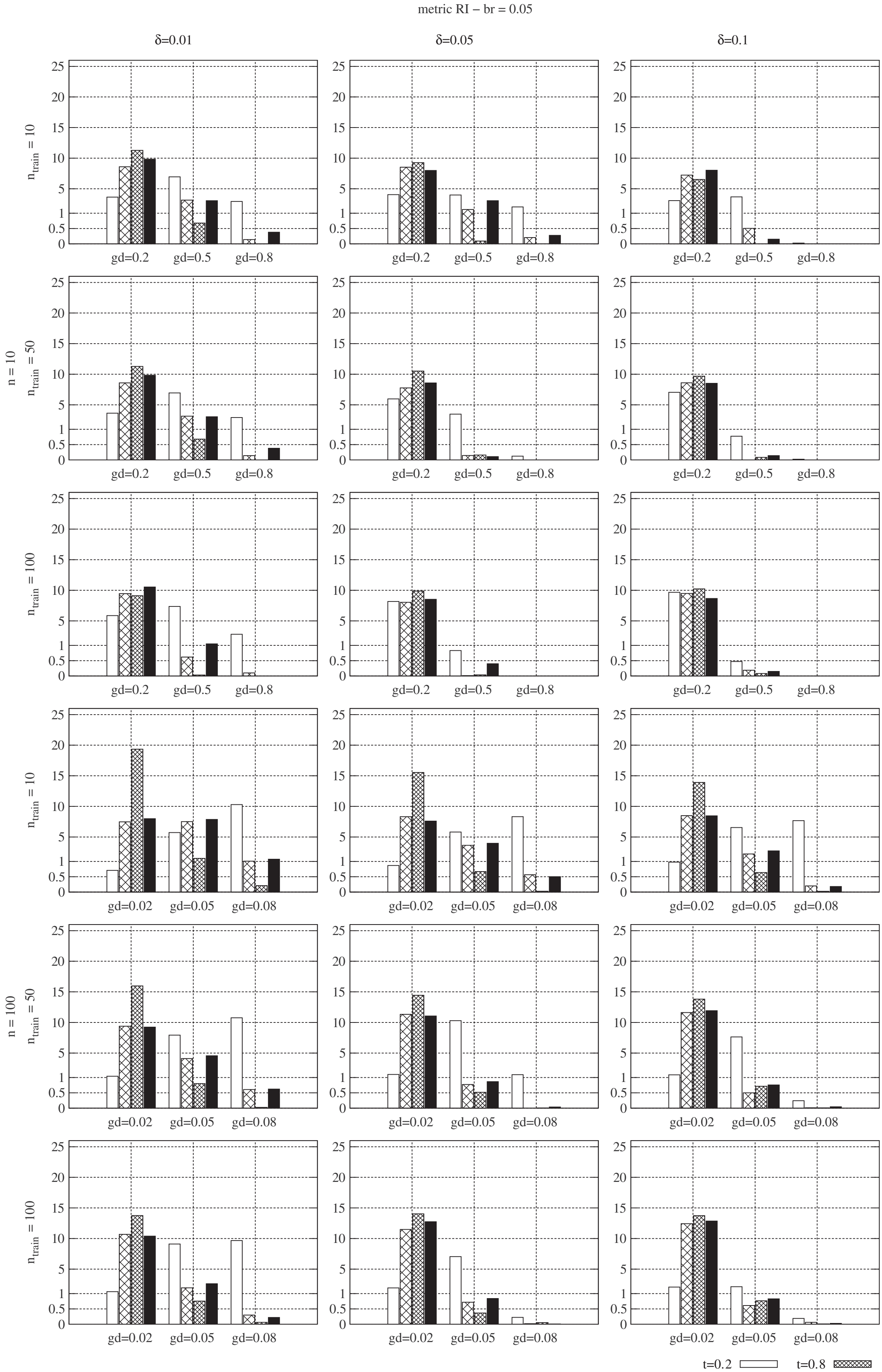

Fig. A.6. Comparison of metric *RI* with $br = 0.05$.

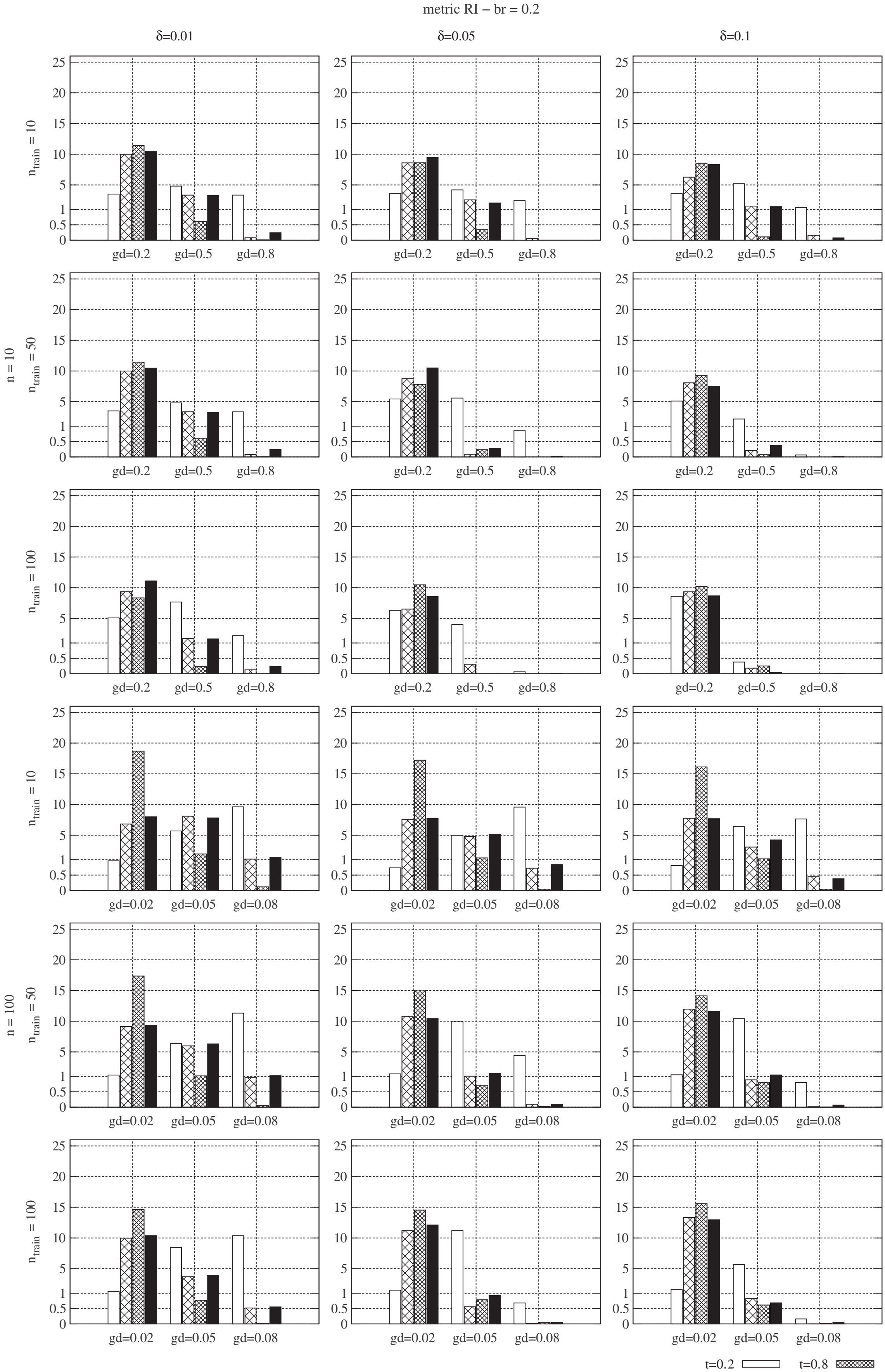

Fig. A.7. Comparison of metric *RI* with $br = 0.2$.

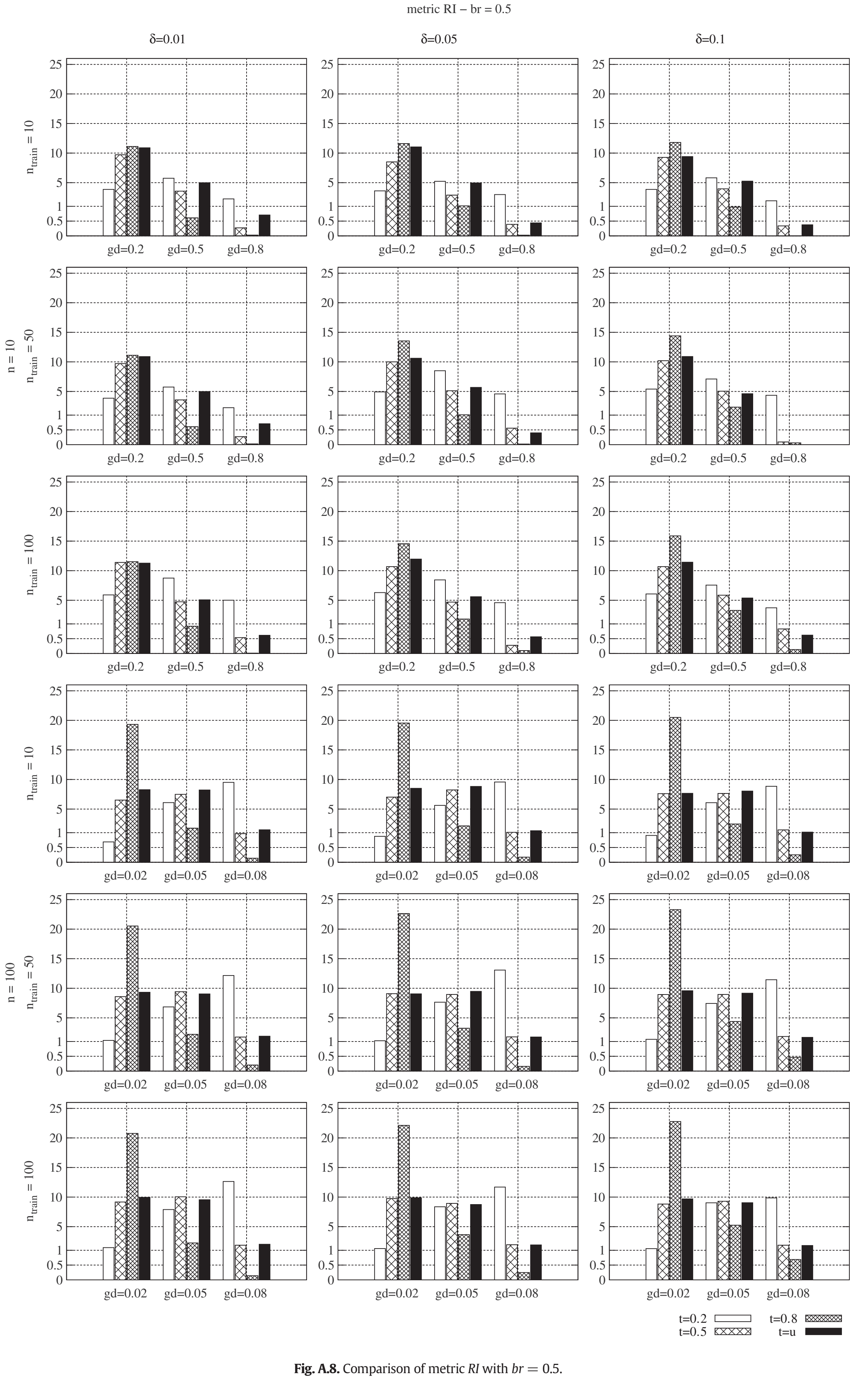

Fig. A.8. Comparison of metric *RI* with $br = 0.5$.

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