

Designing an Automatic Agent for Repeated Language-based Persuasion Games

Maya Raifer, Guy Rotman, Reut Apel, Moshe Tennenholtz, Roi Reichart

Technion—Israel Institute of Technology, Israel
{mayatarno, grotman, reutapel}@campus.technion.ac.il
{roiri, moshet}@technion.ac.il

Abstract

Persuasion games are fundamental in economics and AI research and serve as the basis for important applications. However, work on this setup assumes communication with stylized messages that do not consist of rich human language. In this paper we consider a repeated sender (expert) – receiver (decision maker) game, where the sender is fully informed about the state of the world and aims to persuade the receiver to accept a deal by sending one of several possible natural language reviews. We design an automatic expert that plays this repeated game, aiming to achieve the maximal payoff. Our expert is implemented within the Monte Carlo Tree Search (MCTS) algorithm, with deep learning models that exploit behavioral and linguistic signals in order to predict the next action of the decision maker, and the future payoff of the expert given the state of the game and a candidate review. We demonstrate the superiority of our expert over strong baselines and its adaptability to different decision makers and potential proposed deals.¹

1 Introduction

Natural Language Processing (NLP) has made substantial progress in recent years, excelling on text understanding applications such as machine translation (Bahdanau et al., 2015; Johnson et al., 2017), information extraction (Stanovsky et al., 2018), and question answering (Andreas et al., 2016; Kwiatkowski et al., 2019). However, these applications do not assume that language is used for interaction between strategic participants whose objectives overlap only partially.

In contrast, in the fields of economics and artificial intelligence (AI), such setups have been widely explored. For example, the settings of personalized advertising and targeted recommendation systems (Shapiro and Varian, 1998; Emek et al.,

2014; Bahar et al., 2016) suggest personalized services for their customers, and solutions are formed as strategic sender–receiver interactions (Arieli and Babichenko, 2019). However, this work assumes stylized messaging that does not involve real-world natural language.

In this paper we address the setting of sender–receiver interaction, but, in contrast to previous research, we assume natural language interaction between the players in an iterative non zero-sum persuasion game. In our setting the two participants are strategic players with their own private utilities. Crucially, the sender has more information about the world than the receiver does. Taking the NLP perspective, we are particularly interested in the persuasion game setting, where the sender’s objective is to persuade the receiver, using natural language messages, to select an action from a set of alternatives. The receiver, in turn, has different payoffs for the different actions. The receiver’s payoff depends on properties of the setup that are unavailable to her, and she has a higher level of uncertainty about the setup than the sender has.

Our focus is on repeated non-cooperative setups, where the utilities of the players do not fully overlap. Consider a repeated persuasion game where the interests of the players are aligned. In such a case, the sender should reveal the complete information she possesses, letting the receiver take an action that maximizes both their payoffs. In a repeated non-cooperative setup, in contrast, the sender opts to reveal a piece of information that should yield her a high payoff but also maintain a trustful relationship with the receiver, in order to avoid damaging her reputation and hence possibly also her future payoff.

Designing agents to play games is a long standing goal of deep reinforcement learning (RL) research. However, these games are typically zero-sum games, modeled as a utility maximization problem (see, e.g., Silver et al. [2018] and

¹Our code and data are available at: <https://github.com/mayaraifer/automatic.agent>.

the references within). In contrast, in economic contexts like ours, games are rarely zero-sum. A commerce Web site that aims to recommend a hotel cares about the customer choosing the hotel, while the customer cares about the hotel quality; their incentives are non-identical, but are also non-opposite. These games cannot be solved as a maximization problem, and there is in fact no optimal player in such problems (Fudenberg and Tirole, 1991). In contrast to economic games where the communication among agents is typically through formal signals or bids (Mansour et al., 2015; Bahar et al., 2020), we focus on natural language communication, which is very natural to persuasion games.

Recently, Apel et al. (2020) were the first to adapt the aforementioned setup to natural language messaging. Specifically, they designed a repeated persuasion game in which an *expert* (travel agent) repeatedly interacts with a *decision-maker* (DM, customer). At each trial of the interaction the expert observes a hotel alongside its scored textual reviews, and should choose a single review to reveal to the DM, in a hope to convince her to choose the hotel. The DM, in turn, can choose to either accept or reject the hotel, and her payoff stochastically depends on the review score distribution available to the expert only. Finally, both players observe their payoffs and proceed to the next, similar, step of the game.

While Apel et al. (2020) focus on predicting the DM’s actions, we adapt their setting and aim to design an *artificial expert* (AE) that should take the expert role in a way that maximizes its payoff. Our AE is implemented within the Monte Carlo Tree Search (MCTS) algorithm, which has been extensively used in AI-based game playing (§4.1). We present language- and behavior-based deep learning models for two crucial components of the MCTS: (a) A *Decision Making Model* (DMM), which predicts the actions taken by the DM given the current state of the game; and (b) A *Value Model* (VM), which predicts the future payoff of the AE given the current state of the game and a potential review that can be presented at the current step.

We focus on three questions: (1) Can our AE achieve a high payoff? (2) Does our AE adapt its strategy to different decision maker types? and (3) Do our automated AE’s strategies resemble those of human AEs?

We test our AE against various types of artificial DMs, compare it to strong alternative experts, and demonstrate its superiority. We further show that our AE is able to adapt its strategy to the DM it faces. We evaluate the impact of proper modeling of the linguistic signal (revealed reviews), comparing a BERT-based approach to hand-crafted features, and show that the later are generally better. Further, we analyze the reviews chosen by our AE, shedding light on its strategy.

Lastly, we also test our AE against human DMs, comparing its performance to a strong baseline. We provide a detailed analysis of the pros and cons of our AE, and discuss the differences between evaluation with human and simulation-based DMs.

2 Related Work

Some previous work addressed language-based communication in games where the participants have matched or mismatched objectives (Golland et al., 2010; Frank and Goodman, 2012; Lewis et al., 2017), while other work addressed communication in iterated games (Hawkins et al., 2017). The main novelty of our setup is the intersection between mismatched objectives and iterative games. We survey relevant works along three lines: Human decision predictions, NLP-based persuasion, and artificial agents in textual games.

Human Decision-Making Predictions Previous work used machine learning to predict human decisions based on non-textual information (Altman et al., 2006; Hartford et al., 2016; Plonsky et al., 2017), as well as textual signals—for example, for judicial decisions (Aletas et al., 2016; Zhong et al., 2018; Medvedeva et al., 2020; Yang et al., 2019b) and decisions of leading figures (Bak and Oh, 2018). These studies formulate the problem as a classification task where the classifier is based on textual (and potentially also other) signals. Unlike in our work, these predictions are not made in a strategic environment, where participants have objectives that affect their decisions.

Several studies aim to draw predictions of human decisions in competitive games given textual signals (Ben-Porat et al., 2020; Oved et al., 2020). For example, Niculae et al. (2015) proposed an algorithm for predicting actions in an online strategy game based on the language produced by the players as part of the inter-player communication

required in the game. The setups of these studies differ from ours, and, particularly, they do not address persuasion and repeated games.

The most relevant work to ours is that of Apel et al. (2020): We use their setup and data (§3). However, Apel et al. (2020) only focused on predicting the decisions of the decision-maker. In addition, while they based their predictions on past and future game information, we perform more realistic predictions based on past information only.

Persuasion in NLP Hidey et al. (2017) proposed an annotation scheme to differentiate claims and premises using different persuasion strategies in an online persuasive forum (Tan et al., 2016). Hidey and McKeown (2018) tried to predict persuasiveness in social media posts containing sequential arguments. Yang et al. (2019a), Wang et al. (2019), and Chen and Yang (2021) aimed to quantify persuasiveness and to identify persuasive strategies. This line of study, which aims to analyze and predict persuasive aspects of language, is a step towards developing persuasive agents.

Several studies examined persuasion dialogue tasks. While models for task-oriented dialogue have achieved promising performance on tasks where the users and the system are coordinated in their goals, persuasion dialogue tasks are less common. Hiraoaka et al. (2014) focused on learning a policy which satisfies both user and system goals in a cooperative persuasive dialogue. Li et al. (2020) proposed an end-to-end neural network to generate diverse coherent responses for non-collaborative dialogue tasks, where users and systems do not share a common goal. Efstathiou and Lemon (2014) developed a dialogue agent that learns to perform non-cooperative dialogue turns for utility maximization in a stochastic trading game with very simple linguistic messages. Lewis et al. (2017) trained end-to-end models for negotiation in a semi-cooperative setup. These studies differ from ours because we focus on designing an artificial agent in a repeated persuasion game setting, where the expert should construct a long-term strategy as its choice in a specific trial affects both the outcome of that trial and its future reputation.

Artificial Agents in Textual Games Several studies designed agents for referential games

(Lazaridou et al., 2017; Havrylov and Titov, 2017), where agents should interactively develop a shared language in order to communicate with each other and solve a joint task. Another line of work designs agents for games inspired by Wittgenstein’s (1953) language games (Wang et al., 2016), where a human aims to accomplish a task (e.g., achieving a certain configuration of blocks), but is only able to communicate with an artificial agent which performs the actual actions. Such games are cooperative in nature as the players share their goals. Finally, Narasimhan et al. (2015) address text-based games, where natural language is used both to describe the state of the world and the actions of the participating players. They design a deep RL agent that jointly learns state representations and action policies using game rewards as feedback. This game is also very different from ours.

3 Task Definition

We consider a two-player, travel agent (expert) and customer (decision-maker, DM), repeated persuasion game. The game, first introduced by Apel et al. (2020), consists of a sequence of ten trials. In each trial, the expert observes seven reviews of a given hotel, alongside their scores, and she then sends the DM one of the reviews, without its score. Based on this review, the DM decides between two options: Accepting or rejecting the hotel. If the hotel is not accepted by the DM, the payoff of both players is 0. Otherwise, the expert’s payoff is 1, and the DM’s payoff is a score randomly sampled from the seven scores presented to the expert at the beginning of this trial, referred to as *the lottery result*, minus the constant 8. This constant imposes a zero expected payoff for a DM who chooses to accept the hotel in all the ten trials.²

A more abstract description of each trial in this multi-stage game would be as follows. Every hotel is associated with an unknown distribution over payoffs, corresponding to the distribution over experiences that guests will have at this hotel. The scored reviews are sampled from this distribution, and the DM’s reward is another sample from the distribution. Because in our setting we do not have access to the real payoff distribution of each hotel,

²For full information of the train and test hotels, including their review scores, see Table 1 of Apel et al. (2020).

we approximate it using the empirical distribution from the payoffs observed by the expert.

Formally, denote the suggested hotel at trial t by h_t , the DM’s decision at this trial by a_t , where $a_t = 1$ if the DM accepts the hotel, and the seven scores attached to the reviews of h_t by $s_1^t, s_2^t, \dots, s_7^t$, where $s_i^t \in [0, 10]$. The players’ payoffs are:

$$\text{expert-payoff} = \mathbb{1}_{\{a_t=1\}},$$

$$\text{dm-payoff} = \mathbb{1}_{\{a_t=1\}} \cdot (s_i^t - 8), \\ i \sim \text{uniform}[1, 7].$$

While the two players would ideally like to gain the highest possible payoff (i.e., this is not a zero-sum game), their strategies are not necessarily coordinated. Particularly, while the expert aims to sell as many hotels as possible, the DM aims to accept only hotels that are likely to yield a positive payoff. Note that the DM is not fully informed of the hotel state, and should make her decision based on the partial information provided by the expert. The repeated nature of the game adds complexity to the decisions, as the expert’s choice in a specific trial affects not only the DM’s decision in this trial but also the expert’s reputation in the next trials.

Let us consider the game from the expert’s point of view. Consider an expert who cares solely about the present and reveals a high-score review in order to tempt the DM to choose the hotel, even if the acceptance decision is likely to yield a negative payoff. This expert is likely to gain a high payoff at the first few rounds. However, as the game proceeds the DM would probably understand that the expert is unreliable. On the other hand, if the expert reveals only reviews that reliably describe the hotel (e.g., the median scoring reviews), the DM is likely not to choose the hotel when she is presented with mediocre reviews.

Apel et al. (2020) provide an equilibrium analysis of our game. This is a theoretical analysis, under some constraining assumptions and, as the authors demonstrate, the players do not follow it in practice. This further motivates our work, which aims to design an NLP-based agent of the expert in this game. Note, that our approach is different from that of Apel et al. (2020), who aimed to predict individual decisions of the DM, rather than constructing an artificial DM or expert.

Score: 8.0/10.0



Positive: “Great hotel. Friendly and very helpful staff. Spotless.”
Negative: “Booked a double room. Surprised and disappointed that this was in fact two single beds joint together.”

Figure 1: An example review from the Apel et al. (2020) dataset. Each review consists of a continuous score ranging from 0 to 10, alongside positive and negative textual descriptions.

Data We use the dataset collected by Apel et al. (2020) using Amazon Mechanical Turk.³ The dataset is composed of 509 ten-trial games. The participants were randomly and anonymously paired, and each of them was randomly selected to be in one of the two roles: DM or expert.

The training set consists of 408 games. In these games the same hotels and reviews were used, but the hotels were randomly permuted between the 10 trials. The test set consists of 101 games, played with a different set of hotels and reviews, such that the hotels are again randomly permuted. Each participant was allowed to participate in the experiment only once, such that the training and test sets consist of different players.

Each hotel is accompanied by seven reviews collected from the Booking.com Web site along with their scores, continuously ranging between 0 and 10 (see an example review in Figure 1). All the reviews contain at least 100 characters and are separated into positive and negative parts. Figure 1 demonstrates a sampled review from the dataset. The order in which each of these parts were presented to the experts was also assigned at random. For more details, see Apel et al. (2020).

4 Method

We design an AE that aims to maximize its payoff in the persuasion game.

The High-level Structure of our Algorithm

Our algorithm is composed of three components: (a) **MCTS** – an online search algorithm that looks for the best action out of a predefined set (in terms of maximum expected payoff) at each game trial. In our setting, actions correspond to review selection, so the MCTS determines which review should be revealed to the DM in each trial.

³<https://github.com/reutapel/Predicting-Decisions-in-Language-Based-Persuasion-Games>.

(b) The DM Model (DMM) – a model that predicts the decision made by the DM in each trial of the game. This model allows the MCTS algorithm to simulate the DM’s response to revealed reviews.

(c) The Value Model (VM) – a model that predicts the expert’s future payoff in each trial of the game. It is used by the MCTS to initialize the expected return values of new explored decision paths.

Note that MCTS is the core component of our AE and the two other models are integrated into it after they have been trained offline. We next describe these three components in detail, concluding the section with a description of the two feature sets used by the DMM and the VM.

4.1 The MCTS Algorithm

MCTS (Coulom, 2006) is a heuristic search technique, presented in the field of RL. It has received considerable attention due to its success in the difficult problem of computer Go (Gelly et al., 2006) and has been used widely in challenging domains such as general game playing (Finnsson and Björnsson, 2008; Kim and Kim, 2017; Baier and Cowling, 2018; Sironi et al., 2018) and real-time strategy games (Balla and Fern, 2009; Ontanón, 2016). We briefly describe MCTS in the context of our game settings. A detailed survey can be found in Coulom (2006) and Browne et al. (2012).

The MCTS determines the best action out of a set of available actions by balancing the exploration-exploitation trade-off. It constructs a search tree, node-by-node, starting from a root node defined by the current state of the game. In our setting, $s(v)$, the state of the node v , is uniquely defined by the complete history of the game and the current suggested hotel h . Therefore, the action space $A(s(v))$ of $s(v)$ consists of the corresponding reviews of its current suggested hotel h , $A(s(v)) = \{r_{hi} | i \in \{1, \dots, 7\}\}$, where r_{hi} denotes the i ’th review of hotel h .

We initialize the values of each state node variable $s(v)$ according to our VM function, to predict its expected future payoff. For each trial t of the game the MCTS is provided with the new candidate hotel, and the next steps of the game are simulated with the VM and DMM. Based on this simulation the algorithm selects the optimal expert

action, that is, the optimal review that should be revealed to the DM.

4.2 The DMM and VM Models

The DMM and the VM are applied in each trial of the game, for predicting the DM’s decision (DMM) and the expert’s future payoff (VM). The predictions at trial t are based on information about the previous trials and the current trial. Both models have identical architectures, and they are trained off-policy on the training set of Apel et al. (2020). Due to the different nature of prediction, however, they are trained to optimize different loss functions: Binary cross entropy (DMM) and mean squared error (VM). In both cases training is done with the Adagrad algorithm (Duchi et al., 2011).

We consider two architectures (Figure 2). Due to the sequential nature of the decision making process, we based the two models on the Long Short-Term Memory (LSTM) architecture (Hochreiter and Schmidhuber, 1997). We feed the first LSTM variant, denoted by HC-LSTM, with two types of features: (a) statistical game features, representing the information about the previous and the current trials; and (b) hand-crafted textual features (Apel et al., 2020), automatically extracted from the review. A detailed description of both types of features is provided in §4.3. The binary hand-crafted features are passed through the Sigmoid activation function and are concatenated to the continuous statistical game features before being passed to the LSTM encoder.

The second architecture, denoted by BERT-LSTM, is an LSTM fed by the statistical game features and the pooler output of BERT (Devlin et al., 2019). Because the encoded output of BERT is processed by the Tanh activation function, we pass the statistical game features through it before performing the concatenation and passing the resulted vectors to the LSTM encoder.

4.3 Features

We explore two types of hand-crafted features: Hand-crafted textual features (HC), capturing textual knowledge from the reviews, and statistical game features (SG), capturing properties of the human interactions during the game.

The HC set, consisting of 42 binary features that can be split into three feature types, was created by Apel et al. (2020). Features of the first type indicate whether some predefined topics are

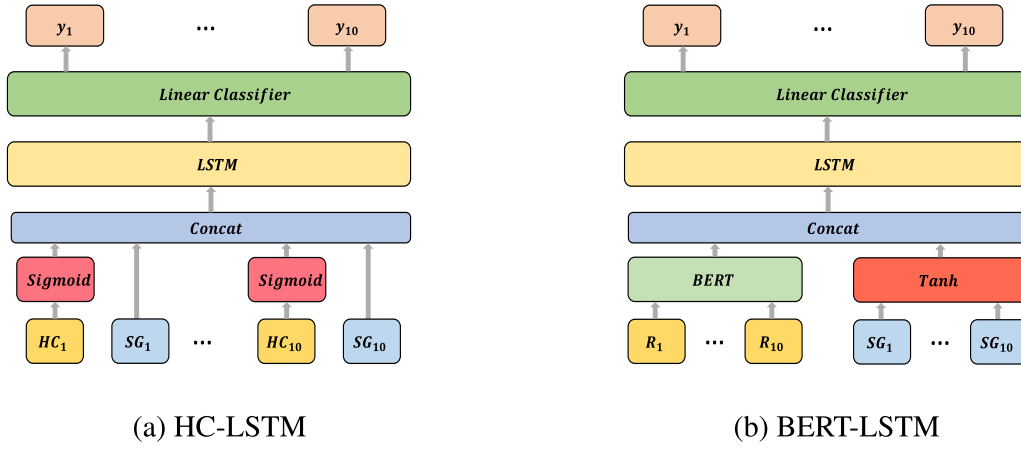


Figure 2: Illustration of our two model architectures. HC_t , SG_t , and R_t denote the hand-crafted features, the statistical game features and the presented review in trial t , respectively. For DMM, y_t is the DM’s decision in trial t , and for VM, y_t is the expert’s future payoff in trial t .

mentioned in the positive and negative parts of the review (facilities, price, location, staff, transportation, food, etc.). Features of the second type correspond to predefined textual properties of the positive and negative parts of the review, for example, the length of each part (short/medium/long), existence of words with high, medium or low intensity, and so forth. Finally, features of the third type capture the structural properties of the overall review, for example, the ratio between the lengths of the positive and negative parts. While these features are hand-crafted, they are automatically extracted from the text. We refer the reader to Apel et al. (2020) for further details.

Table 1 provides a detailed description of the SG features, some of which are a contribution of this paper. The SG set includes two main types of features: (a) Features that represent information about the DM’s behavior up to trial t . For example, HotelAcceptance measures the proportion of trials where the DM accepted a hotel; and (b) Features that represent general information about the game up to trial t . For example, the proportion of trials where the lottery result was low, high or medium and whether the proposed hotel has a low, high or medium average score.

5 Experiments

Experimental Setting Evaluating our AE against humans is highly expensive and time-consuming, and hence infeasible at large scales. We hence start with another, widely used solution: Human simulations (Jung et al., 2008; Ai and Weng, 2008;

González et al., 2010; Shi et al., 2019; Zhang and Balog, 2020). In this approach we evaluate the AE against an automatic algorithm that simulates human DMs. Although this evaluation is not performed against actual humans, it allows us to evaluate the AE against various types of players, by changing the data-driven DM in a controlled manner. We perform 1000 simulated games over the test set per DM simulator, where the order in which the hotels are presented to the AE is randomly permuted at each simulation.

We employ two DMMs (**HC-LSTM** and **BERT-LSTM**) as our basic DM simulators, as they are trained to imitate the human DM’s behavior in the game. We further modify the behavior of these “human like” DMMs, by changing their hotel acceptance probability in a controlled manner. We consider: (a) α -**compromised** DMMs, where the acceptance probability is increased by $\alpha = 0.1$ or $\alpha = 0.2$ over the prediction of the basic DMM; and (b) α -**inflexible** DMMs, where the acceptance probability is similarly decreased.

Baselines We next describe the baselines for the AE and for its components, the DMM variants (**HC-LSTM** and **BERT-LSTM**), and the VM variants (**HC-LSTM** and **BERT-LSTM**).

DMM. The DMM decides in each trial whether to accept a suggested hotel or not. We propose four different DMM variants, differing in their decision strategy, architecture and features: (a) **HC-SVM** – a Support Vector Machine (SVM; Cortes and Vapnik, 1995) based on the HC and SG features. It allows us to evaluate the power

| Feature Name | Feature Description | Feature Formulation |
|----------------------------------|--|---|
| Behavioral Features | | |
| HotelAcceptance | Avg #trials where the hotel was accepted | $\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{a_i=1\}}}{t-1}$ |
| HotelAcceptance Earn | Avg #trials where the hotel was accepted and the DM achieved a negative payoff.* | $\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{a_i=1 \cap dmp_i > 0\}}}{t-1}$ |
| HotelAcceptance Lose | Avg #trials where the hotel was accepted and the DM achieved a positive payoff.* | $\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{a_i=1 \cap dmp_i < 0\}}}{t-1}$ |
| \neg HotelAcceptance Earn | Avg #trials where the hotel was not accepted but the payoff would have been positive if the DM had accepted it.* | $\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{a_i=0 \cap dmp_i > 0\}}}{t-1}$ |
| \neg HotelAcceptance Lose | Avg #trials where the hotel was not accepted but the payoff would have been negative if the DM had accepted it.* | $\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{a_i=0 \cap dmp_i < 0\}}}{t-1}$ |
| BadHotel Acceptance | Avg #trials where a hotel with average score lower than 7.5 was accepted. | $\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{a_i=1 \cap s(h_i) < 7.5\}}}{t-1}$ |
| \neg ExcellentHotel Acceptance | Avg #trials where a hotel with average score higher than 9.5 was accepted. | $\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{a_i=1 \cap s(h_i) > 9.5\}}}{t-1}$ |
| DMPayoff | Avg DM's payoff per trial | $\frac{\sum_{i=1}^{t-1} dmp_i}{t-1}$ |
| General Features | | |
| LotteryLow | Avg #trials where the lottery result was lower than 3.* | $\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{l_i < 3\}}}{t-1}$ |
| LotteryMed | Avg #trials where the lottery result was between 3 to 5.* | $\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{3 \leq l_i < 5\}}}{t-1}$ |
| LotteryHigh | Avg #trials where the lottery result was higher than 8.* | $\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{l_i \geq 8\}}}{t-1}$ |
| CompletedTrials | The proportion of trials that have already been played. | $\frac{t-1}{10}$ |
| GoodHotel | Avg score of the current hotel is higher than 8.5. | $\mathbb{1}_{\{s(h_t) \geq 8.5\}}$ |
| MedHotel | Avg score of the current hotel is between 7.8 to 8.5. | $\mathbb{1}_{\{s(h_t) < 8.5 \cap s(h_t) \geq 7.5\}}$ |
| BadHotel | Avg score of the hotel is lower than 7.5. | $\mathbb{1}_{\{s(h_t) \leq 7.5\}}$ |
| HighScore | The attached score of the presented review is higher than 8.5. | $\mathbb{1}_{\{s(r_t) \geq 8.5\}}$ |
| MedScore | The attached score of the presented review is between 7.5 to 8.5. | $\mathbb{1}_{\{s(r_t) < 8.5 \cap s(r_t) \geq 7.5\}}$ |
| LowScore | The attached score of the presented review is lower than 7.5. | $\mathbb{1}_{\{s(r_t) < 7.5\}}$ |
| TopReview | The attached score of the presented review is in the top 3 scoring reviews. | $\mathbb{1}_{\{s(r_t) \in \text{top 3 scores}\}}$ |
| BottomReview | The attached score of the presented review is not in the top 3 scoring reviews. | $\mathbb{1}_{\{s(r_t) \notin \text{top 3 scores}\}}$ |

Table 1: SG features of trial t . a_i , l_i , and dmp_i denote the DM's action, lottery result, and DM's payoff in trial t , respectively. $s(h_t)$ is the average score of the suggested hotel in trial t , r_t is its revealed review, and $s(r_t)$ is the revealed review score. * indicates that the feature is taken from Apel et al. (2020).

of a non-DNN and non-sequential modeling approach; **(b) BERT-SVM** – This model is similar to HC-SVM, except that the text is represented with BERT; **(c) Expected Weighted Guess (EWG)** – a

random baseline that applies the hotel acceptance probability of the training set ($p = 0.72$); and **(d) Previous Decisions (PD)** – a deterministic baseline which predicts that the DM accepts the hotel

only if it accepted at least half of the previous hotels.

VM. The VM predicts the expert’s future payoff in each trial. We propose five different variants of it: **(a) HC-SVR** – a Support Vector Regression (SVR) (Drucker et al., 1997) model based on the HC and SG features. This is a non-DNN and non-sequential approach; **(b) BERT-SVR** – an SVR model based on the SG and the encoded BERT features; **(c) Maximal Future Payoff (MFO)** – a deterministic baseline that assumes that all future hotels will be accepted and hence the future payoff at each trial is maximal; **(d) Average Value (AV)** – a deterministic baseline that assigns the value in trial t to the average expert’s future payoff as observed in the training set; and **(e) History Proportion (HP)** – a deterministic baseline which predicts that the future hotel choice rate is identical to the choice rate in previous steps.⁴

AE. We compare our AE to ten alternatives, divided to four groups: (a-d) static rules; (e-g) dynamic rules, which adjust their predictions according to the behavior of the DM; (h) a greedy baseline that tests the VM classifier without the MCTS; and (i-j) variants of our original AE.

(a) RAND – an expert that randomly chooses a review from the available set; **(b) MEDIAN** – an expert that chooses the median scoring review at each trial. This baseline honestly communicates the value of the hotel; **(c) HIGHEST** – an expert that chooses the highest scoring review at each trial. This expert always overestimates the value of the hotel; **(d) EXTREMIST** – an expert that chooses the highest scoring review if the average review score is at least 8, and otherwise chooses the lowest scoring review. This expert makes the strongest positive recommendation when the hotel crosses the “likely gain” threshold, and the strongest negative recommendation otherwise. **(e) ADAPTIVE LIAR (A-LIAR)** – An expert that reveals the highest scoring review as long as the DM keeps accepting the hotels. After the first rejection by the DM, the expert chooses randomly between the second and third highest scoring reviews. After the second rejection it reveals the median review for the remaining hotels; **(f+g) PERSONAL TASTE DETECTION (PTD)** – this expert selects the review that is most similar

⁴In this baseline, as well as in the PD decision maker baseline, the past experiences are based on the gold standard.

to the average review representation, among the hotels accepted in previous trials. We consider either the HC features (**PTD-HC**) or the BERT features (**PTD-BERT**) of the reviews, and compute similarity with the cosine operator;⁵ **(h) VM SOFTMAX (VM-SM)** – a greedy expert that at each trial selects a review with a probability proportional to the expected expert payoff associated with it according to the VM. This expert helps us quantify the added value of MCTS over a greedy strategy; **(i+j)** our AE when using the second best DMM (**AE-DM2**) and the second best VM (**AE-VM2**).

Numerical Communication The success of our AE depends both on our modeling approach and on the use of text-based communication between the expert and the DM. In order to separate the impact of these two characteristics, we replicate our experiments where the communication between the expert and the DM is purely numerical. To achieve this goal we utilize another dataset collected by Apel et al. (2020). The authors collected data from 493 games (392 train and 101 test) with the same hotels and reviews discussed in § 3 (including the split to training and test hotels), but with a different set of participants. In these numerical communication experiments the experts are presented with all seven reviews but are told that they can only reveal to the DM the score of one of them, rather than its text. The DM, in turn, decides whether or not to accept the hotel based solely on the revealed numerical score. Other than that the experimental setup in this condition is identical to that of the textual communication experiments.

This data allows us to test a numerical communication version of our AE. To this end we trained the following models: **(a) DMM: SG-LSTM:** Our original LSTM-based DMM trained on the numerical communication training set, employing only the SG features; and **(b) VM: SG-LSTM:** Our original LSTM-based VM trained on the numerical communication training set, employing only the SG features. Finally, we test the **AE-SG** model, an MCTS-based expert identical to our AE, except that it uses the SG-LSTM variants of the DMM and VM. The test setup is identical to the above, except that the simulations are based on the numerical communication DMM and VM.

⁵In the first round the review is randomly selected.

Training Procedure and Hyperparameters

We apply a 5-fold cross validation protocol on the training set, and determine the optimal configuration of hyperparameters according to the best average F1 score of the minority class—hotel rejection. Next, we train the DMM and VM with their optimal configurations on the entire training set, and report results on the test set.

For the HC-LSTM models we optimize the hidden layer size (64, 128, 256), the batch size (5, 10, 15, 20, 25), and the dropout value (0.3, 0.4, 0.5, 0.6). Training is carried out for 100 epochs with an early stopping criterion. For the BERT-LSTM models we use HuggingFace’s implementation of the pre-trained uncased BERT-Base model.⁶ We tune the hidden layer size (64, 128, 256) and the dropout value (0.3, 0.4, 0.5, 0.6) of the LSTM component, and set the batch size to 5. During the training of BERT-LSTM we keep BERT’s parameters fixed for the first 8 epochs, and fine-tune them for additional 4 to 12 epochs with early stopping.

For MCTS we set the exploration constant c to 0.5, after normalizing the rewards to be in the $[0,1]$ range, and the time limit constant to 1.5 minutes. Our AE uses the MCTS with the HC-LSTM variant for DMM and VM, which were selected in cross-validation experiments on the training data. Likewise, VM-SM uses the HC-LSTM model.

6 Results

This section presents our results. We would first like (§6.1) to evaluate the performance of our DMM and VM models, since they are key elements of our AE. After verifying their quality, we turn to present our main results (§6.2), comparing our AE to the various baselines. This will allow us to answer our three research questions (§1), related to the AE performance (Q1), its adaptation to different decision maker types (Q2), and its strategy compared to humans (Q3).

6.1 The DMM and VM Models

DMM Results Table 2 (top) presents the accuracy and macro average F1-score results of the DMM variants on the binary task of predicting whether or not a human DM will choose to accept a suggested hotel. The results show that the best performing model is the HC-LSTM, which yields an accuracy of 82.40% and a macro average

| DMM | Accuracy \uparrow | F1-score \uparrow |
|-----------|---------------------|---------------------|
| HC-LSTM | 82.40% | 73.20 |
| BERT-LSTM | 80.80% | 68.30 |
| SG-LSTM | 77.00% | 65.70 |
| HC-SVM | 79.50% | 68.50 |
| BERT-SVM | 75.80% | 52.00 |
| PD | 69.90% | 45.21 |
| EWG | 60.00% | 50.00 |

| VM | Accuracy \uparrow | RMSE \downarrow |
|-----------|---------------------|-------------------|
| HC-LSTM | 38.90% | 1.11 |
| BERT-LSTM | 16.70% | 2.14 |
| SG-LSTM | 33.95% | 1.40 |
| HC-SVR | 35.40% | 1.13 |
| BERT-SVR | 25.54% | 1.41 |
| AVG | 33.70% | 1.08 |
| DO | 26.20% | 1.94 |
| HP | 29.10% | 1.90 |

Table 2: Evaluation of DMM and VM variants.

F1-score of 73.20. This result reflects the value of the hand-crafted textual features, a pattern that was also reported by Apel et al. (2020). BERT-LSTM lags a bit behind (accuracy of 80.80%, macro F1 score of 68.30), demonstrating that clever feature design can outperform this strong language encoder. In general, the SVM baselines fall short of the neural networks, whereas the deterministic baselines PD and EWG are not very successful.

VM Results Table 2 (bottom) presents the exact accuracy and Root Mean Square Error (RMSE) of the VM variants on the task of predicting the experts’ future payoff. The strongest model is HC-LSTM (best exact accuracy, second-best RMSE). Moreover, the second-best model is HC-SVR, which also exploits the hand-crafted textual features. In contrast, the BERT-based models perform quite poorly. This illustrates once again the strong positive impact of the HC features, which are very effective even when the task classifier does not model the structure of the data. Interestingly, the same features and architecture perform best both for the DMM and for the VM.

The AVG baseline, which always predicts the average score, obtains the lowest RMSE score, but it is not as accurate as our HC-based models. DO and HP, which are based on simple statistical rules, also perform quite poorly.

⁶<https://github.com/huggingface/transformers>.

| Expert/DM | HC-LSTM | BERT-LSTM | HC-LSTM+0.1 | HC-LSTM+0.2 | HC-LSTM-0.1 | HC-LSTM-0.2 | AVG |
|-----------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|-------------|
| AE | 7.12 [7.02, 7.22] | 7.04 [7.03, 7.29] | 8.10 [8.02, 8.19] | 8.77 [8.70, 8.84] | 6.04 [5.93, 6.20] | 5.02 [4.90, 5.13] | 7.02 |
| RAND | 6.54 [6.49, 6.70] | 6.67 [6.56, 6.77] | 7.56 [7.47, 7.65] | 8.31 [8.24, 8.38] | 5.58 [5.47, 5.68] | 4.49 [4.38, 4.60] | 6.53 |
| MEDIAN | 6.46 [6.37, 6.54] | 6.85 [6.76, 6.96] | 7.24 [7.16, 7.33] | 8.02 [7.96, 8.11] | 5.45 [5.37, 5.54] | 4.66 [4.56, 4.76] | 6.45 |
| HIGHEST | 6.77 [6.65, 6.89] | 7.82 [7.73, 7.92] | 7.94 [7.84, 8.04] | 8.82 [8.74, 8.89] | 5.55 [5.42, 5.68] | 4.46 [4.33, 4.58] | 6.89 |
| EXTREMIST | 6.21 [6.11, 6.32] | 6.86 [6.76, 6.96] | 7.24 [7.14, 7.34] | 7.99 [7.92, 8.09] | 5.14 [5.04, 5.26] | 4.08 [3.97, 4.19] | 6.25 |
| A-LIAR | 6.54 [6.42, 6.65] | 7.14 [7.06, 7.28] | 7.15 [7.06, 7.28] | 8.69 [8.61, 8.77] | 5.40 [5.28, 5.51] | 4.35 [4.24, 4.47] | 6.55 |
| PTD-HC | 6.88 [6.78, 6.99] | 7.03 [6.86, 7.06] | 7.68 [7.63, 7.80] | 8.49 [8.43, 8.57] | 5.83 [5.72, 5.95] | 4.92 [4.79, 5.02] | 6.83 |
| PTD-BERT | 6.79 [6.67, 6.88] | 6.59 [6.51, 6.73] | 7.72 [7.63, 7.82] | 8.46 [8.38, 8.54] | 5.77 [5.64, 5.88] | 4.82 [4.71, 4.93] | 6.69 |
| VM-SM | 6.58 [6.50, 6.71] | 7.00 [6.91, 7.12] | 7.70 [7.60, 7.77] | 8.34 [8.26, 8.41] | 5.65 [5.58, 5.79] | 4.67 [4.57, 4.80] | 6.66 |
| AE-DM2 | 7.05 [6.93, 7.14] | 7.23 [7.13, 7.33] | 7.94 [7.86, 8.02] | 8.66 [8.58, 8.73] | 5.92 [5.84, 6.07] | 4.97 [4.89, 5.10] | 6.96 |
| AE-VM2 | 7.03 [6.93, 7.13] | 7.05 [6.96, 7.17] | 8.00 [7.93, 8.09] | 8.76 [8.72, 8.85] | 5.98 [5.88, 6.09] | 4.98 [4.90, 5.12] | 6.97 |
| AE-SG | 7.53 [7.39, 7.64] | – | 8.63 [8.48, 8.65] | 9.10 [9.09, 9.22] | 6.02 [5.93, 6.23] | 4.85 [4.61, 4.93] | 7.23 |

Table 3: Average expert’s payoff over 1000 simulations against different DMs. The table is split into five sections, from top to bottom: Our model (AE), static rules, dynamic rules, algorithms, and the results in the numerical communication setup, which are not directly comparable to the above, text-based communication results. For each condition, we report the average expert payoff over our 1000 simulations, as well as 95% CI (in brackets, using bootstrap re-sampling with 1000 re-samples of our original 1000 simulations; see Dror et al., 2018). The human experts in the experiments of Apel et al. (2020) achieve an average payoff of 7.36.

6.2 Main Results: Automated Expert Performance against Different DMs

Table 3 presents AE results (averaged over 1000 simulated games) when playing with 6 different DMs. Notice that our AE employs the HC-LSTM based DMM and VM variants at all times—the columns of the table correspond to the different DMs it plays with. Recall that the AE can adapt itself to its rival through the statistical game features, which reflect the behavior of the rival DM at previous trials. This allows us to test how well our AE generalizes to new players with different strategies than those it assumes.

The results suggest that our AE is the best expert, reaching the best average payoff overall, the best average payoff when playing against 4 of the 6 DMs, and the second- and fifth-best payoffs when playing against the remaining 2 DMs. These encouraging results indicate the capability of our AE to adapt itself to various DM types, providing a positive answer for Q1 and Q2.

The human experts in the experiments of Apel et al. (2020) achieved an average payoff of 7.36, somewhat higher than the 7.02 average of our AE. Note, however, that the human experts of Apel et al. (2020) played against human DMs and hence the results are not directly comparable. Yet, hoping that the various automated DMs provide a representation of the prominent types of human DMs, we consider the small gap between the two numbers to provide an optimistic indication that the answer to Q3 may be positive and our

AE performs similarly to human experts, at least with respect to its payoff. Below (§7) we further analyze the choices made by our AE, demonstrating interesting properties of its revealed texts and comparing its decisions to those of the human experts of Apel et al. (2020).

Interestingly, the HIGHEST baseline performs best and third-best, respectively, against HC-LSTM+0.2 and HC-LSTM+0.1. This is because these compromised DMs tend to accept the hotel for almost every review that they are presented with. However, for HC-LSTM, and for the inflexible DMs, HC-LSTM-0.1 and HC-LSTM-0.2, HIGHEST is far from being the best model.

Additionally, the EXTREMIST and MEDIAN baselines, which aim to select the review that best reflects the different hotel scores, are inferior to our AE in all setups. Two possible explanations can be considered. First, unlike the AE that is trained to maximize its payoff, EXTREMIST and MEDIAN favor the DM by being transparent in their choices at the expense of their own benefits. Second, unlike the AE, these baselines do not exploit the textual features of the reviews. The strong performance of the AE is an indication of the importance of textual features for strategy design.

Finally, the dynamic rules (A-LIAR, PTD-HC, and PTD-BERT), the greedy VM-SM, and the AE-DM2 and AE-VM2 versions of our AE, which use the second best DMM (BERT-LSTM) or VM

(HC-SVR), respectively, are inferior to our AE. We consider this an indication of the importance of a wise search procedure, that carefully balances the long (explore) and the short (exploit) terms, and of careful selection of suitable DMM and VM.

7 Ablation Analysis

In this section we analyze several aspects of the main results presented above. We start by analyzing the impact of text-based communication on our results, evaluating the performance of our AE when performing numerical communication. Then, we analyze different aspects of the observed behavior of our AE in our main text-based communication experiments: The average payoff of the DMs (indicating whether our AE facilitates fairness), the decision patterns of our AE when playing against the various DMs (shedding more light on Q2—does the AE adapt to the DM it plays with), comparing the reviews revealed by our AE to those revealed by the human experts in Apel et al. (2020) (thus shedding more light on Q3), and, finally, analyzing the textual properties of the reviews revealed by our AE.

Numerical Communication Results To put our textual communication results in context, we also report results for the numerical communication setup (Table 3, bottom line). As above, we report results for the DMM and VM models, based on the SG-LSTM architecture, and for the eventual AE-SG expert. We cannot compare these results directly to the textual communication numbers, as they are based on another set of games and a different type of communication, but we do hope to learn about the difference between the communication types based on the observed patterns.

The numerical communication DMM:SG-LSTM and VM:SG-LSTM models achieve accuracy scores of 77.00% and 33.95%, respectively. The F1-score of the DMM is 65.70 and the RMSE score of the VM is 1.4. Interestingly, these numbers are substantially lower than the comparable numbers of the leading textual communication models (see Table 2). This is an indication that it is harder to predict the DM behavior as well as the future AE payoff when the communication is numerical and hence only behavioral features can be used for prediction.

Interestingly, the AE-SG model achieved payoffs of 7.53, 8.63, 9.1, 6.02, and 4.85 against the numerical HC-LSTM, HC-LSTM+0.1, HC-LSTM+0.2,

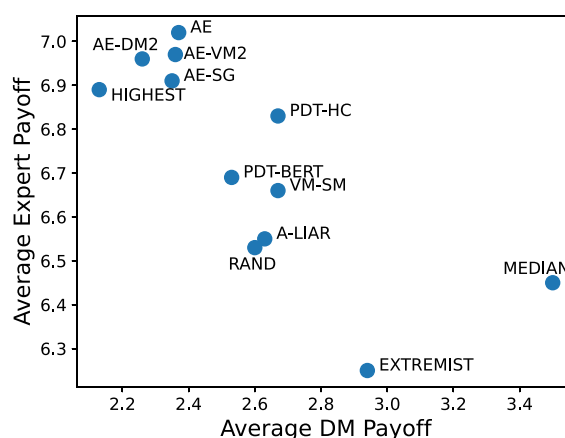


Figure 3: Average expert payoff as a function of the average payoff of the DMs it played with.

HC-LSTM-0.1, and HC-LSTM-0.2, respectively (there is no BERT-LSTM simulation when communication is numerical). These payoffs are higher than the best AE payoff in the textual communication setups in the first 3 cases, but are lower in the last 2 setups where the acceptance probability of the simulated DM is decreased.

Although this comparison between numerical and textual communication is interesting, we notice that in many real-life scenarios the communication is either numerical or verbal. Hence, it is important to design effective models for both cases.

Average DM Payoff Figure 3 presents the average payoff of each expert as a function of the average payoff of the DMs it played with. The figure suggests that DMs who played with the two experts with the lowest average payoff (MEDIAN and EXTREMIST) achieve the highest payoff on average. Our AE, in contrast, the highest-paid expert on average, leads to one of the lowest average DM payoffs. Generally, we observe a strong negative correlation of -0.76 between the average payoffs of the expert and the DM. As discussed in §1, our game is not a zero-sum game. Yet, the negative correlation between the payoffs of the expert and the DM, even for experts that were not trained to maximize their own payoffs (like our AE and the numerical communication AE-SG), demonstrates the competitive nature of our task. A major goal of future research is to design an expert that can balance the payoffs of the two players, ideally maximizing them at the same time.

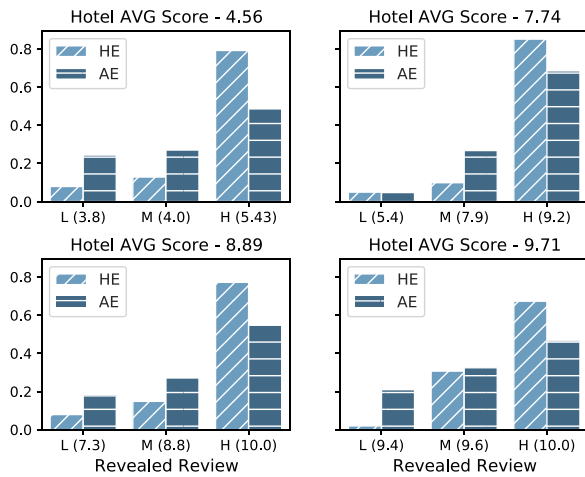


Figure 4: Revealed review score distributions for the AE and the human experts (HEs), for four representative hotels. The reviews are grouped into three bins according to their attached score: Low (L), medium (M), or high (H), and the average score of the reviews in each bin is in parentheses.

Analysis of AE Personalization A desirable characteristic of an AE is the ability to personalize its decisions to the DM it faces. We analyze this behavior by measuring the average review score that our AE chooses to reveal to the five HC-LSTM variants of Table 3.

Our analysis reveals that the higher the tendency of the DM to accept hotels, the higher are the scores of the reviews sent by the AE. We normalize the scores of each hotel to the $[0, 1]$ range and compute the average review score selected across all hotels, for each of the DMs. The average scores are 0.483 (HC-LSTM-0.2), 0.485 (HC-LSTM-0.1), 0.487 (HC-LSTM), 0.488 (HC-LSTM+0.1), and 0.491 (HC-LSTM+0.2). This favorable behavior of our AE serves as an evidence to its generalizability (Q2).

AE vs. Human Experts One of the most interesting aspects of designing an AE is its similarity to human experts (HEs). To address this aspect (Q3), we compare between the AE and the HEs that participated in the experiments of Apel et al. (2020). Notice that the HEs play against human DMs, while our AE plays against artificial DMs, which makes them not directly comparable.

Figure 4 depicts the score distributions of the reviews as revealed by the AE and the HEs for 4 representative test set hotels. We cluster the scores per hotel into 3 bins—Low, medium, and high—and present the average score of each

| Low Scoring Hotels | Medium Scoring Hotels | High Scoring Hotels |
|-----------------------------|-----------------------------|-----------------------------|
| Location-Positive (92.5%) | Room-Positive (67.6%) | Staff-Positive (81.3%) |
| Metro-Positive (52.5%) | Staff-Positive (64.2%) | Location-Positive (74.9%) |
| Staff-Positive (46.8%) | Location-Positive (48.9%) | Room-Positive (47.3%) |
| Staff-Negative (45.0%) | Metro-Positive (38.2%) | Facilities-Positive (29.4%) |
| Facilities-Negative (44.6%) | Facilities-Negative (31.2%) | Metro-Positive (23.9%) |

Table 4: The top 5 topics (ordered by frequency) discussed in the reviews revealed by the AE for low, medium, or high scoring hotels.

bin. The figure indicates that both experts consistently prefer to present highly ranked reviews and tend to reveal reviews that overestimate the hotels’ average scores. Nonetheless, in all cases, the HEs output higher estimations, whereas the AE’s scores are more diverse and closer to the average review score. This analysis sheds light on our AE’s behavior, providing an initial answer to Q3.

Textual Analysis of the AE-revealed Reviews

We also analyze the textual features of the reviews that our AE chose when played against the LSTM-HC DM. Table 4 presents the top 5 topics discussed in the revealed reviews for low (average score (as) < 7.5), medium ($7.5 \leq as \leq 8.5$), or high ($as > 8.5$) scoring hotels. The topics are based on the HC features, that encode topics such as *facilities*, *staff*, *location*, *food*, *design*, and *price*, which are reviewed positively or negatively.

Interestingly, *location*, *staff*, and *metro* are all discussed positively in the revealed reviews of the three hotel groups. However, the lower the hotel score is, the lower the rank of its *staff* and the higher the rank of the *metro*, among the top 5 topics. It hence seems that for low-scoring hotels the AE communicates positive aspects of their outer surroundings. Negative topics are more discussed in low and medium scoring hotels, with *facilities* being negatively discussed in many revealed reviews of low-scoring and medium-scoring hotels.

8 Human Experiments

Finally, we evaluate our AE when playing with human DMs. We do believe that simulation-based evaluation is crucial for our setting as it allows us to test our AE against DMs with a variety of

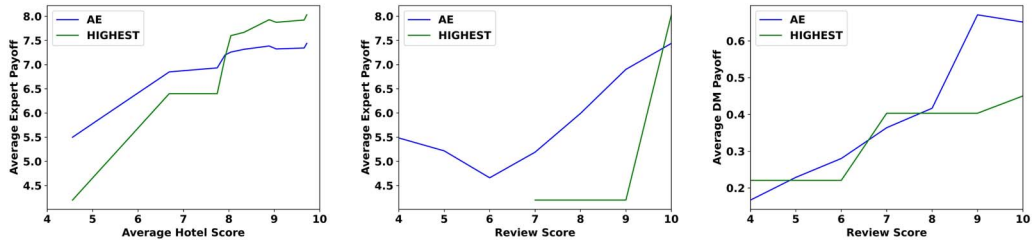


Figure 5: Average AE payoff for average hotel scores (**Left**) and for revealed review scores (**Middle**) that are **up to** a certain threshold (x -axis). (**Right**) Average DM payoff for **revealed** review scores that are **at least** of a certain threshold (x -axis).

controlled characteristics at a relatively low-cost (see §5). Yet, human-based evaluation, even if it is small-scale due to its high cost, provides important complementary information.

Following Apel et al. (2020), our AE plays with 100 different human DMs on the Amazon Mechanical Turk (AMT) platform,⁷ such that no DM competes against more than one expert.⁸ We follow the same experimental setting as in our simulations, and particularly use the same test-set hotels. We compare the performance of our AE to those of the strongest alternative: HIGHEST, the second best baseline in our simulations (in terms of average performance; the various AE agents are not considered as baselines in this definition).

Figure 5 (**Left**) illustrates the average expert payoff for hotels with an average review score of at most $s \in \{4, \dots, 10\}$. The results suggest that our AE achieves the highest average payoffs for the 4 hotels with the lowest average review score (average score of up to 8), that is, the hotels for which the expected DM payoff is negative. This observation implies that our AE is able to maximize its payoff on the most challenging hotels. The HIGHEST agent excels on the other 6 hotels, those with an average review score higher than 8 and hence a positive expected DM payoff. Interestingly, 5 of these 6 hotels have a review with the maximal score of 10, which is chosen by HIGHEST.

We next analyze the scores of the revealed reviews—that is, the reviews that were chosen by the experts and presented to the DMs. Figure 5 (**Middle**) presents the average expert payoff when its revealed review score is at most

| All Games | | | |
|-----------------------------|---------------|-------------|--------------|
| | Expert Payoff | DM Payoff | Num. Players |
| AE | 7.44 | 1.03 | 100 |
| HIGHEST | 8.03 | 2.21 | 100 |
| Acceptance Rate $\leq 80\%$ | | | |
| | Expert Payoff | DM Payoff | Num. Players |
| AE | 6.51 | 0.70 | 70 |
| HIGHEST | 6.60 | 0.72 | 50 |

Table 5: Average payoffs for all games (top) and when the acceptance rate $\leq 80\%$ (bottom).

$s \in \{4, \dots, 10\}$. While the HIGHEST agent achieves the best payoff when it reveals a review with the maximal score of 10, when moving to lower scores we see that our agent maintains a higher average payoff. For such cases where the hotel does not have any review with the score of 10, the HIGHEST agent achieves a low average payoff of 4.2.

The final analysis (Figure 5 (**Right**)) is similar to first two, except that now we are focusing on the average DM payoff, when the revealed review score is at least $s \in \{4, \dots, 10\}$. The leftmost point, corresponding to all experiments, suggests that in total the human DMs who played with our AE achieve the lowest average payoff. However, we notice that as the AE chooses to reveal reviews with higher scores the average DM payoff increases and surpasses the average payoff of the DMs who played with the HIGHEST agent. This is an interesting pattern, given that the AE is trained to maximize its own payoff, and its objective does not take the DM’s payoff into account.

Finally, Table 5 presents the average DM and expert payoffs, considering all the experiments (top) and those experiments where the DMs accepted at most 8 hotels. The table demonstrates that the HIGHEST agent yielded the highest average payoffs for both player types, but this is

⁷<https://www.mturk.com>.

⁸We followed the exact same AMT experimental setup as in Apel et al. (2020). Particularly, we filtered the AMT workers according to the two attention checks described in Section 4.1 of their paper.

mostly due to a large number of DMs who accepted 9 or 10 hotels. Indeed, when focusing only on DMs who considered the hotels more carefully (bottom table), the average of both the DM and the expert payoffs are quite similar for both agents. The results reflect an interesting property of the HIGHEST agent: It makes many more human DMs accept all (or almost all) of the hotels. This may reflect an interesting difference between human and simulation DMs, to be explored in the future.

9 Conclusions

We consider the problem of automatic expert design for a repeated non-cooperative persuasion game. Our AE is based on the MCTS search algorithm with deep learning models for DM decision and expert's future payoff predictions. Our experiments quantitatively and qualitatively analyze the performance of our AE in comparison to a large variety of alternatives. While our main evaluation is with simulated (automatic) DMs, we also examine the generalizability of our results to experiments with human DMs.

Our work relies on the dataset of Apel et al. (2020) for training and testing the various expert models. One limitation of this dataset is its size: It is based on only 10 training and 10 test hotels, each with 7 scored reviews. Moreover, the training set, which is used for training our DMM and VM models, consists of only 408 ten-trial games. We aimed to compensate for this by performing a large number of simulations (1000) for each expert/DM pair, and by reporting 95% confidence intervals (CIs), demonstrating limited overlap between the 95% CI of our AE and the baselines. Yet, richer datasets in terms of the size and diversity of the hotel sets, as well as the richness of interaction between the human players, are required in order to further validate our results.

In future we would like to extend our AE in three main directions: (a) Designing end-to-end architectures, where the DMM and VM are jointly trained in order to maximize the AE's payoff; (b) Letting the AE generate persuasive language rather than choosing from pre-written reviews; and (c) Considering other AE strategies such as fair payoff division between the expert and the DM, instead of maximizing the AE's payoff.

Acknowledgments

We would like to thank the action editor and the reviewers, as well as the members of the IE@Technion NLP group for their valuable feedback and advice. We are also extremely thankful for the valuable guidance and assistance of Christian König-Kersting in conducting the human experiments. This research is partially funded by an ISF personal grant no. 1625/18. The work of R. Apel and M. Tennenholtz is funded by the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement no. 740435).

References

- Hua Ai and Fuliang Weng. 2008. User simulation as testing for spoken dialog systems. In *Proceedings of the 9th SIGdial Workshop on Discourse and Dialogue*, pages 164–171.
- Nikolaos Aletras, Dimitrios Tsarapatsanis, Daniel PreoŃiuc-Pietro, and Vasileios Lampos. 2016. Predicting judicial decisions of the European Court of Human Rights: A natural language processing perspective. *PeerJ Computer Science*, 2:e93.
- Alon Altman, Avivit Bercovici-Boden, and Moshe Tennenholtz. 2006. Learning in one-shot strategic form games. In *European Conference on Machine Learning*, pages 6–17. Springer.
- Jacob Andreas, Marcus Rohrbach, Trevor Darrell, and Dan Klein. 2016. Learning to compose neural networks for question answering. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1545–1554.
- Reut Apel, Ido Erev, Roi Reichart, and Moshe Tennenholtz. 2020. Predicting decisions in language based persuasion games. *arXiv preprint arXiv:2012.09966*.
- Itai Arieli and Yakov Babichenko. 2019. Private Bayesian persuasion. *Journal of Economic Theory*, 182:185–217.
- Gal Bahar, Itai Arieli, Rann Smorodinsky, and Moshe Tennenholtz. 2020. Multi-issue social learning. *Mathematical Social Sciences*, 104:29–39.

- Gal Bahar, Rann Smorodinsky, and Moshe Tennenholtz. 2016. Economic recommendation systems: One page abstract. In *Proceedings of the 2016 ACM Conference on Economics and Computation*, pages 757–757.
- Dzmitry Bahdanau, Kyung Hyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In *International Conference on Learning Representations*.
- Hendrik Baier and Peter I. Cowling. 2018. Evolutionary MCTS for multi-action adversarial games. In *2018 IEEE Conference on Computational Intelligence and Games (CIG)*, pages 1–8. IEEE.
- JinYeong Bak and Alice Oh. 2018. Conversational decision-making model for predicting the king’s decision in the Annals of the Joseon Dynasty. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 956–961. <https://www.aclweb.org/anthology/D18-1115.pdf>.
- Radha-Krishna Balla and Alan Fern. 2009. UCT for tactical assault planning in real-time strategy games. In *Proceedings of the 21st International Joint Conference on Artificial Intelligence*, pages 40–45.
- Omer Ben-Porat, Sharon Hirsch, Lital Kuchi, Guy Elad, Roi Reichart, and Moshe Tennenholtz. 2020. Predicting strategic behavior from free text. *Journal of Artificial Intelligence Research*, 68:413–445.
- Cameron B. Browne, Edward Powley, Daniel Whitehouse, Simon M. Lucas, Peter I. Cowling, Philipp Rohlfshagen, Stephen Tavener, Diego Perez, Spyridon Samothrakis, and Simon Colton. 2012. A survey of Monte Carlo tree search methods. *IEEE Transactions on Computational Intelligence and AI in Games*, 4(1):1–43.
- Jiaao Chen and Diyi Yang. 2021. Weakly-supervised hierarchical models for predicting persuasive strategies in good-faith textual requests. *arXiv preprint arXiv:2101.06351*.
- Corinna Cortes and Vladimir Vapnik. 1995. Support vector machine. *Machine Learning*, 20(3):273–297.
- Rémi Coulom. 2006. Efficient selectivity and backup operators in Monte-Carlo tree search. In *International Conference on Computers and Games*, pages 72–83. Springer.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186.
- Rotem Dror, Gili Baumer, Segev Shlomov, and Roi Reichart. 2018. The hitchhiker’s guide to testing statistical significance in natural language processing. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1383–1392.
- Harris Drucker, Chris J. C. Burges, Linda Kaufman, Alex Smola, and Vladimir Vapnik. 1997. Support vector regression machines. *Advances in Neural Information Processing Systems*, 9:155–161.
- John Duchi, Elad Hazan, and Yoram Singer. 2011. Adaptive subgradient methods for online learning and stochastic optimization. *Journal of Machine Learning Research*, 12(7).
- Ioannis Efstathiou and Oliver Lemon. 2014. Learning non-cooperative dialogue behaviours. In *Proceedings of the 15th Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL)*, pages 60–68.
- Yuval Emek, Michal Feldman, Iftah Gamzu, Renato PaesLeme, and Moshe Tennenholtz. 2014. Signaling schemes for revenue maximization. *ACM Transactions on Economics and Computation (TEAC)*, 2(2):1–19.
- Hilmar Finnsson and Yngvi Björnsson. 2008. Simulation-based approach to general game playing. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 8, pages 259–264.
- Michael C. Frank and Noah D. Goodman. 2012. Predicting pragmatic reasoning in language games. *Science*, 336(6084):998–998.
- Drew Fudenberg and Jean Tirole. 1991. *Game theory*. Cambridge, MA: MIT Press.

- Sylvain Gelly, Yizao Wang, Rémi Munos, and Olivier Teytaud. 2006. Mogo: Improvements in Monte-Carlo computer-go using UCT and sequence-like simulations. *Presentation given at the University of Alberta*.
- Dave Golland, Percy Liang, and Dan Klein. 2010. A game-theoretic approach to generating spatial descriptions. In *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*, pages 410–419.
- Meritxell González, Silvia Quarteroni, Giuseppe Riccardi, and Sebastian Vargas. 2010. Cooperative user models in statistical dialog simulators. In *Proceedings of the SIGDIAL 2010 Conference*, pages 217–220.
- Jason S. Hartford, James R. Wright, and Kevin Leyton-Brown. 2016. Deep learning for predicting human strategic behavior. In *Proceedings of the 30th International Conference on Neural Information Processing Systems*.
- Serhii Havrylov and Ivan Titov. 2017. Emergence of language with multi-agent games: Learning to communicate with sequences of symbols. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, pages 2146–2156.
- Robert X. D. Hawkins, Mike Frank, and Noah D. Goodman. 2017. Convention-formation in iterated reference games. In *CogSci*.
- Christopher Hidey and Kathleen McKeown. 2018. Persuasive influence detection: The role of argument sequencing. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32.
- Christopher Hidey, Elena Musi, Alyssa Hwang, Smaranda Muresan, and Kathleen McKeown. 2017. Analyzing the semantic types of claims and premises in an online persuasive forum. In *Proceedings of the 4th Workshop on Argument Mining*, pages 11–21.
- Takuya Hiraoka, Graham Neubig, Sakriani Sakti, Tomoki Toda, and Satoshi Nakamura. 2014. Reinforcement learning of cooperative persuasive dialogue policies using framing. In *Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers*, pages 1706–1717.
- Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural Computation*, 9(8):1735–1780.
- Melvin Johnson, Mike Schuster, Quoc V. Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, Nikhil Thorat, Fernanda Viégas, Martin Wattenberg, Greg Corrado, Macduff Hughes, and Jeffrey Dean. 2017. Google’s multi-lingual neural machine translation system: Enabling zero-shot translation. *Transactions of the Association for Computational Linguistics*, 5:339–351.
- Sangkeun Jung, Cheongjae Lee, Kyungduk Kim, and Gary Geunbae Lee. 2008. An integrated dialog simulation technique for evaluating spoken dialog systems. In *COLING 2008: Proceedings of the Workshop on Speech Processing for Safety Critical Translation and Pervasive Applications*, pages 9–16.
- Man-Je Kim and Kyung-Joong Kim. 2017. Opponent modeling based on action table for MCTS-based fighting Game AI. In *2017 IEEE Conference on Computational Intelligence and Games (CIG)*, pages 178–180. IEEE.
- Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: A benchmark for question answering research. *Transactions of the Association for Computational Linguistics*, 7:453–466.
- Angeliki Lazaridou, Alexander Peysakhovich, and Marco Baroni. 2017. Multi-agent cooperation and the emergence of (natural) language. In *International Conference on Learning Representations*.
- Mike Lewis, Denis Yarats, Yann Dauphin, Devi Parikh, and Dhruv Batra. 2017. Deal or no deal? End-to-end learning of negotiation dialogues. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2443–2453.
- Yu Li, Kun Qian, Weiyan Shi, and Zhou Yu. 2020. End-to-end trainable non-collaborative dialog system. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 8293–8302.

- Yishay Mansour, Aleksandrs Slivkins, and Vasilis Syrgkanis. 2015. Bayesian incentive-compatible bandit exploration. In *Proceedings of the Sixteenth ACM Conference on Economics and Computation*, pages 565–582.
- Masha Medvedeva, Michel Vols, and Martijn Wieling. 2020. Using machine learning to predict decisions of the European court of human rights. *Artificial Intelligence and Law*, 28(2):237–266.
- Karthik Narasimhan, Tejas Kulkarni, and Regina Barzilay. 2015. Language understanding for text-based games using deep reinforcement learning. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1–11.
- Vlad Niculae, Srijan Kumar, Jordan Boyd-Graber, and Cristian Danescu-Niculescu-Mizil. 2015. Linguistic harbingers of betrayal: A case study on an online strategy game. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 1650–1659, Beijing, China. Association for Computational Linguistics.
- Santiago Ontanón. 2016. Informed Monte Carlo tree search for real-time strategy games. In *2016 IEEE Conference on Computational Intelligence and Games (CIG)*, pages 1–8. IEEE.
- Nadav Oved, Amir Feder, and Roi Reichart. 2020. Predicting in-game actions from interviews of NBA players. *Computational Linguistics*, 46(3):667–712.
- Ori Plonsky, Ido Erev, Tamir Hazan, and Moshe Tennenholtz. 2017. Psychological forest: Predicting human behavior. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 31.
- Carl Shapiro, and Hal R. Varian. 1998. *Information rules: A strategic guide to the network economy*, Harvard Business Press.
- Weiyang Shi, Kun Qian, Xuwei Wang, and Zhou Yu. 2019. How to build user simulators to train RL-based dialog systems. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 1990–2000.
- David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharmashan Kumaran, Thore Graepel, Timothy Lillicrap, Karen Simonyan, and Demis Hassabis. 2018. A general reinforcement learning algorithm that masters chess, shogi, and go through self-play. *Science*, 362(6419):1140–1144.
- Chiara F. Sironi, Jialin Liu, Diego Perez-Liebana, Raluca D. Gaina, Ivan Bravi, Simon M. Lucas, and Mark H. M. Winands. 2018. Self-adaptive mcts for general video game playing. In *International Conference on the Applications of Evolutionary Computation*, pages 358–375.
- Gabriel Stanovsky, Julian Michael, Luke Zettlemoyer, and Ido Dagan. 2018. Supervised open information extraction. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 885–895.
- Chenhao Tan, Vlad Niculae, Cristian Danescu-Niculescu-Mizil, and Lillian Lee. 2016. Winning arguments: Interaction dynamics and persuasion strategies in good-faith online discussions. In *Proceedings of the 25th International Conference on World Wide Web*, pages 613–624.
- Sida I. Wang, Percy Liang, and Christopher D. Manning. 2016. Learning language games through interaction. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2368–2378.
- Xuwei Wang, Weiyan Shi, Richard Kim, Yoojung Oh, Sijia Yang, Jingwen Zhang, and Zhou Yu. 2019. Persuasion for good: Towards a personalized persuasive dialogue system for social good. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5635–5649.
- Ludwig Wittgenstein. 1953. *Philosophical investigations. philosophische untersuchungen*. Macmillan.
- Diyi Yang, Jiaao Chen, Zichao Yang, Dan Jurafsky, and Eduard Hovy. 2019a. Let’s make your request more persuasive: Modeling

- persuasive strategies via semi-supervised neural nets on crowdfunding platforms. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 3620–3630.
- Ze Yang, Pengfei Wang, Lei Zhang, Linjun Shou, and Wenwen Xu. 2019b. A recurrent attention network for judgment prediction. In *International Conference on Artificial Neural Networks*, pages 253–266. Springer.
- Shuo Zhang and Krisztian Balog. 2020. Evaluating conversational recommender systems via user simulation. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1512–1520.
- Haoxi Zhong, Zhipeng Guo, Cunchao Tu, Chaojun Xiao, Zhiyuan Liu, and Maosong Sun. 2018. Legal judgment prediction via topological learning. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3540–3549.