Designing an Automatic Agent for Repeated Language based Persuasion Games

Maya Raifer, Guy Rotman, Reut Apel, Moshe Tennenholtz, Roi Reichart {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, its adaptability to different decision makers, and that its selected reviews are nicely adapted to the proposed deal.

1 Introduction

Natural Language Processing (NLP) has made a 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 per-

sonalized advertising and targeted recommendation systems (Shapiro et al., 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, these works assume stylized messaging that does not involve real-world natural language.

In this work we address the setting of senderreceiver interaction, but, in contrast to previous research, we assume natural language interaction between the players. In our setting the two participants are strategic players with their own private utilities. Crucially, the sender has more information than the receiver about the world. 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 posses, letting the receiver take an action which 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 zerosum games, modeled as a utility maximization

problem (see e.g., (Silver et al., 2018) and 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) was 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) focuses 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, that 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 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 behavior to different decision maker types? and (3) Does the AE behave in a human like manner?

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 behavior 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. Lastly, we analyze the reviews chosen by our AE, shedding light on its strategy.

2 Related Work

We are not aware of previous applications of artificial agents to textual repeated persuasion games. We hence survey relevant works in three related areas: 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, e.g., for judicial decisions (Aletras 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 works 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 works 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 works 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 works, which aims to analyze and predict persuasive aspects of language, is a step towards developing persuasive agents.

Several works have studied 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. Hiraoka 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 which learns to perform non-cooperative dialogue turns for utility maximization in a stochastic trading game with very simple linguistic messages. Lewis et al. (2017) train end-to-end models for negotiation in a semi-cooperative setup. These works differ from ours since 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 works 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. line of work designs agents for games inspired by Wittgenstein (1953)'s 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 reflects a zero expected payoff for a DM who chooses to accept the hotel in all the ten trials.

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 $s_1^t, s_2^t, ...s_7^t$, where $s_i^t \in [0, 10]$. The players' payoffs are:

$$\begin{aligned} \textit{expert-payoff} &= \mathbb{1}_{\{a_t = 1\}}, \\ \textit{dm-payoff} &= \mathbb{1}_{\{a_t = 1\}} \cdot (s_i^t - 8), \\ &i \sim uniform[1, 7]. \end{aligned}$$

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 which 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.

Our work is the first to focus on the design of an automatic expert for such a game. This is in contrast to Apel et al. (2020) which aimed to predict individual decisions of the DM, and did not aim to construct an artificial agent, neither for the DM nor for the expert.

Data We use the dataset collected by Apel et al. (2020) using Amazon Mechanical Turk. ¹ 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 with seven reviews collected from the Booking.com website along with their scores, continuously ranging between 0 and 10. All the reviews contain at least 100 characters and are separated into positive and negative parts. 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 which aims to maximize its payoff in the persuasion game. It is composed of three main components, each having a different role:

- (a) MCTS a search algorithm that determines the best action out of a predefined set. In our setting, actions correspond to review selection, so the MCTS determines which review should be revealed to the DM in each trial.
- **(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 a revealed review.

(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.

The MCTS is an online search algorithm which looks for the best action (in terms of maximum expected payoff) at each game trial. It is the core component of our AE and the two other models are integrated into it after trained offline. The DMM serves as the DM in this simulation, while the VM provides an initial estimate of the value of a new path in the MCTS tree.

We next describe these three components in detail, concluding the section with a desciprtion of the two feature sets used by the DMM and the VM.

4.1 The MCTS Algorithm

MCTS ((Coulom, 2006), Algorithm 1) 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).

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,..7\}\},\$ where r_{hi} denotes the i'th review of hotel h. In addition, each node v holds two values, updated during the search process. The first is Q(s(v), r) $\forall r \in A(s(v))$, representing the expected return after review $r \in A(s(v))$ is chosen in state s(v). The second is N(s(v), r), counting the number of times that review r has been selected in s(v).

The algorithm can be broken down into four modules: selection, expansion, simulation and backpropagation.

(a) Selection - the MCTS algorithm scans the

¹https://github.com/reutapel/Predicti
ng-Decisions-in-Language-Based-Persuasio
n-Games

current tree from the root to a leaf node using a specific strategy. The common strategy is the Upper Confidence Bound for Trees (UCT), which balances the exploration-exploitation trade-off:

$$\pi_{UCT}(s(v)) = \underset{r \in A(s(v))}{\arg \max} Q(s(v), r) + \frac{1}{\sum_{r \in A(S(v))} N(s(v), r)},$$

where c is an exploration parameter.

- (b) Expansion a new child node is added to the tree as a leaf node after it was reached during the selection process for the first time. While in some works Q(s(v),r) of a new node is estimated only by simulation, we train offline the VM and initialize Q(s(v),r) according to its prediction.
- (c) Simulation Once reaching a new child node, a simulation is performed by choosing reviews according to a random policy until reaching a terminal node. The DM's response to this review is simulated using the offline trained DMM.
- (d) Backpropagation After observing the total payoff p at the end of the simulation, we update the values of all observed nodes along the chosen path. That is, for each review r chosen in state s(v) during the current simulation, we have:

$$\begin{split} N(s(v),r) &\leftarrow N(s(v),r) + 1 \\ Q(s(v),r) &\leftarrow Q(s(v),r) + \\ \frac{1}{N(s(v),r)} \cdot (p - Q(s(v),r)) \end{split}$$

Algorithm 1 MCTS with UCT

```
Input: v_0 root state

Output: best possible review r^*
while within time limit do

v_s \leftarrow selection(v_0)
v_l \leftarrow expansion(v_s)
p \leftarrow simulation(s(v_l))
backpropagation(v_l, p)
end while

return r^* = \arg\max_{r \in A(s(v_0))} Q(s(v_0), r)
```

4.2 The DMM & VM Models

As mentioned above, 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

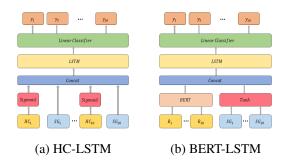


Figure 1: Illustration of our two model architectures. HC_t , SG_t and R_t denote the hand-crafted features, the statistical game features and the presented review in trial t, respectively. For DMM, y_t is the DM's decision in trial t, and for VM, y_t is the expert's future payoff in trial t.

current trial. Both models have identical architectures, but they are trained using different loss functions: binary cross entropy (DMM) and mean squared error (VM).

We consider two architectures (Figure 1). 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). Since 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 mentioned in the positive and negative parts of the review (e.g., 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, e.g., the length of each part (short/medium/long), existence of words with high, medium or low intensity, etc). Finally, features of the third type capture the structural properties of the overall review, e.g., the ratio between the lengths of the positive and negative parts. While these features are hand-crafted, they are automatically extracted form 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 in practice. We hence turn to 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 the human rival (the DM in our case). We hence test our AE, as well as the baselines, by simulating a ten-trial game with different types of DM simulators. We perform 1000 simulated games over the test set, where the order in which the hotels are presented to the AE is randomly permuted at each simulation.

While 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 em-

ploy two DMMs (HC-LSTM and BERT-LSTM) as our basic DM simulators, as they are trained to imitate the DM's behavior after a review is revealed by the AE. 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 DM 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 DM 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 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 which 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 nonsequential 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.²

AE. We compare our AE to eight alternatives,

²In this baseline, as well as in the PD decision maker baseline, the past experiences are based on the gold standard.

Feature Name	Feature Description	Feature Formulation			
Behavioral Feature	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.*	$ \begin{array}{c c} \sum_{i=1}^{t-1} \mathbbm{1}_{\{a_i=1\}} \\ t-1 \\ \hline \sum_{i=1}^{t-1} \mathbbm{1}_{\{a_i=1 \cap dmp_i > 0\}} \\ t-1 \end{array} $			
HotelAcceptance Lose	Avg #trials where the hotel was accepted and the DM achieved a positive payoff.*	$\frac{\sum_{i=1}^{t-1}\mathbbm{1}\{a_i=1\cap dmp_i<0\}}{t-1}$			
¬HotelAcceptance Earn	Avg #trials where the hotel was not accepted but the payoff would have been positive if the DM had accepted it.*	$\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{a_i \equiv 0 \cap dmp_i > 0\}}}{t-1}$			
¬HotelAcceptance Lose	Avg #trials where the hotel was not accepted but the payoff would have been negative if the DM had accepted it.*	$\frac{\sum_{i=1}^{t-1} \mathbb{1}_{\{a_i \equiv 0 \cap dmp_i < 0\}}}{t-1}$			
BadHotel Acceptance	Avg #trials where a hotel with average score lower than 7.5 was accepted.	$\frac{\sum_{i=1}^{t-1} \mathbbm{1}\{a_i = 1 \cap s(hi) < 7.5\}}{t-1}$			
¬ExcellentHotel Acceptance	Avg #trials where a hotel with average score higher than 9.5 was accepted.	$\frac{\sum_{i=1}^{t-1} \mathbbm{1}\{a_i = 0 \cap s(hi) > 9.5\}}{t-1}$			
DMPayoff	Avg DM's payoff pet trial	$\frac{\sum_{i=1}^{t-1} dm p_i}{t-1}$			
General Features					
LotteryLow	Avg #trials where the lottery result was lower than 3.*	$ \begin{array}{c c} \sum_{i=1}^{t-1} \mathbbm{1}_{\{l_i < 3\}} \\ \hline t-1 \\ \hline \sum_{i=1}^{t-1} \mathbbm{1}_{\{l_i \geq 3 \cap l_i < 5\}} \\ \hline t-1 \end{array} $			
LotteryMed	Avg #trials where the lottery result was between 3 to 5.*				
LotteryHigh	Avg #trials where the lottery result was higher than 8.*	$\frac{\sum_{i=1}^{t-1} \mathbbm{1}\{l_i \geq 8\}}{t-1}$			
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.	$\mathbb{1}_{\{s(h_t) \le 7.5\}}$			
HighScore	The attached score of the presented review is higher	$\mathbb{1}_{\{s(r_t) \geq 8.5\}}$			
MedScore	than 8.5.	71			
MedScore	The attached score of the presented review is between 7.5 to 8.5.	$1_{\{s(r_t) < 8.5 \cap s(r_t) \ge 7.5\}}$			
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).

divided to three groups: (a-d) Static rules; (e-g) dynamic rules, which adjust their predictions to the behavior of the DM; and (h) a greedy baseline which tests the VM classifier without the MCTS:

(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 which is most similar 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;³ and **(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 model. This expert helps us quantify the added value of MCTS over a greedy strategy.⁴

Training Procedure and Hyper-parameters We apply a 5-fold cross validation protocol on the training set, and determine the optimal configuration of hyper-parameters according to the best average F1 score of the minority class – hotel rejection. Next, we train the DM and VM models with their optimal configurations on the entire train set, and report results on the test set. As mentioned in §3, the training set consists of 408 DM-expert interactions using the same hotels and reviews, and the test set consists of 101 DM-expert interactions using a different set of hotels and reviews.

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 criteria. For the BERT-LSTM models we use HuggingFace's implementation of the pre-trained uncased BERT-Base model. ⁵ 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

We start by evaluating the DMMs and VMs, the learned components of our model, and then move to the main AE results. We aim to answer our three research questions (§1) related to the AE performance (Q1), the AE generalization (Q2) and the

DMM	Accuracy ↑	F1-score ↑
HC-LSTM	82.40%	73.20%
BERT-LSTM	80.80%	68.30%
HC-SVM	79.50%	68.50%
BERT-SVM	75.80%	52.00%
PD	69.90%	45.21%
EWG	60.00%	50.00%

VM	Accuracy ↑	RMSE ↓
HC-LSTM	38.90%	1.11
BERT-LSTM	16.70%	2.14
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.

AE behavior compared to humans (Q3).

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 F1score 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 expert's future payoff. The strongest model is HC-LSTM (best exact accuracy, second best RMSE). Moreover, the second best model is the 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, that are very effective even when the task classifier does not model the structure of the data. It is also interesting to note that the same features and architecture perform best both for the DMM and for the VM.

Perhaps not surprisingly, the AVG baseline, which always predicts the average score, obtains the lowest RMSE score, but it is not as accurate as our HC features based models. We also note that the DO and HP baselines, that are based on simple

³In the first round the review is randomly selected.

⁴We perform sampling in order to deal with cases where two or more reviews are predicted to have the same payoff.

 $^{^{5}}$ https://github.com/huggingface/transformers.

Expert\DM	HC-	BERT-	HC-	HC-	HC-	HC-	AVG
	LSTM	LSTM	LSTM+0.1	LSTM+0.2	LSTM-0.1	LSTM-0.2	
AE	7.12	7.04	8.10	8.77	6.04	5.02	7.02
RAND	6.54	6.67	7.56	8.31	5.58	4.49	6.53
MEDIAN	6.46	6.85	7.24	8.02	5.45	4.66	6.45
HIGHEST	6.77	7.82	7.94	8.82	5.55	4.46	6.89
EXTREMIST	6.21	6.86	7.24	7.99	5.14	4.08	6.25
A-LIAR	6.54	7.14	7.15	8.69	5.40	4.35	6.55
PDT-HC	6.88	7.03	7.68	8.49	5.83	4.92	6.83
PDT-BERT	6.79	6.59	7.72	8.46	5.77	4.82	6.69
VM-SM	6.58	7.00	7.70	8.34	5.65	4.67	6.66
AE-VM2	7.03	7.05	8.00	8.76	5.98	4.98	6.97
AE-DM2	7.05	7.23	7.94	8.66	5.92	4.97	6.96

Table 3: Average expert's payoff over 1000 simulations against different DM variants. The table is split into four sections, from top to bottom: Our model (AE), static rules, dynamic rules and algorithms. The human experts in the experiments of Apel et al. (2020) achieve an average payoff of 7.36.

statistical rules, perform quite poorly.

AE Results Table 3 presents our AE results (averaged over 1000 simulated games) when playing against six 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 against, rather than to its internal DMM and VM. Of course, 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.

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's scores, are inferior to our AE in all setups. We consider two possible explanations to this result. Firstly, unlike the AE that is trained to maximize its payoff, EXTREMIST and MEDIAN favor the DM by being trans-

parent in their choices at the expense of their own benefits. Secondly and most importantly, unlike the AE, these baselines do not have access to 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, PDT-HC and PDT-BERT), the greedy VM-SM model, and the versions of our AE where everything is kept fixed except that AE-DM2 uses the second best DMM (BERT-LSTM) and AE-VM2 uses the second best VM (HC-SVR), are all inferior to our AE. We consider this as an indication to the importance of a wise search procedure, that carefully balances between the long (explore) and the short (exploit) terms, as well as to the careful selection of a suitable DM and VM models.

7 Ablation Analysis

Analysis of AE Personalization A desirable characteristic of an AE is the ability to personalize its decisions to the DM it faces. We analyse this behaviour 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 behaviour of our AE serves as an evidence to its generalizability (Q2).

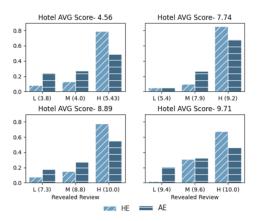


Figure 2: Revealed review score distributions for the AE and the human experts (HEs), for four representative hotels. The reviews are grouped into three bins according to their attached score: Low (L), medium (M) or high (H), and the average score of the reviews in each bin is in parentheses.

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 2 depicts the score distributions of the reviews as revealed by the AE and the HEs for four representative hotels in the test set. We cluster the scores per hotel into three bins: Low, medium and high, and depict the average score of each 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 than our AE, whereas the AE is more diverse in its decisions and is closer to the average review score. This analysis sheds light on our AE's behaviour, providing an initial answer to Q3. An important future direction is testing our AE against human DMs in real-life scenarios.

Textual Analysis of the AE-revealed Reviews

We finally 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 $(7.5 \le as \le 8.5)$ or high (as > 8.5) scoring hotels. The topics are based on the HC features, that encode topics

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

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 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 demonstrate the superiority of our AE over strong baselines and the quality of the linguistic signals it chooses to send.

In future we would like to train and test our AE in real world scenarios, including interactions with humans that are not restricted to lab settings. Moreover, 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.

References

Hua Ai and Fuliang Weng. 2008. User simulation as testing for spoken dialog systems. In *Pro-*

- ceedings of the 9th SIGdial Workshop on Discourse and Dialogue, pages 164–171.
- Nikolaos Aletras, Dimitrios Tsarapatsanis, Daniel Preoţiuc-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.

- Jin Yeong 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.
- Radha-Krishna Balla and Alan Fern. 2009. Uct for tactical assault planning in real-time strategy games. In *Proceedings of the 21st international jont conference on Artifical 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.
- 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.
- Harris Drucker, Chris JC Burges, Linda Kaufman, Alex Smola, Vladimir Vapnik, et al. 1997. Support vector regression machines. *Advances in neural information processing systems*, 9:155–161.
- 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.
- Drew Fudenberg and Jean Tirole. 1991. Game theory. *Cambridge, Massachusetts*, 393(12):80.
- 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*.
- Meritxell González, Silvia Quarteroni, Giuseppe Riccardi, and Sebastian Varges. 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.
- 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, et al. 2017. Google's multilingual 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, et al. 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, Shapiro Carl, Hal R Varian, et al. 1998. *Information rules: A strategic guide to the network economy*. Harvard Business Press.

- Weiyan Shi, Kun Qian, Xuewei 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, Dharshan Kumaran, Thore Graepel, et al. 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 HM Winands. 2018. Self-adaptive mcts for general video game playing. In *International Conference on the Applications of Evolutionary Computation*, pages 358–375. Springer.
- 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.
- Xuewei 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.