Reputation is a central element of social communications, be it with human or artificial intelligence (AI), and as such can be the primary target of malicious communication strategies. There is already a vast amount of literature on trust networks and their dynamics using Bayesian principles and involving Theory of Mind models. An issue for these simulations can be the amount of information that can be stored and managed using discretizing variables and hard thresholds. Here a novel approach to the way information is updated that accounts for knowledge uncertainty and is closer to reality is proposed. Agents use information compression techniques to capture their complex environment and store it in their finite memories. The loss of information that results from this leads to emergent phenomena, such as echo chambers, self-deception, deception symbiosis, and freezing of group opinions. Various malicious strategies of agents are studied for their impact on group sociology, like sycophancy, egocentricity, pathological lying, and aggressiveness. Our set-up already provides insights into social interactions and can be used to investigate the effects of various communication strategies and find ways to counteract malicious ones. Eventually this work should help to safeguard the design of non-abusive AI systems.

1. Introduction

Reputation is essential to human communication. The reputation of a speaker influences strongly how the made statements are perceived, and these statements in turn contribute to the speaker’s reputation. A speaker is for example judged in terms of being competent, honest, or influential. Building up a good reputation is of high importance in any society as it determines the reach of one’s messages. The reputation network of a society is therefore an essential ingredient of it. It is hence not surprising that adapted strategies exist and are used to increase one’s reputation. These might be harmless or harmful to others and the society.

With the raise of social media, which are guided and influenced by artificial intelligence (AI) systems, the need to understand the vulnerabilities and shortcomings of social communication increases. Presently, AI systems seem to shape interactions in social media by influencing which message reaches which participant, or by actively participating in the communications while pretending to be human. Thus, they try to substitute and manipulate human reputation networks.

Here, we explore the hypothesis that the need to gain, maintain, or boost one’s reputation is a central element to many human communication strategies and may lead to some identifiable patterns in their communication dynamics. Especially when there are uncertainties or incomplete information about others’ beliefs and intentions, reputation effects have been shown to be essential to all kinds of interactions, which can in turn be amplified or exploited by AI systems. In order to test this hypothesis and explore its consequences we develop an agent based model, called reputation game simulation, reputation game, or just game in the following. Our reputation game simulation can be regarded as an extension of the many existing socio-physical simulations of gossip or rumor dynamics for example refs. [11–15] and trust networks for example, refs. [16–24] which aims at a more detailed cognitive and psychological modeling of each individual agent. For overviews on the growing field of socio-physics we refer to refs. [25, 26] and references therein.

The game simulates the opinions that agents have about other agents and how these opinions change through communications with others. In the game, the agents are virtual entities that are intended to mimic certain aspects of human beings. All of them will strive for a high reputation, and use strategies to reach this goal. Here, reputation refers only to how honest an agent is...
perceived by the others, the many other facets of human reputation are ignored. A key element of this game is the need for agents to form an opinion about the peers’ honesty, which is achieved by exchanging messages with other agents. Since each message contains some information, although the sender might be misinformed or even deceptive, the message receiving agents use probabilistic logic and some rudimentary rules to determine whether the information received should be considered trustworthy and needed to be memorized or should be ignored and the perceived honesty of the sender adjusted for a lie.\cite{27–29}

Not all agents will interpret a given message in a similar way as their beliefs on the honesty of others will differ; this makes the game highly complex and its outcome non-trivial. The beliefs that agents maintain about each other are stored in a simple cognitive model, which is based on information theoretical principles (probabilistic logic\cite{30} and optimal belief approximation\cite{31}), but has limited capabilities. For efficient lie construction and detection, agents also maintain guesses on the beliefs and intentions of the other agents; that is they possess a rudimentary Theory of Mind.\cite{32}

Our motivation for developing a reputation game simulation is to provide a theoretical framework to test and describe the elements of communication strategies that could affect the self-esteem and reputation of agents. How people share their information depends—among many other things—on their personality.\cite{33} Personality traits are not necessarily obvious, but they can be inferred by observing behavior patterns. AI systems that manage social media communications with the aim to keep the attention of participants\cite{34} might well discover and exploit such patterns to reach their aims. The game presented here is intended to allow testing the link between emerging communication patterns, cognitive states of the participating agents, social situations, and the impact on idealized model characters. It further might help to understand the reputation dynamics of social groups, to decipher strategies observed in real world communications aiming for reputation or exploiting the vulnerability of humans to deception and manipulations, and to support the development of methods to identify and counteract malicious communications. The latter is becoming increasingly important with the rise of AI based communication systems, which have opened the door for large-scale malicious communication attacks on human minds as well as on other AI systems.

The game as it stands is built to reproduce some exaggerated behaviors that show some resemblance with humans. It is designed as a proof of concept that is built on principles of information theory as these should be universal to any functional cognitive system. Thus, some of the effects it exhibits can be expected to capture mechanisms that show resemblance to well-known real-world sociological, cognitive, and psychological phenomena and therefore also to help identifying new ones. Others might just be artifacts of our ad-hoc model choices. Our modeling follows a minimalist spirit, in the tradition of theoretical physical modeling of phenomena, where one tries to strip down a complex phenomenon to the bare essential. Thus, many aspects of real humans are ignored in our toy model. Our work takes inspiration from work in socio-physical simulations, computational cognition and computational psychology\cite{11,13,14,16–22,24,35–37} but the use of information theory\cite{30,31,38,39} enables us to consider more complex phenomena.

The paper is organized as follows: The game’s principles and related approaches are discussed in Section 2. The basic concepts of the game, an overview of the agent’s interactions, and the rules of the game are specified in Section 3, whereas the mathematical details on the formalism can be found in Appendix A. The agents’ receiver strategies are described in Section 4, while their mathematical details are given in Appendix B. The different communication strategies used by agents are described in Section 5 and their mathematical details in Appendix C. Simulation runs of our reputation game in various configurations are discussed in Section 6 and in more detail in Appendix D. We discuss our main findings in Section 7 and conclude in Section 8. An overview on the used mathematical symbols can be found in Table A1 and summaries of the different receiver and communication strategies of agents in Tables B1 and C1, respectively.

2. Principles of the Game

2.1. Related Approaches and Research

Reputation game is becoming an established term in the literature for the game theoretical perspective on reputation systems.\cite{40–46}

The sociological background relevant for our modeling might be spanned by works on Goffman’s Sociology,\cite{47} communication and media studies,\cite{48} reputation in marketing,\cite{49} and economic game theory.\cite{50} More specifically, there exists a rich literature on probabilistic modeling of trust and reputation in a sociological and economical context for example refs. \cite{16–21,23} and on the evolution and maintenance of cooperation for example refs. \cite{51–54} where especially in more recent works agent based modeling of reputation in sociological contexts becomes increasingly important.\cite{55–60} As mentioned already, our work can be regarded as an extension of these works into the direction of modeling the individual cognition and psychology in more detail. Our work uses ideas and principles from socio-physical simulations,\cite{11,14,55} computational cognition,\cite{37} and references therein computational psychology\cite{35,36,61} information theory,\cite{30,31,38,39,62} and complex adaptive system research.\cite{63}

Since our model, just like numerous studies on gossip and rumor dynamics for example refs. \cite{11,14,15} deals with the formation and evolution of opinions, we start from similar approaches. A major difference is, however, that we want to capture some more subtle aspects of human communication needed in the battle of deception and counter-deception. In order to model such behavior, we need more complex agents that are capable of both designing targeted lies and identifying them. Both mechanisms require more parameters and choices than might be typical for a socio-physical model, see for example trust networks in refs. \cite{22,24}. We motivate our modeling choices, but these will need to be questioned, revised, and improved in future research to provide a more realistic setting. Equally necessary for the handling of manipulation in reputation systems is the agents’ awareness of the states, opinions, and intentions of others. The more accurate these assessments are, the better influencing strategies can achieve their effect, but also the more effective are defensive strategies and detection mechanisms. Analogous to the approaches in PsychSim simulations\cite{64–66} or Bayesian Theory of Mind models\cite{67,68} our agents therefore also possess a rudimentary Theory of Mind.
In order to build up an as good as possible judgment it is necessary for the agents to estimate incoming information correctly and to reason with it, that is to think. In the field of computational cognition and computational psychology a bottom up approach is often chosen, by simulating low level brain functionalities like individual neurons and by shaping them in a way that intelligent behavior follows (for example ref. [69]). Here, instead a top down approach is chosen, in which a certain amount of rationality of the agents’ minds is postulated in the spirit of Bayesian models of cognition.[70,71] Also, we assume that rationality tries to align with Bayesian reasoning (or probabilistic logic)[10,39] and follows information theoretical principles.[31,38,62] Bayesian frameworks are used in many works on computational psychology and cognition for example see ref. [35] as well as information theory (ref. [72] and references therein). Unfortunately, however, this amount of rationality is limited both by limited computational resources in simulations and mental limitations, as we know that also human minds are far from being perfect probabilistic logical systems.[73] The relevance of cognitive limitations with respect to perfect reasoning has been recognized for realistic psychological modeling,[74] but can be implemented in different ways. Some works use for example memory loss over time,[72,75] whereas our agents only memorize compressed summaries of the complex network of cross-referencing statements they receive. Information theory specifies how this is done optimally.[31] The limited information available to their reasoning is in turn likely to make agents more vulnerable to manipulative strategies aiming to modify the reputation network.

Our agents strongly interact, adapt to their social environment by learning about the honesty of other agents, and try to shape this environment to their advantage by raising or lowering the reputation of other agents that seem to be beneficial or harmful to them, respectively. Such hedging of other agents’ reputation is also called attribution of credit in complex adaptive system research.[63] Here, we focus on the impact of strategies on group dynamics and the emerging phenomena that they create. We do not study the origin of the strategies themselves. Some of the behavioral patterns that we investigate are inspired from the Dark Triad personalities of the Machiavellian, narcissistic, and sociopathic type for example refs. [76–81]. For example, Babiak et al.[80] write about psychopaths:

Specifically, their game plans involved manipulating communication networks to enhance their own reputation, to disparage others, and to create conflicts and rivalries among organization members, thereby keeping them from sharing information that might uncover the deceit.

Our reputation game simulation allows to assess within its setting how successful such strategies are, and thereby might help to explain why such strategies have evolved in the real world in the first place.[82–84] In the following the model assumptions of the game are stated. These should be regarded as illustrative as several of them could have been made differently.

### 2.2. Players and Their Strategies

The reputation game simulation contains at least two agents. Each can send messages and receive them. All use both a number of receiver strategies. These strategies specify what we call each agent’s personality. In this initial work, we will choose the personalities such that their performance can be studied in isolation. Strategies to send messages can be malicious (e.g., manipulative, destructive, aggressive etc.) or ordinary, if they are devoid of bad intentions. Agents interpret the messages they receive according to their level of psychological awareness or intelligence. For example a naive agent will not have the ability to determine if a message is honest or dishonest. Agents in our simulation can be deaf, naive, uncritical, ordinary, strategic, anti-strategic, flattering, egocentric, aggressive, shameless, smart, deceptive, clever, manipulative, dominant, and destructive. This is fixed at the beginning of the game upon definition of the agents in the game.

The environment for each agent playing the game is defined by the set of other agents. This environment is noisy with a noise level that depends on the agents’ characters (aka the used strategies) and moods (their intrinsic parameters). Agents communicate with each other in binary conversations, and—in order to strip the model from unessential complexity—there is only one single type of conversation topic, namely the honesty of a third agent, or that of one of the conversation partners. The statements agents make can be honest or dishonest. The choice is made randomly, according to agent specific, fixed properties, namely the agents’ honesty. Thus, the agents have to figure out how honest everybody is from the unreliable statements they get and some sparse clues. The only reliable information they get are their self-observations—they are aware whether they speak honestly or dishonestly—and accidental signs of other agents that can give their lies away. In particular, we account for the possibility that an agent may be “blushing” when they lie. This is emulated in the game by introducing a probability to “blush”. In the remainder of the paper, the value for this probability will be set to 10% for most agents.

Even though some communications may be deceptive, they nearly always contain valuable information and, as such, help determining whether agents are trustworthy or not. For example, an agent may recognize that a message is in strong contradiction with their own knowledge, which then adds information about the speaker, for example. Whether a diverging opinion in a message is recognized as valuable information or as a sign of a deception attempt depends among other things on the opinion that the receiver has about the honesty of the speaker. We call this opinion the reputation of the speaker with the receiver in the following. The self-reputation of an agent will be called the self-esteem of that agent.[85]

What each agent thinks about the honesty of other agents and about themselves[86] is described by separate probability distribution functions. If the game contains three agents, then there should be nine such probability functions. These probability functions depend on parameters whose values enable to describe whether an agent is trustworthy or not. After receiving an information, an agent will update these parameters to reflect the new information they got. The result of this opinion update will depend on their previous opinion of the sender and whether they consider the message trustworthy. The apparent honesty of the speaker plays a central role in this information update, as it partly determines how much their message is believed. The influences of opinions on the update of other opinions couple to the beliefs
of the agents in a complicated way and eventually lead to emergent behaviors. Indeed, the messages of a more reputed agent, that is an agent perceived by the others to be more honest, will have a larger impact than messages from a less reputed one. However, more dishonest agents have more opportunities to manipulate others’ beliefs into a direction that is favorable to them. Here the word “favorable” means achieving a higher reputation. When lying, agents can promote others, who seem to talk more positively about them, or try to reduce the reputation of those, who seem to make statements that are more harmful to their own reputation. In order to keep track of whom to support and whom to marginalize, each agent maintains a friend and an enemy list, which are updated by the agents whenever they hear a statement about themselves. Depending on how favorable this statement is in comparison to other agents’ statements, the speaking agent becomes a friend or an enemy to the receiver.

When agents lie, they try to undermine the receiver’s ability to detect the lie. In addition to the speakers reputation, lie detection of the agents is largely based on the similarity of the expressed opinion to the receiver’s own belief, thus liars try to send a slightly modified version of this belief back to their victim. To do this, they need to maintain an idea of what the victim believes on the different topics.

The interactions of agents allow for various strategies to boost their own reputation. Ordinary agents for example pick conversation partners and topics randomly and uniformly from the set of agents, while strategic agents target highest reputed agents as communication partners and egocentric agents prefer to speak about themselves. Reputation game simulations allow to study the impact different strategies have on a social group, in terms of the networks defined by the reputations with each other and the relationships between agents.

3. Reputation Game Simulation

3.1. Basic Elements

In the game, a set $A$ of $n$ agents communicates together in sequential conversations. A conversation is defined as two agents exchanging statements. The conversation initiating agent $a \in A$ chooses a conversation partner $b \in A \setminus \{a\}$ and a conversation topic $c \in A$. Then $a$ and $b$ exchange statements about the reputation of $c$, denoted by $a \xrightarrow{c} b$ ($a$ speaks to $b$ about $c$) and $a \xleftarrow{c} b$ ($b$ speaks to $a$ about $c$) for the individual communications, as well as by $a \xrightarrow{c} b$ for the conversation (of $a$ and $b$ about $c$). Finally both $a$ and $b$ update the reputation of $a$, $b$, and $c$ according to their experiences and interpretations thereof. Agent $c$ could be a third agent, the initial speaker $a$, or the initial receiver $b$. A game round is a sequence of $n$ conversations, in which each agent initiates one conversation. The game ends after a predefined number of rounds. A single conversation and a conversation round are depicted in Figures 1 and 2, respectively. The goal of each agent is to eventually obtain a reputation as high as possible.

The belief an agent $a$ maintains about some other agent $c$’s honesty $x_c \in [0, 1]$ is given by a parametrized, 1D probability density distribution (PDF) $P(x_c | I_{ac})$, where $I_{ac} = (\mu_{ac}, \lambda_{ac}) \in \mathbb{R}^2$ is a tuple of parameters, which store the knowledge of $a$ on $x_c$.

In what follows, we choose $P(x_c | I_{ac})$ to be a Beta distribution, as it is also used in related works for example ref. [20] and is a natural choice, as shown in Appendix A.2. When $\mu_{ab}$ and $\lambda_{ab}$ are natural numbers they can be interpreted as being respectively the number of honest and dishonest statements that $a$ believes $b$ has made. We allow, however, both parameters to take values in the continuous interval (−1, 106) (chosen for numerical reasons). The
two parameters of the distribution allow to express an assumed mean honesty \( \mu_{xa} \), which we identify with \( c \)'s honesty according to \( a \) (aka \( c \)'s reputation with \( a \)), as well as the uncertainty \( \sigma_{xa} \) around that mean, which expresses how sure \( a \) is about \( c \)'s reputation in terms of a standard deviation. The message from \( a \) to \( b \) consists of the topic \( c \) and \( a \)'s belief encoding parameters \( I_{ac} \), in case \( a \) was honest, or a distorted version thereof, in case \( a \) lied. Thus, agents own, maintain, and exchange beliefs in form of probabilities.

Similarly, agent \( a \) will form their own views of the honesty of agent \( b \) they communicate with. This is embodied by the set of parameters \( I_{ba} \) for each \( b \in \mathcal{A} \). We will refer to \( a \)'s belief state as \( I_a = \{I_{ba}\}_{b \in \mathcal{A}} \). If not mentioned otherwise, belief states do not contain information at the beginning of the game. But this changes in the course of the game, as agents’ belief states evolve with time in accordance with their experiences.

The moves an agent \( a \) can make in the game are to choose a conversation partner \( b \) and a topic \( c \), as well as to decide to lie, as depicted in Figure 1. By default, these choices are made randomly. For example, whether an agent \( a \) communicates honestly is chosen randomly according to agent \( a \)'s honesty parameter \( x_a \in [0,1] \). This specifies the frequency with which \( a \) is honest and therefore \( x_a = P(\text{honest}|x_a) \). Other choices might be guided by the agent’s strategy. For example, we will define strategic agents, who preferentially pick highly reputed agents as conversation partners.

3.2. Information Handling

When an agent \( b \) receives a message from agent \( a \) about agent \( c \), agent \( b \) has to judge how reliable the message is. If the message appears honest, the information contained in the message should be used to update \( b \)'s belief about \( c \). The fact that \( a \) was honest is also recorded by \( b \). If the message appears to be a lie, \( b \) should discard the message’s content and only record a lie for \( a \). The problem is that \( b \) rarely knows whether a message is honest or not, and can at best assign a probability to these possibilities. As a consequence, the PDF describing the correct posterior knowledge that an agent should have after receiving a message is a superposition of these two possible updates.

Furthermore, the PDFs, with which agent \( b \) describes the honesty of speaker \( a \) and of topic \( c \), become entangled, as \( b \) needs to recognize whether a sent genuine information about \( c \). The functional form of this potentially bi-modal, 2D, and potentially entangled PDF \( P(x_a, x_c|d, I_b) \), with \( d \) the data obtained by \( b \) from the conversation and \( I_b \) the prior knowledge of \( b \), cannot be precisely captured by the functional form of the 1D PDFs \( P(x_a|I_{ac}) \) and \( P(x_c|I_{bc}) \) agent \( b \) uses to store the updated knowledge \( I_b' \). These only allow for product belief states of the form \( P(x_a, x_c|I_b') = P(x_a|I_{ac})P(x_c|I_{bc}) \), which cannot express entanglements. Thus, information gets lost in an update, and agent \( b \) should choose the new parameters \( I_b' \) such that as much information as possible is kept from \( P(x_a, x_c|d, I_b) \).

We use the principle of minimal information loss for choosing the parameters in \( I_b' \). Information loss can be quantified using the Kullback–Leibler (KL) divergence,\(^{[62]}\) which measures the information difference between original and approximate PDF. This choice of the information measure rests on a solid mathematical proof, which states, that in the absence of any other criteria,\(^{[88,89]}\) the KL is the only consistent choice to quantify how optimal a belief update is\(^{[31]}\). The KL based principle of minimal information loss has also proven to be extremely useful in many areas, like information field theory\(^{[90–92]}\) and information field dynamics.\(^{[93–96]}\)

Some of the information will inevitably get lost during the belief update of an agent due to the limited flexibility of the parametric form and the product structure of belief states. This makes them vulnerable to rumors, misinformation, and self-deception, which in turn can be exploited by special communication strategies of deceptive agents.

For a more detailed introduction into the agent’s information handling we refer to Appendix A.

3.3. Belief Update

In the following, we briefly explain the update due to the initial communication \( a \rightarrow b \). The update due to the response \( a \leftarrow b \) is analogous. Mathematical details of the update can be found in Appendices A.3 and A.4.

First, the speaker \( a \) updates their self-image according to whether \( a \) was honest or lied in the conversation, that is agent \( a \) increases \( \mu_{xa} \) by one if the message was honest, otherwise \( \lambda_{xa} \) is increased by one, as explained in Section A.3. The information agent \( b \) uses for the update is the overall communication setting \( a \rightarrow b \), the messages exchanged \( f(t) \), the blushing observation \( o_c \), and \( b \)'s assessments of \( x_a \) and \( x_c \). We call the tuple
\( d_t = (a \rightarrow b, f(t), \alpha) \) the data of the communication at time \( t \) and
\( P(x_a, x_c | I_a, I_b, A_b) = P(x_a | I_a) P(x_c | I_b) \) the prior of the update. The update of agent \( b \) proceeds in three stages:

### 3.3.1. Assessment of Message

First, \( b \) constructs the joint posterior probability function \( P(x_a, x_c | I_a, I_b, A_b) \propto P(d | x_a, x_c, I_a, I_b, A_b) P(x_a, x_c | I_a, I_b) \). This expression contains the likelihood \( P(d | x_a, x_c, I_a, I_b, A_b) \) to obtain the message \( d_t \). The functional form of this likelihood depends on agent \( b \)'s receiver strategy (see Table B1). A receiver strategy is the background information that determines the form of the likelihood \( I_b \) is using, given \( x_a, x_c, I_b \) and additional auxiliary information \( A_b \), which forms the agent's Theory of Mind knowledge basis. This auxiliary information is dynamical and is used by \( b \) for orientation. It comprises of \( \kappa_b \), the level of surprise marking for \( b \) the border between typical lies and honest statements, agent \( b \)'s guesses for agent \( a \)'s beliefs and intentions w.r.t. \( c \), \( I_{bac} \) and \( \bar{I}_{bac} \), respectively, and other quantities.

### 3.3.2. Information Compression

Second, this joint posterior is then approximated by the parametric form used to store beliefs, \( P(x_a, x_c | I_a, I_b, A_b) = P(x_a | I_a') P(x_c | I_b') = \beta(x_a | \mu_{x_a}, \lambda_{x_a}) \beta(x_c | \mu_{x_c}, \lambda_{x_c}) \), by choosing values of \( I_a' = (\mu_{x_a'}, \lambda_{x_a'}) \) and \( I_b' = (\mu_{x_c'}, \lambda_{x_c'}) \), which then become the new belief parameters at time \( t + 1 \). The principle of least information loss is used to compress data, but information is inevitably lost in this step. i) the parametric form of the beta function is not able to represent all posterior structures and ii) the entanglement of the variable \( x_a \) and \( x_c \) due to the received information cannot be represented by the product structure of the belief representation. The mathematical details of this update can be found in Appendix A.4 and its numerical details in Appendix B.4.

### 3.3.3. Theory of Mind Update

Finally, the Theory of Mind of the agents, which tries to track the other’s beliefs and intention, as well as the typical scale surprise used by them to lie are updated. The corresponding auxiliary variables are stored in \( A_c \). How this is done in detail is explained in Appendix B.4.

### 3.4. Strategies

A communication strategy consists of a set of rules about whom to pick as a conversation partner and as a topic, as well as rules that guide the decisions on how to lie. For example, a malicious communication strategy could be to expose a victim to propaganda in form of massive self-appraisal. This can lead to a nearly complete conversion of the victim to the position expressed in the propaganda, as we show later on (Section 6.2).

A communication \( a \rightarrow b \) received by agent \( b \) may provide relevant information on agent \( c \) if the information is trustworthy, but also on the speaker \( a \)'s honesty and intention. A receiver might judge the honesty of a message on the basis of various signs of deception. How an agent analyzes a message is the agent's receiver strategy. All, but naive agents, use the reputation of the speaker with them as one of the indicators that gives weight to the message. This makes more reputed agents automatically more influential and being influential is what we regard as the agents’ ultimate goal.

Since agents do not know their objective honesty a priori, they have to learn this from self-observations and feedback of the other agents. The resulting self-esteem is an important variable as well, as it is the basis of the communicated self-picture of an agent in case of honest communications. Obtaining a high self-esteem might therefore be a secondary goal of agents, as this permits self-appraisal without the risks involved in lying.

### 3.5. Rules of the Game

The protocol of our reputation game consists of the following steps:

1. A set of labeled agents \( A = \{ \text{red, black, cyan, yellow, blue, ...} \} \) participates in the game. Each agent \( a \in A \) has a number of static properties \( \{ x_a, \text{the set of used strategies, ...} \} \) specifying the agent’s communication strategy and a set of dynamical variables \( \{ I_a, \bar{I}_a, K_a, k_a, ..., \} \), being the parameters of the agent’s world model.
2. Time \( t \) is measured in communication events, which happen sequentially.
3. The central property of each agent \( a \) is the agent’s frequency to be honest, \( x_a = P(a \text{ is honest}(x_a)). \) Other properties determine other aspects of the agent’s communication and receiving strategies.
4. The belief of agent \( a \) regarding the honesty of agent \( b \) is encoded in the parametric probability distribution \( P(x_b | I_{ab}) = \beta(x_b | \mu_{x_b}, \lambda_{x_b}) \), where \( I_{ab} = (\mu_{x_b}, \lambda_{x_b}) \) is the tuple of dynamical variables parameterizing \( b \)'s belief and Beta is the beta distribution. The joint belief state of an agent regarding the honesty of all other agents is set to the direct product of the single agent beliefs, \( P(x | I) = \prod_{b \in A} P(x_b | I_{ab}) \), with \( x = (x_a)_{a \in A} \) and \( I_{ab} = (I_{ab})_{a \in A} \). This implies that agents are unable to keep track of entangled information of the sort “only one of \( b \) and \( c \) can be honest, not both”. Such an knowledge state would actually be appropriate in case the two agents \( b \) and \( c \) accuse each other to be liars.
5. A conversation \( a \leftrightarrow b \) is an exchange of statements between two agents \( a \) and \( b \) about agent \( c \), who is the topic of the conversation. The conversation starts at time \( t \) with the conversation initiator choosing another agent \( b \in A \setminus \{a\} \) (excluding themselves to avoid a soliloquy without information exchange), and \( c \in A \setminus \{a, b\} \) out of the set of all agents. Then \( a \) composes and transmits a statement \( f(t) \) about \( c \), which we also refer to as \( J = f(t) = \int_{d_{c \rightarrow b}} f(t) \) to clarify that message \( f \) is associated with the communication \( a \rightarrow b \). The initial communication is followed by a reciprocal message \( J(t + 1) \) from \( b \) to \( a \) about \( c \), denoted by \( a \rightarrow c \). The full conversation is denoted by \( a \leftrightarrow b \). Only after the statements are exchanged, the
agents update their beliefs. By choosing conversation partner and topic, the initiating agent a basically requests b to make a statement on c (which could as well be a or b). How agents make these choices depends on their communication strategy (see Table C1). Agents that are initiating conversations about themselves, for example, will get to know who are their friends and enemies. See Figure 1 for an illustration of a conversation.

6. The game is played in a number of \( N_{\text{rounds}} \) rounds. In each round, each agent initiates exactly one conversation with another agent, which consists of two communications and subsequent belief updates. The game ends after \( N_{\text{rounds}} \) rounds at time \( t_{\text{end}} = 2N_{\text{rounds}}|\mathcal{A}| \). See Figure 2 for an illustration of a round of conversations.

7. The format of the messages is that of the internal belief representation. For an honest communication \( a \leftrightarrow b \) at time \( t \), we therefore have the message \( f_{a \leftrightarrow b}(t) = I_a(t) \).

8. Whether an agent a lies in a given conversation is usually decided by chance, with the agent specific frequency \( x_a \). When lying, all, except one category of agents called shameless agents, risk to accidentally reveal to their communication partner the fact that they are lying. The probability of being caught lying is \( f_b = 0.1 \). Here b stands for “blushing”, to mimic the fact that agents can give away the act of lying. This gives other agents some direct information about one’s honesty. We denote the observation of the blushing status of the speaker at time \( t \) as \( o_t \). Note, that agent b can also become convinced that a was honest. This happens when a makes a confession, a disadvantageous self-statement (without blushing).

9. After a conversation about agent c, both communicating agents a and b update their beliefs in response to the information perceived about all involved agents, that is a, b, and c as explained before. With this slightly delayed update for the initial receiver b, a communicated opinion \( f'_{a \leftrightarrow b} \) of the conversation initiator a is not directly mirrored back to a in b’s response \( f'_{b \leftrightarrow c} \). Side effects on other agents \( \mathcal{A} \setminus \{a, b, c\} \) need not to be taken care of in the update due to the independent product structure of the belief representation, as detailed in Appendix A.3.

10. After the game is over, the performance of the agents is judged with respect to a number of performance metrics, such as the average reputation of an agent, which is an average of the other agents’ posterior means on the agent’s honesty, the frequency of obtaining a top reputation, and the like.

4. Receiver Strategies

Receiver strategies determine how agents deal with incoming information and generally which mental updates they perform after having received a message \( j \). A stepwise description of this update mechanism is shown in the right part of Figure 3. Most importantly the receiving agent b has to judge the message’s content. In order to find the right trade-off between believing the message and thereby gaining new information, and distrusting the message to not blindly follow a possible lie the receiver has to assign a credibility value \( y_j := \mathcal{P}(j \text{ is honest}|d, I_b) \) to the message. Here, \( d \) is again all the data agent b got from the conversation and \( I_b \) is the information agent b already had before the communication. In reality there are of course endless means and criteria humans use to determine the trustworthiness of others and their statements.[97] In our model we try to capture at least some of these means and test different combinations thereof to observe their influence. These combinations, which we call...
receiver strategies, basically differ in their usage of the conversation data $d$ and the agents’ mental capacities in both lie detection and maintaining an accurate Theory of Mind.

4.1. Lie Detection Strategies

First of all there is the naive agent, who listens to the message and naively trusts it all the time, that is assigns the credibility $y_i = 1$ to every message. This, of course, is not a very sophisticated receiver strategy, but the simplest possible and will therefore serve as a reference for the others. A second type are deaf agents, who primarily use the direct sign whether or not the speaker has blushed to identify lies, as well as the current reputation of the speaker in their eyes. The message’s content, however, is completely ignored. This way deaf agents do not risk being confused by lies, but also do not benefit from honestly communicated, valuable information, which makes their learning progress very slow. A bit more advanced is the receiver strategy of uncritical agents. Just like all of the following strategies, uncritical agents listen to the communicated message and use its content to rapidly gain knowledge. This, together with the right judgment criteria for credibility, clearly is superior to ignoring the content. Besides the speaker’s reputation and blusters uncritical agents can also observe a second clear signal, confessions. If a statement about the speaker themselves turns out to be much worse than what the receiver has believed about the speaker so far, it can be assumed that the message has been honest. Because otherwise, if the speaker had lied, the message would have been based on the knowledge of the receiver (as assumed by the speaker) and would have been biased upwards, that is the speaker would have made a statement that is more positive than what the receiver believes. On top of those criteria, critical agents additionally use the content of the message to judge its credibility based on surprise. When the surprise of a received message is high, or in other words its content deviates strongly from the receiver’s current belief, the latter becomes skeptical and down rates the message’s credibility. Analogously, if the surprise is low and the communicated message fits well to the receiver’s belief it is much more likely to be accepted as true. This strategy seems totally natural at a first glance, although it can easily be exploited. In reality, most of the time lies are not just randomly created statements that others are supposed to accept, but rather are designed carefully and adapted to the intended receiver. In terms of our simulation that means, that lies are always based on the speaker’s assumption on the receiver’s current opinion and from there shifted into the desired direction. Smart agents are aware of this mechanism and use it additionally to all previous criteria in order to detect lies. For this they compare the received message with different scenarios the message could have been created. When the message seems to match the speaker’s real opinion it is likely to be honest. When, however, the message better coincides with the speaker’s guess on the receiver’s opinion plus a little distortion, smart agents identify it as a probable lie. This requires the awareness of other’s opinions, that is a Theory of Mind, and helps the agents to distinguish between lies and honest statements on an advanced level. A more detailed and mathematical description of the above receiver strategies can be found in Appendix B1.

After having assigned a credibility value to the received message, taking into account all criteria that are set by the agents’ strategies, they update their knowledge accordingly. This way our model allows for a continuous transition between trust and distrust, which leads to realistic, individual, and situation based decisions and therefore very complex learning processes.

4.2. Theory of Mind Update

Besides the update of the agents’ opinions on others’ honesties, there are also the Theory of Mind parameters the agents need to track in order to be oriented well in their environment. However, unlike the lie detection, this is updated in the same way for all types of agents. First, the agents update their friends and enemies lists in case the conversation topic were themselves. For this the other’s statement is compared to the opinions the agent heard about themselves last from each of others. If the reputation expressed in the message at hand was above the median of the others’, the speaker is seen as a friend from now on. If it was below the median, the speaker is regarded an enemy in the following. Friends and enemies are therefore defined in our simulation as agents, who have recently spoken more positively or negatively about a certain agent with respect to the peer group, respectively. Second, the agents update their Theory of Mind, that is their knowledge on the others’ beliefs. If on the one hand the communicated message was honest, the receiver directly got to know the belief of the speaker. If on the other hand the message was a lie, the receiver at least got information on what the speaker wants them to believe and remembers that. Since most of the time it is not clear which one of the cases applies, the message credibility value $y_j$ is used as a weight that decides how much this message $j$ influences the receiver’s assumption about the speaker’s belief (not at all if $y_j = 0$, completely if $y_j = 1$), and its complement, $1 - y_j$, how much the assumption about the speakers intention. Finally, the surprise caused by the message is measured and remembered. Here, the median of the last ten such surprise values is used as a reference scale $s_{a_j}$ that each agent a stores individually. On the one hand this serves as a reference to distinguish lies from honest statements in the next conversations, since there is no absolute scale how large lies may be. On the other hand the agents use this scale also to determine the right size of their own lies, in order them to have a chance to go unnoticed, assuming the receiver uses a similar value to detect lies. We identify the scale with the by the agent perceived social atmosphere. This updating mechanism of the reference surprise scale enables the adaption of the agents’ reasoning to a changing social atmosphere, maybe in a way that somehow resembles such processes in real-world social systems. More about the consequences of the surprise scale adaption can be found in Section 6 and its technical details in Appendix B.4.

5. Communication Strategies

Communication strategies, in comparison to receiver strategies, are a set of rules (or frequencies) that specify how to select the conversation partner $b$, which topic $c$ to choose, how frequently to lie, and in which way, that is how to send messages. Figure 3
again shows a step-wise description of these processes. We will use the names of strategies also as adjectives for agents, meaning that an aggressive agent always uses an aggressive communication strategy. In our simulations we define several basic communication strategies, which can be combined resulting in the so called special strategies.

The basic reference communication strategy is that of an ordinary agent, and all other basic strategies are described in terms of their differences to this in Section 5.1. For special agents, that is agents that use a combination of various basic strategies, the reference will be the clever agent as discussed in Section 5.2. An overview of the different communication and receiver strategies is given by Table C1.

We would like to emphasize at this point, that all the following strategies are ad-hoc choices we made in the hope that they capture some aspects of real-life personality types. Of course, we do not claim that these strategies are even close to being realistic enough to emulate real personalities, nor that our selection of strategies is exhaustive. They only serve as a possible set of strategies that we want to investigate and observe the reputation dynamics resulting from these particular choices.

### 5.1. Basic Strategies

**Ordinary agents** make all their decisions randomly. They choose a conversation partner randomly among all other agents, a communication topic among all others or themselves, communicate honestly according to their predefined honesty value, lie positively about friends and negatively about enemies and use a critical receiver strategy for lie detection. Two opposing strategies are used by **strategic** and **anti-strategic agents**, who choose their conversation partners according to the agents’ reputation, that is their presumed honesty. Strategic agents thereby aim for the most reputed, presumably most honest agents, whereas anti-strategic agents preferentially talk to least reputed, and therefore presumably most dishonest ones. These two strategies aim for different effects. Being strategic, the agents benefit when they manage to convince their interlocutors of their own honesty, as this opinion is then efficiently passed on to third parties by the honest and reputed agents. First, those mostly say what they believe and second, they are trusted by the others. Being anti-strategic, however, is not aiming that the targeted agent distributes their honest opinions, but instead that lies are favorable for the anti-strategic agent. Since less reputed, and therefore presumably more dishonest agents can be assumed to lie more frequently, anti-strategic agents mostly benefit from simply being their friends and therefore passively taking advantage of all the good rumors that dishonest agents spread about them. Other types of agents choose the conversation topic with special care. **Flattering agents**, for example, make their interlocutors compliments, that is make positive lies to their interlocutors whenever possible in order to befriended them. Of course it is therefore very reasonable to always choose the conversation partner also as conversation topic, as it is part of the flattering strategy. **Egocentric agents** also choose the conversation topic with a special motivation, namely to promote themselves. This is why in more than half of the cases where egocentric agents start a conversation they choose themselves as conversation topics. A third way of choosing the topic is used by **aggressive agents**, who always talk about their enemies in order to harm their reputation. At the same time, however, they do not promote themselves nor their friends, such that the aggressive strategy might generally cause low reputations in a simulation for all participating agents, but is designed to damage others’ even more than their own. **Shameless agents** do not run the risk, in comparison to all others, to blush when lying. This makes it harder for their interlocutors to identify lies, which in turn helps to keep the agents’ reputation up. Another strategy to appear honest is to create a complete illusion of oneself and never let reality show through. This is what **deceptive agents** do, by lying in every single communication. Thus, they never make confessions or otherwise reveal their true opinions to anyone else.

A more detailed and mathematical description of these basic strategies can be found in Appendix C.

The impact of most of these strategies on the agent’s reputation is modest if used alone. Therefore, we use matching combinations where the individual basic strategies can unfold their power best. These are what we call special strategies.

### 5.2. Special Strategies

**A clever agent** is smart and deceptive and is the reference point for the special agents, which are all smart and deceptive as well. Smartness permits the agent to understand the beliefs and intentions of other agents better, allowing for more precisely placed lies.

The **manipulative agent** is clever, flattering, and anti-strategic. This should enable the agent to efficiently identify and befriend other dishonest agents, who more frequently praise their friends and therefore the befriended manipulative agent than other agents. Manipulative agents should thereby become popular and influential. Their presence in a social group is expected to lift the self-esteem of the group members, owning to flattering. This lift should be stronger for less reputed agents, as those are preferentially targeted for conversations. These are often the more dishonest agents, which then, as a friend of the manipulative agent, hopefully give positively biased testimonies about the manipulative agent. As a consequence, we expect manipulative agents to frequently establish mutual friendship.

The **dominant agent** is clever, egocentric, and strategic. The agent’s communications are targeting the most reputed agents to praise themselves. If successful, these will most efficiently propagate a positive image of the dominant agent to others as well as mirroring this image back to the dominant agent themselves. The latter effect might efficiently boost the self-esteem of the dominant agent. Dominant agents will be best informed about their own reputation, by making themselves the conversation topic. This will, however, couple their self-esteem more to their reputation compared to other special agents. This will also provide them with a more accurate friend and enemy classification, as they see how other agents talk about them. This classification will not be accurate, however, in case they are interacting with manipulative agents, as the latter speak differently about a topic depending on whether the topic is also their conversation partner or not. Nevertheless, dominant agents are expected to be drawn toward manipulative agents with respect to their
communication partner choice and friendship, whenever the manipulative agent manages to become reputed.

Finally, the destructive agent is clever, deceptive, aggressive, and shameless. By also targeting reputed agents for communications, the agent’s disrespectful propaganda about the agent’s enemies can unfold best. Since destructive agents are shameless, they are not risking to blush while lying. This might compensate for the lack of direct self-promotion of the destructive agent. Their lack of self- and friend-promotion lowers the surprise variance the receivers experience compared to just deceptive or clever agents, which helps the destructive agent to appear more honest. The presence of a destructive agent in a social group is expected to lower the reputation and self-esteem values of the other agents significantly due to that agent’s tendency to concentrate conversation topics on enemies, about which the agent talks disrespectfully.

To summarize, we have defined a number of communication and receiver strategies and can now see how agents equipped with different sets of such strategies interact.

6. Simulations

We now discuss our reputation game simulations. All agents’ initial beliefs and assumptions on honesty and reputations of other agents are set to be non-informative. \( I_{ab}(0) = I_{abc}(0) = \hat{I}_{ab}(0) = I_0 = (0, 0) \), if not specified differently. In the displayed simulation runs, individual random sequences for the different processes like choosing conversation partners, topics, whether to lie, how strong to lie and the like are kept identical between the simulations. The intrinsic honesty of agents is also kept identical, with \( x = (x_{red}, x_{blue}, x_{black}) = (0.27, 0.80, 0.97) \), if not specified differently. Differences in dynamics therefore only arise here because of the different strategies used by agents in the different simulation runs, as these specify how the random number sequences are used in detail. This should help to highlight the effects of the strategies, and to facilitate their comparison. However, differences in the performance of individual strategies observed this way are only indicative. The dynamics is chaotic and thus firm conclusions about the efficiency of strategies can only be drawn when the strategies are used in detail. This should help to highlight the effects of the different deceptive strategies quantitatively, and provide statistics of the resulting reputation and friendship relations between agents.

6.1. Receiver Strategies

First, we investigate different receiver strategies. The sender strategy is that of ordinary agents in what follows. An overview on the different receiver strategies is given in Table B1.

6.1.1. Deaf Agents

We want to demonstrate the agent’s ability to learn from unbiased signals, like the agents’ self-observations and the blushing signals. These are the only information sources available to deaf agents. To this end, the top left panel in Figure 4 shows the reputation dynamics of three deaf agents performing 300 conversation rounds. These agents learn relatively quickly and accurately their true honesty from their self-observations. Whenever they are honest, their self-esteem increases; when they lie, it decreases. The learning about the honesty of others is much more difficult, as it relies on the occasional blushing signals, which are visible as the sudden drops of the otherwise monotonically increasing reputation lines. Despite this difficulty, agents manage nevertheless to get the tendencies right. The discrepancies between correct honesty and their reputation seem to be consistent with the associated uncertainty estimates.

Despite the deaf agents not hearing each other, the patterns of their statements are instructive. These are shown in the top left panel of Figure 5. This is a busy figure that we discuss briefly.

All honest statements from agent \( a \) to \( b \) about \( c \) are displayed as circles with the outer, middle, and inner color indicating the agent \( a \), \( b \), and \( c \), respectively. These honest statements reflect the beliefs of the speaker \( a \) on topic \( c \). For this reason, they are on top of the agents’ belief curves \( \overline{x}_a(t) \), which are displayed as well. The main color of any of these lines is that of \( a \) and the dots on top are in the color of \( a \). The circles on the uni-color lines are self-statements. Their densities reflect the intrinsic honesty of the speaking agent, with agent black making most frequently honest statements and agent red least frequently.

All lies \( \{ I_{abc}, I_{abc} \} = I_{abc} + a D \), where \( I_{abc} \) is the speaker \( a \)’s assumption about the receiver \( b \)’s belief on \( c \), \( D \) the direction of the lie, and \( a \) the size of its distortion) are displayed as triangles with the same color coding (speaker \( a \) specifying the outer, receiver \( b \) the intermediate, and topic \( c \) the inner color). The lies are mostly from agent red and fall into two categories: First, all lies about other agents \((a \neq c)\) are located at the horizontal line \( \overline{x}_a = \frac{1}{2} \). The reason for this is that deaf agents do neither get friends nor enemies (as they do not listen to each other), and therefore make only white lies \((a = 0 \Rightarrow I_{abc} = I_{abc})\). Since deaf agents can not update \( I_{abc} \) (they do not hear others’ opinions), their white lies are the initial value of this quantity, \( I_{abc} = I_{abc} = I_0 \), and therefore displayed at \( \overline{x}_a = \frac{1}{2} \). The lies agents make about themselves, \( I_{abc} \), are bisected positively \((a > 0, D = 1 \Rightarrow \overline{x}_{I_{abc}} \approx \overline{x}_{I_{abc}} = \overline{x}_{I_{abc}} = \frac{1}{2})\), and thus are found in the upper half of the diagram.

6.1.2. Uncritical Agents

Agents should get much better estimates of each other’s honesty compared to the deaf agent scenario, if they exchange the information they collect. This is shown in the top right panel of Figure 4, where uncritical agents, who listen to each other, perform the same set of conversations (as specified by \( a \rightleftharpoons b(t) \)) as the deaf agents did (top left panel), with also being honest or lying at exactly the same instances. What they say, however, differs from the deaf agents simulation, as agents now listen to each other and therefore their opinions and assumptions evolve differently to those of the previous run.
Figure 4. Reputation game simulations for three agents with the panels showing different receiver strategies: deaf agents (top left), uncritical agents (top right), ordinary agents, which have a critical receiver strategy (bottom left), and agent red being a smart agent (bottom right). All simulations are run with the same random number sequences, implying that the communication configurations (like $a \rightarrow b$) and message honesty states (honest or lie) exhibit exactly the same sequences. Differences are solely caused by differences in receiver strategies. This and other figures showing communication patterns intend to give an overview. To inspect details, we recommend to magnify their electronic, vector graphics versions. Text statements about certain precise communication events were not taken from these figures, but from the simulation log files. The self-esteem $v_a$ of agent $a$ is shown as a thick solid line in the color of $a$, agent $b$’s reputation $v_{ab}$ in the eyes of agent $a$ is shown as a thin line, which carries the color of agent $b$ and has dots in the color of agent $a$ on it. One sigma uncertainties of self-esteem and reputations are displayed as transparently shaded areas in the color of agent $a$. The dashed lines show the actual honesty of the individual agents, the fraction of honest statements made, which is close to their intrinsic honesty of $x = (x_{red}, x_{cyan}, x_{black}) = (0.27, 0.80, 0.97)$. The data points with bars at the right side display summary statistics of the full dynamics. The squares and their bars indicate the mean and variance of the reputation of the agent in the corresponding color. Similarly, the circles and bar indicate mean and variance of self-esteem of agents.

It is apparent that the agent’s guesses on each other’s honesty become much more accurate and definite. Actually, some overconfidence can be observed for the opinions on agent cyan, which have converged to a value significantly below the agent’s true honesty with a confidence that excludes the correct value. The self-esteem of cyan even follows this slightly incorrect value, despite cyan’s self-observation should inform cyan better. However, the opinions expressed by the others on cyan, in particular the ones of the most reputed agent black, seem to have a stronger pull. The collective development of the overconfident, but incorrect opinions on cyan is the result of an echo chamber: The initially more dispersed opinions of the different agents converge to a value that is partly decoupled from reality (cyan’s true honesty), and this value is largely determined by the group dynamics.

Inspecting the corresponding communication patterns in the top right panel of Figure 5 shows for example the concentration of statements about agent cyan around cyan’s self-esteem. It is apparent that agent red regards cyan as a friend for most of the time, as agent red’s lies for cyan are typically above cyan’s self-esteem. Consequently, red regards black mostly as an enemy, as the lies about black are aiming for lowering black’s reputation and self-esteem. These lies by red, however, have little influence compared to the opinions expressed by cyan and in particular by black, due to the much higher reputations of black and cyan compared to red.

Investigating red’s reputation is also instructive. Initially it is high, as red’s early self-promoting lies fly. However, two confessions of red to cyan (at $t = 52$ and $100$), who thereafter regards red as unreliable, and cyan’s repeated spreading of these news to black (cyan $\rightarrow$ black at $t = 57, 84, 93,$ and $150$), destroy red’s initially high reputation in an irreparable way.

Red would probably have overcome this resistance if red’s lies would simply have been much stronger. This is because the weight of a message, which an uncritical agent assigns, does not depend on how extreme the position of a message is, but the shift of the receiver’s opinion does depend on this. Uncritical agents are therefore very prone to propaganda in form of exaggerated lies, as we show in Section 6.2.
6.1.3. Critical Agents

Ordinary agents use a critical receiver strategy, which is able to recognize exaggerated statements. A simulation run with such agents is shown in the bottom left panel of Figure 4, again for the same sequence of communication decisions. Overall, the outcome of the simulation is similar to that of uncritical agents, in the sense that the final reputations and self-esteem converge to values not too far from the correct honesty of the agents. However, at least two interesting differences to the uncritical agent simulation can be spotted here and should be discussed: The more volatile evolution of beliefs about cyan, with a significant gap between cyan’s self-esteem and cyan’s reputation (in the period 100 to 800) and the much later time in the critical simulation compared to the ordinary one (\( t = 291 \) instead of \( t = 150 \)) at which agent black’s opinion about red joins that of cyan. Both are a consequence of critical agents being more reluctant to accept diverging opinions. This allows the self-esteem of cyan to evolve more decoupled from the lower opinions expressed by red and black, and makes black more skeptical about cyan’s reports on red’s dishonesty.

6.1.4. Smart Agents

Smart agents have an even more sophisticated receiver strategy compared to critical agents. This should allow them to maintain a more accurate picture of the other agents’ beliefs, which improves their lie detection and lie construction. To illustrate this, the bottom right panels of Figures 4 and 5 show a simulation run in which agents black and cyan still use critical receiver strategies (as in the bottom left panel), but red uses a smart strategy.

In this smart scenario (agent red being smart), the self-esteem and reputation of cyan do not show the strong growth that is visible in the critical scenario (agent red being only critical). The reason for this are the better targeted lies of red in the smart run, which undermine cyan’s and black’s lie detection more efficiently than in the critical run. This makes red’s lies more effective. As these lies mirror the other agents’ previously communicated beliefs, just in a slightly distorted manner, they counteract rapid evolution of these beliefs by pulling them back toward those previous values. Additionally, the echo chamber effect of group opinions converging to overconfident, but incorrect
positions is strong, also due to the better targeted lies of red. Both, the retarding back-reaction and the opinion focusing effect of red’s more effective lies, effectively add inertia to cyan’s self-esteem and reputation, which keeps those from reaching the correct honesty value of cyan.

6.2. Propaganda and Resilience

6.2.1. Simulation Setups

We claimed that agents with naive or uncritical strategies are very susceptible to exaggerated lies and that critical and smart receiver strategies provide some resilience against such lies. To demonstrate this, but also to illustrate the inner working of the cognitive model adapted, a number of propaganda situations are simulated. In those, all agents, except agent red, who will be the propagandist, will be absolutely honest.

The basic propaganda situation is depicted on the left of Figure 6: There, only agent red communicates to black, cyan, yellow, by repeatedly sending strong self-appraisal ($J_{\text{red} \rightarrow \cdot} = (10^3, 0)$) to them without blushing. Red’s initial reputation with them differs, being initially low with black ($\bar{x}_{\text{black} \text{red}}(0) = 0.2$), medium with cyan ($\bar{x}_{\text{cyan} \text{red}}(0) = 0.5$), and high with yellow ($\bar{x}_{\text{yellow} \text{red}}(0) = 0.8$). These agents are isolated in this setup, as they only receive the propaganda, but can not exchange their positions among themselves.

This is changed in the setup with cross-communication among the propaganda receiving agents shown on the right of Figure 6. There, every receiver communicates honestly the updated opinion on red to all other receivers after every exposure to the propaganda.

Simulations with the basic setup are shown in Figure 7 for three uncritical agents (top left panel) and for three critical agents (top right) as receivers. Simulations with the cross-communication setup are run for three critical receivers (bottom left) and for one smart among two critical ones (bottom right). In all simulations, 75 propaganda rounds are performed.

6.2.2. Isolated Uncritical Agents

All uncritical, isolated agents rapidly adapt a high reputation for red under red’s propaganda (top left panel of Figure 7), as the strong messages received are only slightly moderated by their initial limited respect for red. Although red’s reputation with them is steadily growing, it does not reach the position announced in the propaganda message of $\bar{x}_{\text{red} \text{red}} = 0.999$. This is caused by the receiver mechanism that tries to identify the novel part of a message, and disregards the part that already seems to be accounted for. Naive agents would have fully adopted that latter position on the first exposure to the propaganda (not shown).

6.2.3. Isolated Critical Agents

Ordinary agents, which have critical minds, have much more resilience against propaganda, as can be seen in the top right panel of Figure 7. Agents black and cyan, who are initially skeptical about red’s honesty, become immediately more skeptical under the exposure of the propaganda, as they perceive this as lies. This changes at $t = 15$, after five propaganda rounds, when red’s reputation with them starts to grow. What causes this change is that at this point in time, the large divergence of the propaganda messages from their own beliefs start to affect the scale $\kappa$, which agents use to discriminate lies from honest statements, as this is based on the median of the last ten message surprises. Consequently, the mechanism to separate lies from honest statements starts to fail, which lets the propaganda appear slightly more trustworthy. Since the propaganda makes strong claims, it shifts—despite being still more distrusted than believed—black’s and cyan’s opinions on red upward.

Agent black, who is initially most skeptical, is hit the strongest by this effect. Being initially most skeptical about red, black experiences the largest opinion divergence by the propaganda, and therefore the largest shift in $\kappa_{\text{black}}$. This then makes black most vulnerable to propaganda.
Impact of propaganda

Figure 7. Impact of propaganda on agents with differing initial beliefs in various social situations as depicted in Figure 6. Here, agent red constantly claims (without blushing) to be extremely honest, $J_{red}^{red} = (10^2, 0)$. The initial beliefs of the receiver of red’s self-propaganda range from being slightly reserved with $I_{black}^{red}(t = 0) = (0, 3)$ over neutral with $I_{cyan}^{red}(0) = (0, 0)$ to positively inclined with $I_{yellow}^{red}(0) = (3, 0)$. The panels show the belief dynamics of isolated uncritical agents (top left), isolated ordinary (critical) agents (top right), honestly cross-communicating ordinary agents (bottom left), and the same, just with black being smart (bottom right). Only non-trivial beliefs ($\neq I_0 = (0, 0)$) on other agents are plotted in the color coding of Figure 4 (only red in the top panels, all agents in the bottom panels). Self-estees are not shown.

We see that even critical agents, who are more wary, can be prone to propaganda. All their beliefs in red’s reliability increase and do this the more, the lower the initial trust was. At some moment, the novelty of the propaganda message wears off and red’s reputation stops to increase further. The propaganda statements are still received as mostly being lies, which thus makes the prestige of red finally disappear for each of the recipients again.

To summarize, the strategy to classify lies only according to the surprise they create works as long as the reference surprise value is not inflated. This quantity is determined empirically and increases to a too high value if there are many more lies than expected. This effectively shuts down the full rejection of strong claims by the agents’ lie detection system and thereby enables propaganda to affect their minds.

6.2.4. Cross-Communicating Critical Agents

A counter measure against attacks on the lie detection system can be the exposure to honest messages, or just messages with low surprise values. This can be achieved by honest and frequent exchanges with other honest agents. Such exchanges should help to a healthy lie detection system, and should provide corrective inputs that counteract the pull of the propaganda.

A propaganda simulation with such honest cross-communication is shown in the bottom left panel of Figure 7. As soon as the receiving agents cross-communicate their beliefs about red, the dynamics gets even more complicated. Although the receiving agents communicate honestly, they first have to build trust. This process exhibits a complex dynamic, which lets only agent cyan and yellow trust each other in the end and distrust red. Agent black, despite being initially very reputed, loses the trust of the other agents as well as black loses the trust in them.

This isolates black from the protecting effect of their communications, and lets black accept the propaganda even more than in the scenario without cross-communication. The reason for this is that diverging opinions of cyan and yellow about red harm black’s lie detection in addition to what the propaganda does to it.

Nevertheless, this simulation shows that honest cross-communication among recipients of propaganda can mitigate the propaganda’s impact to some degree.

6.2.5. Impact and Resilience of a Smart Agent

The bottom right panel of Figure 7 shows a simulation with a similar setup as before, but this time we assume agent black uses a smart receiver strategy. This means that black maintains and
uses a set of guesses about the other agents’ beliefs (as stored in \( l_{\text{black red red}} \) for red) and intentions (as \( l_{\text{black red red}} \)) to detect lies. The smart receiver strategy allows black to identify red’s communications as propaganda, after a period of varying opinions about red, and to convince cyan and yellow also to distrust red in the end. Thus, the smart receiver strategy offers more resilience against exaggerated lies than the critical one.

We note that at the peak of red’s reputation with black, black has a bimodal belief state about red with \( s_{\text{black red}} = (−0.39, −0.92) \). This is expressing that at that moment black is aware that either red is very honest or very dishonest, but certainly not anything in the middle between these extremes.\(^{[101]}\)

### 6.3. Communication Strategies

We now discuss the impact of the basic and special communication strategies. The setup will be as in Section 6.1.1, but now agent red uses basic or special communication strategies. The intrinsic honesty of the three agents and the random sequences determining the course of simulation events will again be identical to what they were in the simulations shown in Figures 4 and 5 for some of the runs. These are the runs with random number sequence No. 1 from our statistical set of one hundred simulations to be discussed later. For the special agents, we will also show runs with random sequence No. 2 to illustrate the variance in the dynamics with otherwise identical setup.

#### 6.3.1. Basic Communication Strategies

**Figure 8** shows simulation runs, with the setup of Figure 4, but here agent red is either strategic, egocentric, flattering, shameless, aggressive, or deceptive. The corresponding communication patterns can be found in Appendix C. None of the basic strategies adapted by agent red appears to be efficient in boosting red’s reputation, except for the flattering and the deceptive strategies, which both let red lie more often.

The **strategic agent** red concentrates opinion exchanges on the most reputed agent black, and thereby manages to convince black that cyan is untrustworthy. This lets cyan, who actually is trustworthy, doubt black’s honesty as a reaction to black’s opinion on them. However, black’s and cyan’s reputations still stay well above that of red, as red’s reputation suffers from red’s occasional confessions.

The **egocentric agent** red speaks mostly about themselves. This has two visible consequences: First, the others’ opinions on red converge faster, due to the larger number of confessions made by red. Second, the lies of red are not able to follow the development of the other agent’s opinions on other agents that well.\(^{[102]}\)

The **flattering agent** red is somehow successful in obtaining an enhanced reputation. The key factor is that red is preferentially talking about others, thereby avoiding giving information about themselves away via confessions. This helps red to establish a slightly higher reputation than in the other scenarios discussed so far. The feedback to red by the other agents lets red’s self-esteem grow to this enlarged value until \( t = 1000 \). Thereafter, confessions by red are based on this enhanced value and do not let the other agents’ opinions fall below it. We witness here a successful and advantageous self-deception of an agent.

The **shameless agent** red lies without blushing, and therefore is more convincing. As a result red’s reputation grows slightly higher than in the ordinary agent scenario. Red’s reputation is held back by red’s confessions and the inertia the converging group opinion generates against the pull of red’s self-appraisal. We note, however, the significantly reduced reputations of black owning to the more convincing lies of a shameless agent red.

The **aggressive agent** red attacks preferentially cyan, whose reputation and self-esteem suffer significantly from red’s vilification.

Finally, the **deceptive agent** red manages to get the highest reputation and self-esteem of red in all the scenarios discussed so far, since red does not make a single confession, and self-promotes with a high frequency.

#### 6.3.2. Special Communication Strategies

**Figures 9** shows runs for agent red being clever (smart and deceptive), manipulative (clever, anti-strategic, and flattering), dominant (clever, strategic, and egocentric), and destructive (clever, strategic, aggressive, and shameless). On the left panels of Figure 9 the random sequences are chosen as before (and like runs No. 1 of the statistics ensemble), whereas on the right panels different sequences (runs No. 2) were chosen. The latter highlight how different dynamical regimes can appear in otherwise identical setups. The corresponding communication patterns can be found in Appendix C. For the dominant agent we display them also in **Figure 10** for a more detailed discussion.

Furthermore, **Figure 11** shows the evolution of the lie detection scale \( \kappa_a \) for an instructive selection of simulation runs. A larger \( \kappa_a \) of agent a implies that this agent is used to receive messages that diverge more from the own opinions. This can make the agent blind for smaller lies.

The runs shown there with red being an **ordinary agent** shows that usually \( \kappa_a \) varies on a logarithmic scale around unity, with a typical variance of one order of magnitude up or down.

The **clever agent** red performs slightly worse in terms of reputation than in the runs where red is deceptive (see discussion before). The lie detection scale \( \kappa_a \) of the clever agent red is significantly larger than that of the other two agents in the same run. However, thanks to being clever, red’s lies match the beliefs of the other agents better and these experience therefore reduced surprises compared to what they experience in the deceptive scenario. This will also be the case for many of the runs with the other special agents, to which the clever agent scenario is a reference for comparison.

Compared to the case when agent red is clever, the **manipulative agent** red is much more successful. As red is mostly flattering cyan, the latter gets a significant self-esteem boost in the simulation No. 1 (second row, left panel of Figure 9), and partly also in No. 2 (second row, right panel).

By focusing on their reputation, the **dominant agent** red freezes the group opinion on red (third row, left panel of Figure 9), preventing red to obtain a high reputation in about half of the simulations with red being dominant. This is accompanied by strongly reduced variances in opinions and therefore in \( \kappa_a \) for every agent \( a \) in such runs (see central panel of Figure 11). The other half of the runs show much more volatility in red’s reputation with about one fifth of these runs leading to a top reputation and self-esteem.
for red. In the third row, right panel of Figure 9 shows run No. 2 for the dominant agent red, which illustrates this latter case, and seems to be typical for this outcome. Before red’s dominance is established, a period of high opinion volatility and large uncertainty seems to be necessary. Red’s lies in this scenario are often on the extremes (see right panel of Figure 10 for the period 600–1200), creating a social atmosphere that might be characterized as toxic, as any enemy of red is often blamed to be a complete liar. The reason for this is that red’s self-esteem does not manage to catch up with red’s inflated reputation due to red knowing their lies. Therefore, the many conversations of red about red lead to a high level of cognitive dissonance, which inflates $\kappa_{\text{red}}$ by two orders of magnitude above the usual $\kappa$ values (see bottom middle panel of Figure 11). As $\kappa_{\text{red}}$ is also used by red in lie construction, red’s expressed opinions tend to be largely on the extreme, either very positive (about red and friends) or very negative (about enemies). Only after red’s self-esteem manages to become as high as red’s reputation, does $\kappa_{\text{red}}$ fall to a more normal level.

The destructive agent red manages to establish a high reputation in run No. 1, but not in run No. 2. In the latter red largely destroys cyan’s reputation during the initial period with a concentrated attack, though. Red’s surprise scale $\kappa_{\text{red}}$ in this run takes very extreme values, mostly due to the large difference between red’s and the others’ opinions about them. As a consequence, red speaks extremely negative about them, however, without being believed.
Figure 9. As Figure 8, but for agent red being deceptive (first row), manipulative (second row), dominant (third row), and destructive (fourth row). The left column shows simulations using random sequences No. 1 and the right using No. 2.
6.4. Statistics

6.4.1. Reputation Statistics

In order to see how robust the observed impact of special agents on the individual runs are, an ensemble of one hundred simulations with differing random sequences was performed for each of the setups in which red is ordinary, deceptive, clever, manipulative, dominant, and destructive. All other configuration parameters are kept identical. Figure 12 shows the time evolution of the ensemble mean and dispersion of the agent’s reputations and self-estees for the different scenarios. Figure D3 displays the correlations between the reputation of agent red (the least honest one) and that of agents cyan and black (the two more honest ones) for the different scenarios [103,104]. Figure 13 shows histograms of the agents’ reputations and their self-estes occurring during the simulations for the different scenarios. We name these scenarios after the strategy agent red uses in them.

In the ordinary scenario, with ordinary agent red, reputation and self-esteem values of agents roughly reflect their honesty.
Red is not able to significantly increase their reputation or self-esteem beyond red’s honesty ($x_{\text{red}} = 0.14$) in most of the runs, only in a few cases high values are reached (Figure 13 shows a peak in the histogram of red’s reputation at 0.2, with a fat tail toward larger reputations up to 0.9). Agent cyan’s reputation ($\approx 0.7$) and self-esteem ($\approx 0.75$) are only slightly lower than they should be ($x_{\text{cyan}} = 0.80$). The largest disparity between reputation and honesty happens typically for agent black, who is too honest to defend their reputation (black’s reputation is on average at $\approx 0.65$, but shows large variance, whereas $x_{\text{black}} = 0.97$). Black’s reputation shows even a bimodal distribution, with a high reputation peak (at 0.925) shortly below black’s honesty ($x_{\text{black}} = 0.97$) and a low reputation peak at a much lower value (0.325). The reason for this low reputation peak is again black’s high honesty, which lets black more often express positions that are in contradiction to those of the other agents, letting black appear as untrustworthy. This can be regarded as a reputation game manifestation of the Cassandra syndrome: the most honest agent may appear less trustworthy than more dishonest agents. We note that agent cyan’s reputation, who is also mostly honest, is slightly bimodal as well.

In the scenario with the deceptive agent red, red reaches on average a significantly higher reputation (0.4) and self-esteem (0.26) than in the ordinary scenario (0.2 and 0.16, respectively). Red’s reputation distribution histogram shows now a broad plateau (from 0.05 to 0.3), a fat tail toward higher reputations (up to 0.95),
and a distinct peak at highest reputations (> 0.95). This peak indicates that once accepted as being very honest, red can defend this position thanks to the higher influence a reputed agent has.

We note that cyan’s and black’s self-estees are higher than in the ordinary scenario and more focused on their intrinsic honesty values. Red’s more frequent lies in this scenario exhibit a stabilizing force to the other’s self-estees. As lies mostly mirror the other’s beliefs, they can strengthen those beliefs if they are not too biased.

The scenario with the clever agent red looks nearly indistinguishable to the previous one, except for the self-esteem of agent red, which is now slightly higher (0.3) near the end of the simulation time. Being smart, red realizes that black and cyan are mostly honest when they speak about red’s honesty (which appears to them to be 0.4). Therefore, red’s self-opinion is more strongly drawn toward this value than in the previous scenario.

The scenario with the manipulative agent red shows that the manipulative strategy is the most successful in allowing red to reach on average the highest reputation and self-esteem among all scenarios investigated. Both quantities show also the strongest rising trends at the end of the simulated period. Red’s chance of being regarded as very reputed (> 0.95) is nearly five times higher in the manipulative scenario compared to the clever one. Compared to the clever scenario, cyan and black’s reputations are lower and show more variance. Cyan’s reputation is now reaching lowest values nearly as frequently as black’s, thanks to cyan’s higher exposure to red’s confusing lies (red is anti-strategical here, thus mostly talking to cyan). It is noteworthy that the
self-esteem of black and cyan are enhanced not only with respect to the clever scenario, but also with respect to black and cyan's intrinsic honesty. This is due to the flattering they get from red, which boosts their self-esteem. Although all agent's reputations are generally higher here compared to the clever scenario, the number of cases in which red's reputation surpasses the ones of the others is strongly increased (see Figure D3).

The dominant agent red does not reach a higher average reputation than the clever agent red, but red's reputation displays a larger dispersion in the dominant scenario than in the clever one or any of the others. Red's chances to be regarded as very reputed (> 0.95) is the largest in the dominant scenario, being ten and two times higher than in the clever and manipulative scenarios, respectively. Red's self-esteem is higher on average by being dominant than being only clever, despite the lower average reputation of red in the dominant scenario. The higher frequency of conversations about red in the dominant scenario couples red's self-esteem more strongly to red's reputation. This effect outweighs the lower average reputation of red in this scenario. Being strategic, red targets predominantly black with self-promotion lies and thereby drives black's opinion away from the other's. As a consequence, black gets often confused and this lets black's reputation reach lowest values (< 0.05) so frequently that black's reputation distribution histogram exhibits a distinct peak there. Figure 14 confirms this interpretation, with exhibiting the lowest reputations for black for moments when red reaches highest reputation values.

In the scenario with the destructive agent red, red reaches on average a reputation significantly higher (0.45) than in the clever and dominant scenarios (0.4). However, the destructive red's reputation exhibits a slowly declining temporal trend, whereas the ones of them being manipulative or dominant are increasing or constant, respectively. Destructive red's reputation is uni-modal (with a broad peak centered on ≈ 0.5) and reaches neither the highest nor the lowest reputation values. Red's self-esteem evolution is initially low but constantly raising during the further simulated period. Their self-esteem distribution function, however, peaks strongly at lowest values (< 0.05). This stronger detaching of red's self-esteem from their reputation in the destructive scenario is caused by them avoiding themselves as a topic; red mostly talks about enemies, not about red. The impact of red's destructive strategy on red's enemies is also clearly visible. Both
other agents, black and cyan, experience now a high chance to be without any reputation. Furthermore, their reputations with red show a declining temporal trend, meaning that red believes more and more red’s own lies. Despite having a low reputation on average in the destructive scenario, agent red surpasses the other agent’s reputations frequently by destroying those. If the goal is to be highly deceptive, but still more reputed than other agents, the destructive strategy seems to be a choice as good as the manipulative one.

A comparison of red’s reputation histogram for the different strategies used is given by Figure 15. This shows that among the strategies investigated here of deceptive agents, on average, the manipulative one seems to be the most successful, followed by the destructive one. If, however, success is defined as reaching the highest reputation values, the dominant strategy seems to be most favorable.

Figure 15 also shows the reputation histogram results for runs with four or five agents. The three agents of the previous simulations were kept, just one or two additional agents are introduced there, who have a low honesty of \( x_{\text{yellow}} = 0.31 \) and \( x_{\text{blue}} = 0.35 \). These simulations can be regarded to be statistically independent of the simulation with three agents and with respect to each other for most practical purposes.

The corresponding reputation density plots for the four and five agent simulations for ordinary and dominant agents are shown in Figure 14. One sees that the reputations of these additional, mostly dishonest agents are correlated with that of red, and the correlation gets stronger the more dishonest agents are present. This indicates that there is some synergy between these least honest agents. There are two effects that can cause this. First, less honest agents are better in befriending each other. Second, there is a generic benefit for liars to draw from an atmosphere of general confusion that a larger number of dishonest agents creates. Their lies fly easier there.

These plots show further that the special strategies still pay off within larger groups, but with a reduced reputation gain compared to the three agent scenario. Now, the destructive agent red manages to reach higher average reputation values than by being manipulative or dominant. The latter are still more efficient in reaching the highest reputation values.

It seems safe to claim that these simulations show that the introduced special deceptive strategies are more successful than just being deceptive or clever. The details of which strategy is best with respect to the different success metrics might also depend on the precise composition of the social group. This was not varied much here, as we kept agent black very honest and agent cyan mostly honest in all runs. We leave the investigation of such effects to future research.

6.4.2. Friendship Statistics

In the following, we want to investigate the friendship relational network of agents in the different setups. For the simulations with three agents, these are displayed in Figure 16 and show that the most dishonest agent (red) manages to befriend best the others, in particular when being manipulative (bottom left). Red’s own friendship budget is nearly equally distributed among the other two agents, with a slight preference for cyan, who, also being a bit dishonest, is slightly better in maintaining friendships than black.

The correlation of friendship and reputation relations can be studied in Figure 17. For each of the hundred runs time-average \( a \rightarrow b \) reputation relation values (with \( a \rightarrow b \) meaning agent \( b \)’s reputation with \( a \)) and the time-fraction of \( a \rightarrow b \) friendships (meaning agent \( a \) regards \( b \) as friend) were calculated and displayed. For visual clarity of the plot, the hundred points in the friendship-reputation plane of each \( a \rightarrow b \) relation were converted into a density. Figure 17 confirms the observation made with Figure 16 that the most dishonest agents are preferentially regarded as friends. No distinct correlation between

![Figure 15. Top: Frequency densities of the red agent being an ordinary or special agent (as indicated by the color of the lines) to have a certain reputation based on the runs underlying also Figures 12 and 13. Middle: The same as top panel, now just with an additional ordinary agent with honesty \( x_{\text{yellow}} = 0.31 \). Bottom: The same as middle panel, just with a further ordinary agent with honesty \( x_{\text{blue}} = 0.35 \). A uniform distribution would appear as marked by the thin horizontal gray lines.](Image)
the friendship strengths and reputation values within the same $a \rightarrow b$ relation is seen, with two exceptions, the dominant and the destructive agents. The density distributions show different levels of dispersion in the friendship and reputation dimensions, but not much (linear) correlation between these variables.

The different strategies of agent red manifest themselves by clearly distinct friendship-reputation relation patterns. The ordinary agent red (top left panel of Figure 17) manages to become both other agents’ preferred friend, at a moderate time averaged reputation of about 0.2. Becoming deceptive (top middle panel) increases red’s reputation to typically 0.4 without changing the friendship network much. The other agents’ reputations increase thereby also by a comparable margin. Red becoming clever (deceptive and smart, top right panel) lets the other agents’ reputations increase further on average, as red’s higher smartness now less often classifies them incorrectly as dishonest. The manipulative agent red (bottom left panel) manages to nearly monopolize black and cyan’s friendship, which turns them thereby into permanent mutual enemies. As the manipulative agent red interviews the others frequently about their self-images, red is well informed about their honesty. In contrast to this, the dominant agent red, who mostly speaks about red and less about others, therefore often incorrectly classifies black as less reliable (see distinct lower red contour in bottom middle panel). The dominant red’s own reputation can occasionally become very large, but usually stays below that of the other two agents and that of the manipulative red agent. Finally, the destructive agent red (bottom right panel) creates the largest dispersion in other agents’ reputation and friendship values.

For the destructive agent red a clear correlation exists between the reputation and friendship red has for others, which is caused by the destructive agent’s tendency to heavily damage the reputations of any enemy. This primarily destroys red’s enemies reputation with red’s friends, but red’s disrespectful opinions are mirrored by red’s friend and thereby imprints also onto red’s own beliefs on red’s enemies. It is interesting that this friendship-reputation correlation effect is stronger for red’s view on black than on cyan. This is a consequence of cyan’s lower honesty, which allows cyan to participate in the destruction of black’s reputation whenever being in a mutual friendship with red.

The relation of run averaged reputations and friendship relations for the simulations with four and five agents are shown in Appendix C. The trends observed with three agents are less obvious there.

6.5. Social Atmospheres

The visual inspection of the belief state and reputation dynamics in Figures 4 and 5, Figures 7–10, and Appendix C shows a variety of social atmospheres, ranging from frozen situations, in which opinions quickly converge to static values (e.g., dominant agent run shown on the left of Figures 9–10), over adaptive regimes, in which individual and collective learning curves can be observed (e.g., ordinary agent run in Figures 4 and 5), to very chaotic situations, in which the beliefs and expressed opinions change rapidly (e.g., dominant agent run shown on the right of Figures 9 and 10). In order to classify these different regimes and to see how different strategies are related to those we introduce a measure of social chaos in a run as

$$\text{chaos} := \left\langle (\langle x_{ij}(t) - \bar{x}_{ij} \rangle)^2 \right\rangle_{[0;T]}$$

where

$$\bar{x}_{ij} := \langle x_{ij}(t) \rangle_{[0;T]}$$

This characterizes the average volatility of all beliefs of a run.

Figure 18 displays the relation of run averaged reputations of agents and this measure of social chaos in different scenarios (ordinary, deceptive, clever, manipulative, dominant, and destructive). All fully deceptive agents (all agents red except the ordinary agent red) seem to create and benefit from social chaos, as higher chaos values are reached and the average reputation of agent red correlates with this. The manipulative and dominant agents seem to benefit most strongly from chaos, whereas the destructive agent red shows the lowest level of a correlation between red’s reputation and the level of social chaos.

The reputation of the more honest agents black and cyan is mostly anti-correlated with the level of social chaos, at least in the cases where those exhibit a high reputation. Agent black sometimes gets into the Cassandra-syndrome regime, where black’s reputation is low, despite black being very honest. Interestingly, in this low reputation regime black’s reputation is positively correlated with the level of social chaos. The steeper reputation-chaos correlation of black in black’s low reputation regime compared to the corresponding correlation for red indicates that a different mechanism is here at work for black (in comparison to red). A plausible explanation is that the effect generating the Cassandra syndrome for black becomes inefficient beyond a certain level of chaos. Chaos increases the lie detection threshold $\kappa$ of every agent $i$, and therefore makes them more tolerant for deviating opinions and thus for those expressed by black when being in the Cassandra syndrome mode.

The relation of run averaged reputations with social chaos for simulations with four and five agents are displayed in Appendix C. The correlations visible in the three agent case are not visible there.
7. Discussion

7.1. The Game and Its Players

We introduced a reputation game simulation to study emerging social and psychological phenomena. The game illustrates the vulnerability of individuals or groups to certain kinds of malicious communications. The rules of the game were designed to study a number of effects witnessed in group dynamics and can be summarized (and generalized) as follows:

A number of players exchange opinions on the other’s reputations (a partly shared reality) while aiming for orientation, reputation, and power.

The terms opinion, reputation, and power should be briefly explained in the game’s context. Here, the exchanged opinions are messages that can be honest or dishonest. Honesty is defined in the game as the frequency in which the players communicate their beliefs. Orientation, knowledge about the environment (or reality), is necessary for the agents to reach their other two goals, reputation, and power. Reputation is defined as the beliefs of others about a player’s honesty. In the game, reputation is a prerequisite for power, which here is the ability to influence the environment, as only the statements of reputed players have a significant chance to impact other’s belief systems. Ultimately, reputation and power are helpful in the real world to obtain other resources, which are, however, not modeled explicitly in the game. Although a high reputation can be reached by an agent by being honest, this typically does not imply a large empowerment, as is shown by the fact that the most honest agent often receives a low reputation in the presence of a deceptive agent. An honest player has little ability to steer others’ beliefs in comparison to a frequent liar. Thus, the most powerful players should be the ones that are least honest, but with a high reputation. The increase of their reputation with respect to their intrinsic honesty therefore seems to be a good measure of power. Honest agents might become reputed, but are rarely powerful.

A number of decisions of agents in the game appear to be driven by chance, but this does not need to be the case. In principle, agents could make decisions according to more sophisticated, deterministic calculations. However, using randomness for now permits to set up the game without having to discuss all principles behind decisions in detail. Nevertheless, a number of behavior strategies were introduced to understand their impact on the game.
These strategies were chosen to resemble to a certain degree deceptive strategies used by humans. In particular, the manipulative, dominant, and destructive strategies introduced here resemble real-world strategies that are used (neither necessarily nor exclusively) by members of the dark triad, Machiavellian, narcissistic, and sociopathic personalities.

7.2. The Player’s Minds

The agent’s information processing is designed to follow information theoretical principles, within some limits. The used cognitive model tries to follow the optimal Bayesian logic, however, agents are unable to memorize all fine details of the resulting high dimensional probability distributions. We believe that such a bound rationality model roughly captures how a human mind operates. Trying to maintain orientation in a complex and changing world requires to follow information principles. These principles, however, demand computational resources beyond what is available to most finite physical systems, such as humans, our agents, or other AI systems. Thus, compromises in the accuracy to represent and process information are always necessary, and these could be the basis of some of the cognitive biases observed in real-world psychology, see for example refs. [73, 108, 109], and in AI.[110,111]

The limitations of the agents’ knowledge representation, which is only a direct product of 1D, parametrized probability functions and not a multidimensional, non-parametric distribution as required by Bayesian logic, can be exploited by adverse strategies of other agents. For example, a statement about some agent’s honesty that strongly disagrees with the receiver’s belief implies a bimodal posterior probability, with a peak associated with the possibility of an honest message and a second peak associated with the possibility of a lie. The relative height of these peaks depends on the clues the receiver got about the message honesty. However, this bimodal distribution cannot be stored in the agents’ belief representation and the information needs to be compressed into this form. As information is inevitably lost in this compression, the resulting reasoning of agents will be imperfect or irrational to a certain degree. This imperfection can be exploited by adversarial attacks, for example in form of large scale propaganda.

To decide whether a message is reliable, agents use a number of signs. Critical agents judge the trustworthiness of a message according to how much it fits their own beliefs or how surprising it is. The surprise of a message is measured in terms of the divergence of the belief resulting from accepting the message in comparison to the present belief. This divergence (or surprise) is measured in the number of bits that would be obtained by this update. The scale against which this surprise is compared
to decide the trustworthiness of messages needs to be learned and kept updated in a changing social environment. This adaptability, however, opens the door to manipulative attacks. Exposing an agent to a large number of strongly diverging opinions inflates this scale, thereby reduces the ability to detect lies, and thus makes manipulations easier. This seems to be the principle of gas lighting communication patterns used by dark triad personalities. We simulated the case where agents are exposed to many propaganda messages, which strongly diverge from their own beliefs, and observed that even agents, which were initially getting more and more skeptical about the trustworthiness of the propaganda, converted eventually to the opinion expressed by the propaganda. The exposure to the propaganda let their reference surprise scale inflate, and thereby their lie detection break. Interestingly, the initially most skeptical agents convert most strongly to the propaganda position, since the propaganda causes the largest mental dissonance in the more skeptical minds within our simulation.

In order to make agents more immune to propaganda we also introduced a smart receiver strategy, which compares a message with what the speaker seems to believe on a topic as well as what the speaker’s typical lies on a topic seem to be. These two reference points, but also the need to construct credible lies, require agents to maintain a mental representation of other’s belief systems, that is a rudimentary Theory of Mind. Here, we propose a simple description of the Theory of Mind updates, which is certainly ad-hoc and should be revised in future research. Smart agents, which are better in maintaining and using their Theory of Mind, are indeed more immune against propaganda and slightly better in discriminating lies from honest statements. Our special agents are all smart as well as deceptive (= pathological liars).

7.3. The Player’s Strategies

The basic strategies that agents can adopt are referred to as being strategic, anti-strategic, egocentric, flattering, aggressive, shameless, and deceptive. They can all be combined to form more complex, special strategies such as the clever (deceptive and smart), manipulative (clever, anti-strategic, and flattering), dominant (clever, strategic, and egocentric), and destructive (clever, strategic, aggressive, and shameless) strategies. The latter three are introduced to emulate communication patterns frequently associated with Machiavellian, narcissistic, and sociopathic personalities, respectively. Reputation game simulations permit to investigate the effectiveness of such communication patterns in achieving the goal of a high reputation and large power. Our simulations verify that such strategies are indeed effective to achieve such goals, at least in a statistical sense, not only in comparison to ordinary agents, but also if we compare to clever agents (= deceptive and smart).

The manipulative strategy most often leads to the highest relative reputation within small groups, the dominant strategy is able to reach the absolute highest reputation values most frequently, and the destructive strategy seems to become more efficient than the other two in larger groups (see Section 6.4). How many of these results can be transferred to real human communication settings will require more detailed investigations.

7.4. Emergent Phenomena

The dynamic of the game is complex, stochastic, and chaotic. Nevertheless, emergent trends and patterns can be observed that resemble real world socio-psychological phenomena. Here, we list the ones we observed in the simulations.

The game setup is an echo-chamber, with only a few agents talking to each other, and who, thanks to the imperfect tracking of other agents’ information sources, do not realize when another agent’s apparent new information is in fact an echo of an earlier, own statement. Emergent echo-chambers in sub-sets of agents can also be observed in simulation runs (even though the size of the population is below the size of real world echo chambers). The reputation network between agents defines who really listens to each other, where “really listening” is meant in the sense of accepting a received message as honest. The formation of an echo-chamber can for example clearly be observed in the simulation of cross-communicating ordinary agents under constant propaganda shown in Figure 7 and discussed in Section 6.2. There, agents cyan and yellow form an echo-chamber, characterized by a growing mutual trust and converging opinions on red, a process in which agent black does not participate.

The occurrence of group opinion building is very manifest in most simulations and is discussed in the context of the smart agent in Section 6.1, of the shameless agent in Section 6.3.1, and the dominant agent in Section 6.3.2. There the phenomena of a freeze-in of group opinions was explicitly mentioned, which happens frequently thanks to the general echo-chamber setup of our reputation game.

The echo-chamber effect allows also for self-deception of agents, which can be observed in many simulation runs. For example the run with the flattering among ordinary agents shown in Figure 8 and discussed in Section 6.3 shows clearly self-deception of the mostly dishonest agent red. Despite the better direct information from the own self-observations, red’s final self-esteem follows red’s enhanced reputation (with respect to red’s honesty), despite the basis for this enhancement being red’s own lies.

The largest self-deceptions in the simulations can be found in some of the runs with dominant agents. There, the self-deception might be classified as an self-esteem boost via narcissistic supply. By preferring as conversation partners the most reputed agents and as topics the dominant agent themselves, dominant agents set up their environment in a way that makes efficient self-deception most likely. If the most reputed agent talks positively and frequently about the dominant agent to that agent, the dominant agent will start to believe in the echo of the own propaganda. The reputed agent has thereby become the supplier of the self-esteem boost. The transition from a realistic self-perception to the boosted self-esteem state can be seen in Figure 9 (third row, right panel, e.g., shortly after time \( t = 250, 400, \) and 750), and is a frequent phenomena for dominant agents as visible from the statistics presented in Figures 13 and 15, and Section 6.4.

Different social atmospheres can also be observed, for example by comparing the runs with dominant agents displayed in the left and right panel of Figures 9 and 10. In the first of the two displayed runs, the group opinions quickly freeze in, thanks to rapidly converging statements of the different agents. In the second run, the dynamics of the opinions is highly volatile and the expressed opinions scatter largely. Not only the opinions of the
This large diversity of opinions leads for all agents to an enlarged surprise reference scale for identifying lies. It also leads to larger lies, as the size of a lie is gauged against this scale during lie construction. This again leads to an even larger scale, forming a run away effect. As a consequence, the agent’s critical lie detection breaks down and the propaganda of the dominant agent can pull opinions as strongly as if it would act on uncritical agents. See Figure 7 for the reduced resilience of uncritical agents against propaganda and Figure 11 (bottom middle and right panels) and Section 6.5 for the run away effect of the lie detection scale.

Thus, an attack on the lie detection system by exposing the victims to a large quantity of strong lies or just statements that create cognitive dissonances can be a successful strategy in the simulation, in particular for strongly self-promoting agents. A real world counterpart of such a strategy is gas lighting in which the victims are exposed to statements designed to confuse the victim’s belief system, see for example ref. [112] and references therein. Gas lighting is a strategy often associated to narcissistic personalities. It is currently not explicitly implemented in the repertoire of strategies used by the dominant agent. Nevertheless, a variant of gas lighting seems to occur in our reputation game as a side product of the dominant agent’s strong focus on a single topic (the dominant agent) and a single conversation partner (the most reputed agent). If dominant agents become reputed, their self-esteem might stay low, for their many lies. This leads to a large cognitive dissonance for them, as in the frequent conversations they have about themselves, they are confronted with opinions that largely diverge from their self-picture. As a consequence, their reference scale for lies increases. Since they use this scale for lie construction and all their communications are lies, they express extreme opinions on any conversation topic.[113]

Since the extreme statements made by such a dominant agent with diverging reputation and self-image also affects the lie reference scales of other agents, the lies of those also become more extreme as well. A toxic social atmosphere can therefore result, which persists until the dominant agent’s self esteem and reputation agree, either on a high or on a low level. If the reputation and self-esteem of a dominant agent are both high, this agent has managed to manipulate the others into providing narcissistic supply, that is helping to maintain the inflated self-image of the dominant agent (see right panel of Figure 10).

Too much cognitive dissonance, which agents experience if exposed to large scale propaganda, can lead to a breakdown of the mental defense against lies, as shown in Figure 7. Working countermeasures that agents can take are honest and trustful exchanges with other propaganda victims and being smart in detecting lies. Both measures make agents more resilient against propaganda, as discussed in Section 6.2.

We also observed some form of Cassandra syndrome within the simulations, in which the most honest agents experience the largest chance to get the lowest reputation and are unlikely to be believed anymore. The opinions expressed of an honest agent are bound to this agent’s beliefs and therefore do not follow as much an evolving group opinion as the opinions expressed by a dishonest agent, who targets other beliefs when lying. As a consequence, the expressed opinions of an honest agent might detach from the group position, which then lets the others perceive this agent as dishonest. These will then discard the opinions expressed by the most honest agent. Such a Cassandra syndrome situation can occur among ordinary agents, but becomes substantially more frequent when a dominant agent is present and manages to dominate the group. Interestingly, the Cassandra syndrome effect weakens with increasing levels of social chaos, probably due to the general loss of the other agents’ ability to discriminate between honest and dishonest messages.

Finally, we see a strong positive correlation of the reputations of the least honest agents. The mechanism generating this are the more easily maintained mutual friendships of dishonest agents, the general liar’s benefit from confusion, and the resulting inflation of the lie detection surprise scale in the presence of more other dishonest agents. This can lead to a deception symbiosis, in which the confusion created by a pathological liar makes it easier for other liars to plant their lies as well. This not only seems to hold for our agents. The negative impact of confusing, extreme messages on the ability of humans to discriminate correct and false statements is a documented psychological effect.[114]

### 7.5. Robustness and Assumptions

The dynamics of our simulations are highly chaotic, which raises the question how robust the results are in particular with respect to the model assumptions. In this initial study, we are unable to answer this question fully and have to leave this open for future research.

However, a number of parameter studies were performed in order to calibrate the model parameters such that a meaningful dynamics appeared. For example, a scan of different values of the caution parameter used in lie construction $f_{\text{caution}}$, revealed that having smaller values helps deceptive agents to build up a higher reputation. However, for the sake of being brief, we just picked the from this perspective sub-optimal value of $f_{\text{caution}} = 0.3$ and did not present results for other values. Another robustness check performed was changing the number of agents from three to five. The friendship and reputation distributions observed for the different strategies with three agents could be observed there as well, however, they were less pronounced.

For these reasons, the numerical results of our simulations should not be regarded as proofs of certain relations, but rather as possible scenarios.

### 7.6. Future Directions

Our reputation game simulation, as introduced here, is intended as a starting point for further developments and investigations. Probably most of its ingredients need to be revised and extended. Here, we want to discuss a few possible future directions.

Currently, the beliefs of agents about others’ honesty and their representation of other agents’ own beliefs have disparate dynamics. In principle, this could be unified by agents just emulating other agents in their minds by using the same computational infrastructure for this, which they use for their own thinking. With such an architecture for the Theory of Mind, not only
the description might become more natural, it might also be possible to simulate phenomena like hallucination as cross-talk between an emulated and the own personality of an agent.

The characters of agents are currently static, programmed strategies. Agents could be enabled to discover and learn strategies on their own, from trial and error, or by watching the actions of other agents. The level of randomness of their actions could also become an adjustable parameter. It would be interesting to see under which conditions for example the malicious strategies introduced here would develop on their own in an evolutionary scenario.

The language of agents can be enriched. More topics could be introduced, as aspects of an outer reality, or additional properties of agents. Also enabling agents to quote each other would be very interesting.

The mental representation agents used to memorize the learned can be made more complex. Real humans are, to some degree, able to remember an entanglement of statements. They can even remove information partly if it turns out that its source was deceptive. Agents could be provided with similar abilities.

Furthermore, the parameters of the used cognitive model might be calibrated against real world data. Finally, the sizes of the simulated social networks need to be increased significantly to mimic real social networks or even social media interactions. For simulation of the latter, the effects of attention steering AI systems should be included, in order to emulate their impact on society.

8. Conclusions

To conclude, we have introduced a reputation game as a socio-psychological simulation that is built on the premise that agents should process information according to simplified information theoretical principles. We showed that a large number of sociological and psychological effects naturally seem to emerge from this premise.

With sufficient care, a number of conclusions might be drawn from our agent based model that can be of interest to different communities. Most of these insights might not be new, and well known in the corresponding fields, however, we believe that there is a value to having them confirmed by a reputation game simulation.

For a social scientist our reputation game simulation might indicate the minimal set of rules and parameters that are necessary to reproduce known socio-psychological effects. The simulation shows that despite being highly chaotic, the outcome of social dynamics might depend in a stochastic, but statistically robust way on a small number of key parameters. For example, the simulations show that a single maliciously deceptive individual can drastically change the character of interactions in a small social group. For the cognition researcher, the level to which the necessary information compression of cognitive systems makes them more prone to manipulations might be an interesting aspect of our model. A psychologist might be interested in the regime of large cognitive dissonance that agents using a dominant strategy often experience when they already managed to build up a high reputation, but still have a low-self esteem. It manifests in a very toxic behavior that only stops when self-image and external image start to coincide, either due to the “narcissistic supply” of the other agents having become strong enough to boost the self-perception of the dominant agent, or when it becomes absent. For social media policy makers, the simulation might illustrate how toxic social atmospheres develop when the participants’ belief systems are challenged too much. Finally, we not only show how indoctrination via propaganda might work on the individual mind, but also how one can resist it. Not surprisingly, honest exchange with other critical minds seems to be effective. We believe that this should be of interest to basically everyone.

Appendix A: Information Representation

We first introduce probabilistic reasoning, before discussing the agent’s belief representation and updating in Sections A.2 and A.3, respectively. The optimal data compression is introduced in Section A.4. An overview on the used mathematical symbols is provided with Table A1.

A.1. Probabilistic Reasoning

Agents need to maintain a picture of their social environment, to know who is honest and who is not. Since they do not have direct access to the intrinsic honesty parameters of any other agent, nor even to their own, they need to deduce these values from the information they get. This information, however, is incomplete, noisy, and often biased, with a noise level that depends on the evolving social atmosphere. Therefore, agents have to cope with significant amounts of uncertainty.

Bayesian probabilities are ideal for logical reasoning under uncertainty. Thereby, probabilities are regarded as a device that keeps book of the plausibility of different possibilities given some information $I$. Assigning a probability value $P(E|I) \in [0, 1]$ to a possibility or an event $E$ therefore is not necessarily expressing how often $E$ happens on average, that is its frequency, but expresses the strength of the belief in $E$ being the case. If, however, an event $E$ has a frequency $f$, then the event’s probability equals this frequency if the latter is known, $P(E|I,f) = f$ with $I = \{f\}$ is the frequency of $E$.

Probabilities are subjective, in the sense that different probability values are assigned by agents with different knowledge. They are objective, in the sense that given the same knowledge state, any ideal mind should assign the same probability values. We use this in the following by only labeling the belief state $I_a$ of an agent $a$ on some quantity $x$, but not explicitly the induced probability $P(x|I_a)$ used by this agent. Any other agent $b$ with an identical belief state $I_b = I_a$ would assign exactly the same probability to $x$, $P(x|I_b) = P(x|I_a)$.

If there is a number of imperfectly known continuous quantities $x_1, \ldots, x_n$ then the PDF $P(x|I)$, with $z = (x_1, \ldots, x_n)$, expresses their joint probability density. The probability (density) of individual quantities is obtained from this by marginalization over the other parameters,

$$P(x|I) = \int dx_1 \cdots dx_{n-1} dx_{n+1} \cdots dx_n P(z|I)$$

(A1)

In case the quantities are independent, the joint probability factorizes into marginal ones,

$$P(z|\text{independence}) = P(x_1|I) \cdots P(x_n|I)$$

(A2)

Often, probabilities do not factorize, $P(z|I) \neq P(x|I)$, independence. This expresses the entanglement between quantities, like that certain combination of two variables are particularly probable. Complicated entanglements can arise in the setting of a reputation game, since agents make statements about the trustworthiness of each other that are only believed in case they appear trustworthy themselves. Here, $x_a$ will denote the honesty of agent $a$, with $x_a = 0$ stating that agent $a$ always lies and $x_a = 1$ that $a$ is always honest. These honesty values are denoted by the tuple $x = (x_a)_{a \in A}$.
Table A1. Used variables and symbols, the Section or Equation of their definition, their ranges, and meanings.

| Variable or symbol | Ref. | Range | Meaning |
|--------------------|------|-------|---------|
| \( P(A|B) \), \( P(x|y) \) | A.1  | [0,1]\( \mathbb{R}^n_0 \) | Probability of \( A \) given \( B \), PDF of \( x \) given \( y \) |
| \( n \) | 3.1  | \( \mathbb{N} \) | Number of agents |
| \( \mathcal{A} \) | 3.1  | \{red, cyan, \ldots\} | Set of \( n \) named agents |
| \( a, b, c, i \) | 3.1  | \( \mathcal{A} \) | Some agents |
| \( \mu, \lambda \) | 3.5  | \( \mathbb{R} \) | Usually sender, receiver, and topic of a communication |
| \( \xi \) | 3.5  | [0,1] | Honesty of agent \( i \) |
| \( \gamma = (\gamma_i)_{i\in\mathcal{A}} \) | 3.5  | [0,1]\( ^n \) | Indexed set of honesty of all agents |
| \( \text{Beta}(\alpha, \beta) \) | (A12) | \( \mathbb{R}^n_0 \) | Beta distribution |
| \( P(\alpha, \beta), \Gamma(\alpha) \) | (A11) | \( \mathbb{R}^n_0 \) | Beta, gamma function |
| \( \psi(\alpha) = d \ln \Gamma(\alpha)/d\alpha \) | (A42) | \( \mathbb{R}^n_0 \) | Digamma function |
| \( l = (\mu, \lambda) \) | 3.5  | (\( -1, \infty \))^2 | Stored belief about honesty of an agent |
| \( t \) | 3.2  | | Some other belief, not necessarily in the format of \( l \) |
| \( j = (\mu, \lambda) \) | 3.5  | (\( -1, \infty \))^2 | Encoding of \( l \) into storage format |
| \( I_{ab} \) | 3.1  | (\( -1, \infty \))^2 | Number of honest statements counted for an agent |
| \( l_{ab} \) | 3.1  | (\( -1, \infty \))^2 | Number of lies counted for an agent |
| \( \tilde{I}_{ab} := (\tilde{I}_{ab}, \tilde{I}_{ab}) \) | (B32) | (\( -1, \infty \))^2 | Belief of agent \( a \) on honesty of agent \( b \) |
| \( \tilde{I}_{ab} \) | (B33) | (\( -1, \infty \))^2 | Beliefs of a on honesty of all agents |
| \( K_L(J, J') \) | (A29) | \( \mathbb{R}^n_0 \) | Kullback–Leibler divergence \( D_{KL}(P(x^l)/P(x^{l'})) \) |
| \( \tilde{I}_{c} := (\tilde{I}_{c})_{j\in\mathcal{J}} \) | (A13) | [0,1] | Expected \( x \) given information \( l \) |
| \( (x)^2 := (x - \tilde{I}^2)_{j\in\mathcal{J}} \) | (A14) | [0,1]\( ^n \) | Uncertainty dispersion of \( x \) given information \( l \) |
| \( \tilde{I}_{ab} := (\tilde{I}_{ab}, \tilde{I}_{ab}) \) | (A13) | [0,1] | Reputation of \( b \) with \( a \) |
| \( t \) | 3.5  | \( \mathbb{N} \) | Time as measured in communication events |
| \( \alpha \rightarrow \beta \) | 3.5  | \( \mathbb{A}^1 \) | Communication of a to b about c |
| \( J_{ab} = f_{\tilde{I}_{ab}}(t) = (\tilde{I}_{ab}, \tilde{I}_{ab}) \) | 3.5  | (\( -1, \infty \))^2 | Message in communication \( a \rightarrow \beta \) at time \( t \) |
| \( \Delta J = f_{\tilde{I}_{ab}} - l_{ab} \) | (A19) | \( \mathbb{R}^2 \) | Apparent novel information in \( f_{\tilde{I}_{ab}} \) on c |
| \( h = \text{honest} \) | A.2  | \{true, false\} | Whether message was honest, meaning \( J_{ab} = l_{ab} \) |
| \( \neg h = \text{lie} \) | A.2  | \{true, false\} | Whether message was a lie, meaning \( J_{ab} \neq l_{ab} \) |
| \( \text{state} \) | B.1  | \{\( h, \neg h \}\} | State of a message |
| \( b = \text{blush} \) | B.1  | \{true, false\} | Whether speaker blushed because of lying |
| \( a = o_j \) | B.1  | \{\( b, \neg b \}\} | Blushing observation of comm. \( J, b = \text{blush} \) |
| \( f_b \) | (B10) | 0.1 | Frequency of blushing while lying |
| \( d = (a \rightarrow b, j, a) \) | (B1) | \( \mathbb{A}^1(-1, \infty)^2(b, \neg b) \) | Data: communication, message, blushing observation |
| \( \mu, \lambda \) := \begin{cases} \mu, \lambda & \text{if } \mu, \lambda \geq 0 \\ 0 & \text{else} \end{cases} \) | (A20) | (\( -1, \infty \))^2 | Ensures convex PDFs, reduces confusing updates |
| \( \eta \) | (B1) | [0,1] | Probability of received message being honest |
| \( K_L \) | B.1  | \( \mathbb{R}^n_0 \) | Amount of new information in message \( j \) if honest |
| \( K_b \) | B.1  | \( \mathbb{R}^n_0 \) | Last ten non-zero \( K_L \)s encountered by agent \( b \) |
| \( \delta = \text{median}(K_b) \) | (B34) | \( \mathbb{R}^n_0 \) | Scale \( b \) compares \( K_L \) against to judge honesty of \( j \) |
| \( S_j = \delta u_j \) | (B18) | \( \mathbb{R}^n_0 \) | Relative surprise of message \( j \) for agent \( b \) |
| \( R(d) \) | (B4) | \( \mathbb{R}^n_0 \) | Ratio of likelihoods for \( j \) lie and for \( J \) honest |
| \( P^0 \) | 1(1, 0) | A.3  | Belief \( I \) on speaker, updated for being honest |
| \( P^0 \) | 1(0, 1) | A.3  | Belief \( I \) on speaker, updated for being dishonest |
| \( \text{const, const', \ldots} \) | (A35) | \( \mathbb{R} \) | Irrelevant constants |
with \( \mathcal{A} \) the set of agents. Any agent \( b \) will maintain a belief state \( I_{ab} \) about these honesty values in form of the PDF \( P(x|I_{ba}) \). This is updated when new data \( d \) becomes available according to Bayes’ theorem,

\[
P(x|d, I_{ba}) = \frac{P(d|x, I_{ba}) P(x|I_{ba})}{\int P(d|x, I_{ba}) P(x|I_{ba}) dx} \tag{A3}
\]

Here, \( P(d|x, I_{ba}) \) is the likelihood, the probability to have obtained the data \( d \) given \( x \) and \( I_{ba} \), \( P(x|I_{ba}) \) is the posterior, the probability for \( x \) given \( d \) and \( I_{ba} \). The latter PDF is the knowledge about \( x \) updated by the data.

### A.2. Belief Representation

Ideally, after receiving new data \( d \), agent \( b \) would update the knowledge by just memorizing it, that is \( I_{ba} \rightarrow I_{ba}' = (d, I_{ba}) \), and use all recorded statements and Bayes’ theorem to construct their current beliefs. However, this would be computationally expensive, as then all reasoning has to be repeated over and over again whenever new information arrives or an action has to be chosen. Therefore, our agents will follow the design of many cognitive systems, which only store and update some compressed information. This will be the tuple \( I_{ba} = (I_{bab}, I_{ba}) \) consisting of \( n \) parameter tuples \( I_{ba} \), that describe agent \( b \)’s honesty impression of agent \( i \), as well as some auxiliary information \( A_b \). As we will not use probabilistic updates for the auxiliary information to limit the complexity of the simulation, we will omit \( A_b \) in our equations in the following. Thus, we write \( P(d|x, I_{ba}) \) instead of the more accurate \( P(d|x, I_{ba}, A_b) \).

We will assume that agents do not store information on parameter entanglements, but simply keep track of the individual marginal probabilities, about the honesty of each other agent and themselves. The knowledge of agent \( b \) about the honesty of all agents is then given by the direct product of individual marginal probabilities,

\[
P(x|I_{ba}) = \prod_{i \in \mathcal{A}} P(x_i|I_{bi}) \tag{A4}
\]

The functional form of the belief about the honesty of a single agent, \( P(x_i|I_{bi}) \), should be derived here from the case where agent \( a \) makes unambiguous observations, namely the state “honest” = \( h \). This happens with the frequency \( x_a \). The update of the self-belief state \( I_{ba} \) of agent \( a \) should then be according to Equation (A3)

\[
P(x_a|I_{ba}, h) = \frac{P(h|x_a, I_{ba}) P(x_a|I_{ba})}{P(h|I_{ba})} \tag{A5}
\]

\[
x_a P(x_a|I_{ba}) \tag{A6}
\]

since \( P(h|x_a, I_{ba}) = x_a \). Thus, whenever agent \( a \) communicates honestly, the probability expressing the self-perception should be multiplied with \( x_a \) and then normalized.

Now, let us investigate the case of agent \( a \) lying, the message is in the state “lie” = \( l \), which happens with frequency \( 1 - x_a \). Then we have

\[
P(x_a|I_{ba}, l) = \frac{P(-h|x_a, I_{ba}) P(x_a|I_{ba})}{P(-h|I_{ba})} \tag{A7}
\]

\[
\propto (1 - x_a) P(x_a|I_{ba}) \tag{A8}
\]

since \( P(-h|x_a, I_{ba}) = 1 - x_a \). Thus, whenever lying, the self-perception probability should be multiplied with \( 1 - x_a \).

It is therefore reasonable to represent the self-perception via numbers of honest and dishonest statements, \( \mu_{ba} \) and \( \lambda_{ba} \), respectively. The corresponding probability is then

\[
P(x_a|I_{ba}) = \frac{(\mu_{ba} + \lambda_{ba} + 1)!}{\mu_{ba}! \lambda_{ba}!} x_a^{\mu_{ba}} (1 - x_a)^{\lambda_{ba}} \tag{A9}
\]

with \( l_{ba} = (\mu_{ba}, \lambda_{ba}) \). Here, it is assumed that the prior distribution in absence of further information is flat, \( P(x_a|I_{ba}) = 1 \) with \( I_{ba} = (0, 0) \).

We adopt this functional form for the honesty information representation for all agents. We drop agent indices for a moment and the requirement of integer parameters \( \mu \) and \( \lambda \) by allowing \( \mu, \lambda \in (-1, 10] \) in the following, where the lower limit ensures proper (integrable) PDFs and the upper limit numerical stability. With this, the corresponding probability generalizes to

\[
P(x) := \frac{x^\mu (1 - x)^\lambda}{B(\mu + 1, \lambda + 1)} = \text{Beta}(x|\mu + 1, \lambda + 1) \tag{A10}
\]

with \( I = (\mu, \lambda) \).

\[
B(a, b) := \int_0^1 dx x^{a-1}(1 - x)^{b-1} = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a + b)} \tag{A11}
\]

being the beta function, and

\[
\text{Beta}(x|a, b) := \frac{x^{a-1}(1 - x)^{b-1}}{B(a, b)} \tag{A12}
\]

the beta distribution. This provides a bit more flexibility compared to the case of \( a, b \in \mathbb{N} \) to express small information gains, which is needed in case the obtained data contains ambiguous information. Such probabilities \( P(x|i) \) for a number of belief states for an agent’s honesty are shown in Figure A1.

We note that \( P(x|i) \) defined this way has a mean and variance of

\[
\bar{x}_i := \langle x \rangle_{(i)} = \int_0^1 dx x P(x|i) = \frac{\mu + 1}{\mu + \lambda + 2} \tag{A13}
\]

\[
\sigma_i^2 := \langle (x - \bar{x}_i)^2 \rangle_{(i)} = \frac{\bar{x}_i(1 - \bar{x}_i)}{\mu + \lambda + 3} \tag{A14}
\]

and denote with \( \bar{x}_{ab} := \bar{x}_{ab} \) the reputation \( b \) has in the eyes of \( a \).

### A.3. Belief Update

When receiving a statement \( J = J_{ab}=c(t) = (\mu_J, \lambda_J) \) from agent \( a \) at time \( t \), agent \( b \) assesses the reliability of the statement by assigning the probability

\[
y_j = P(h|d, I_{ba}) \tag{A15}
\]

to the possibility that \( a \) communicated honestly depending on \( b \)'s receiver strategy as will be discussed in Appendix B. This assignment is based on the prior belief \( I_{ba} \) on \( a \)'s honesty (and some auxiliary information \( A_b \) and the data \( d = d(t) = (a \rightarrow b, o, t) \), which consist of the message \( J \) and the observation \( o \) whether agent \( a \) blushed or not (accidentally revealed a lie or not).

#### A.3.1. Untrustworthy Message

If a communication \( J \) appears completely untrustworthy to the receiver \( b \) they will set \( y_j = 0 \) and ignore the statement made about the conversation topic. However, \( b \)'s opinion about the speaker \( a \) will be updated. Agent \( b \)'s posterior about \( a \) will change according to

\[
P(x_a|\mu_{ba}, \lambda_{ba}) = \frac{P(-h|x_a, I_{ba}) P(x_a|I_{ba})}{P(-h|I_{ba})} \tag{A16}
\]

\[
\propto x_a^{\mu_{ba}} (1 - x_a)^{\lambda_{ba}} \tag{A17}
\]
since \( P(\neg h|x_a, I_{ba}) = 1 - x_a \) irrespective of \( I_{ba} \). This new belief state is represented by increasing \( b \)'s lie-counter \( \lambda_{ba} \) for \( a \) by one, \( I_{ba}(t) \to I_{ba}(t + 1) = (\mu_{ba}(t), \lambda_{ba}(t) + 1) = I_{ba}^0(t) \) (A18)

All other beliefs of agent \( b \) stay unchanged, \( I_{ba}(t + 1) = I_{ba}(t) \) for all \( i \in \mathcal{A} \setminus \{a\} \). For later usage we introduced the notation \( I^0 := I + (1, 0) \) for a belief state \( I \) updated by one lie. Similarly, \( I^0 := I + (1, 0) \) should denote a belief state \( I \) updated by one observed honest statement.

### A.3.2. Trustful Update

For spotting the news in an expressed opinion, the honest \( (\mu_{ba} = 1, \lambda_{ba} = 0) \) or dishonest statements \( \lambda_{ba} > 0 \). For later usage we introduced the notation \( \lambda_{ba} := I_{ba}(t) \) (A19). For spotting the news in an expressed opinion, the receiver needs to know the opinion of the speaker at the time of their last conversation. Agents maintain guesses on each other's previous beliefs for this purpose. The guess of agent \( b \) at time \( t \) what \( a \) believed about \( c \) at their last conversation is denoted as \( I_{bac}(t) = I_{bac} = (\mu_{bac}, \lambda_{bac}) \). How this is maintained is explained later in Section B.4. The new information in an honest statement of \( a \) on \( c \) is then

\[
\Delta J = J(t) = (\Delta \mu, \Delta \lambda) = (1_{I_{bac}(t)} - I_{bac}(t))
\]

(A19)

If all accounting was correct, \( \Delta \mu, \Delta \lambda \geq 0 \) should be the case. If this is not the case, something went wrong and agent \( b \) better assumes not to have received any new information, as expressed in \( \Delta J \to I_{bac} = (0, 0) \). We denote this by

\[
\Delta J^* = (\Delta \mu^*, \Delta \lambda^*) := \begin{cases} (\Delta \mu, \Delta \lambda) & \text{if } \Delta \mu, \Delta \lambda \geq 0 \\ I_{bac} & \text{else} \end{cases}
\]

(A20)

Agent \( b \) therefore realizes that agent \( a \) is reporting agent \( c \) to have made \( \Delta \mu^* \) new honest and \( \Delta \lambda^* \) new dishonest statements since they spoke last about \( c \). The belief update on \( c \) should then be \cite{118}

\[
P(x_c | \Delta J^*, h, I_{bac}) = \frac{P(\Delta J^* | x_c, I_{bac}) P(x_c | I_{bac})}{P(\Delta J^* | I_{bac})} \propto x_c^{\lambda_{bac} + \Delta \lambda^*} (1 - x_c)^{1 - \lambda_{bac} + \Delta \mu^*}
\]

(A21)

This can be represented by agent \( b \) just increasing the counts for assumed honest and dishonest statements of \( c \), that is

\[
l_{bc}(t) \to l_{bc}(t + 1) = l_{bc}(t) + \Delta J^*(t)
\]

(A23)

Such a trustful update is illustrated in Figure A2.

Since agent \( b \) assumes that agent \( a \) has said the truth, \( b \) registers

\[
l_{bc}(t) \to l_{bc}(t + 1) = (\mu_{bc}(t) + 1, \lambda_{bc}(t) = I_{bac}(t))
\]

(A24)

All other beliefs of agent \( b \) stay unchanged, \( l_{bc}(t + 1) = l_{bc}(t) \) for all \( i \in \mathcal{A} \setminus \{a, c\} \).

Finally, we need to deal with the case that agent \( a \) made a self-statement that agent \( b \) regards as absolutely honest. Then, the two above update rules for \( c \) and \( a \) just need to be merged into a single one for \( a \),

\[
l_{bc}(t) \to l_{bc}(t + 1) = I_{bac}(t) + \Delta J^*(t)
\]

(A25)

and \( I_{bac}(t + 1) = I_{bac}(t) \) for all \( i \in \mathcal{A} \setminus \{a\} \).

### A.3.3. Skeptical Update

The two cases of updates discussed above lead to joint belief states on \( a \) and \( c \) for agent \( b \) that again are represented by product states without any entanglement,

\[
P(x_a, x_c | d(t), I_{bac}(t)) = P(x_a | I_{bac}(t + 1)) P(x_c | I_{bac}(t + 1))
\]

(A26)

When agent \( b \) is unsure whether \( a \) was honest or lied, the resulting belief state should be a superposition of the state after an assumed honest communication and a perceived lie. The former is given by Equation (A23) (Equation (A24) for \( a \neq c \) or Equation (A25) for \( a = c \)) and the latter by Equation (A18). The superimposed states should have weights according to their probabilities. Thus, \( y_j = P(h \mid d, I_{bac}) \) is the weight of the honest message state and \( 1 - y_j = P(\neg h \mid d, I_{bac}) \) the weight of the dishonest message state.

Let us first assume that \( a \neq c \). We then have

\[
P(x_a, x_c | d, I_{bac}) = y_j P(x_a | I_{bac}) P(x_c | I_{bac}) + (1 - y_j) P(x_a | I_{bac}) P(x_c | I_{bac})
\]

(A27)

\[
= y_j \text{Beta}(x_a, |I_{bac}) \text{Beta}(x_c | I_{bac}) + (1 - y_j) \text{Beta}(x_a, |I_{bac}) \text{Beta}(x_c | I_{bac})
\]

(A28)
We note that this is not a direct product of marginal distributions any more used in the agent’s memories since b’s knowledge on the honesty of a and c got entangled.

When a speaks about themselves, we have c = a and assign\[^{[19]}\]
\[
P(x_a | d, l_b) = y_i \text{Beta}(x_a | l_{b0}^i + \Delta I^a) + (1 - y_i) \text{Beta}(x_a | l_{b0}^i)
\]
(A28)

In general, this is also not in the format used by agent b to memorize beliefs, \( P(x_b | l_{bc}(t + 1)) \equiv \text{Beta}(x_b | l_{bc}(t + 1)) \), which raises the need for a compression of the correct new belief state into a memorizable, simpler form.

Since the cases of a certainly honest and a certainly dishonest message are enclosed in Equations (A27) and (A28) by setting \( y_j = 1 \) and \( y_j = 0 \), respectively, we only have to consider skeptical updates in the following.

### A.4. Optimal Belief Approximation

Usually the honesty of a message is unclear to the receiver b. In this case, the belief state \( P(x_b | l') \) with \( l' = (d(t), l_b(t)) \) as given by Equation (A27) is a superposition of the two belief states that would arise if the message is known to be honest and to be dishonest. In order to cast \( P(x_b | l') \) into the functional form of \( P(x_b | l) \) a new \( l'' = l_b(t + 1) \) has to be found that captures as much as possible the information of \( l' \). The information loss in this approximation of \( l' \) by \( l'' \) is measured by the Kullback-Leibler (KL) divergence

\[
KL_{\text{KL}}(l', l'') := D_{\text{KL}}(P(x_b | l') || P(x_b | l''))
\]
(A29)

in units of nits (\( = 1.44 \) bits).\[^{[31]}\] Thus, \( KL_{\text{KL}}(l', l'') \) should be minimized with respect to \( l'' \), the parameters of the approximate belief state.\[^{[120]}\] These then form the next information state \( l_{bc}(t + 1) = l'' \).

Since the update concerns only the knowledge about agents a and c, the sender and topic of a message, only the beliefs about those need updating. Side effects do not occur here as agents do not track entanglements. Learning that a’s honesty is different from what b previously has assumed is not letting b reevaluate a’s past statements as b neither memorizes those precisely, nor the entanglements these imply.

Thus, the relevant KL for agent b’s belief update after receiving information from a about c is \( KL_{\text{KL}}(x_a, x_b)(l', l''') \) with \( P(x_a, x_b | l') = P(x_a | d, l_{ba} l_{bc}) \) being the accurate, potentially entangled belief state and

\[
P(x_a, x_b | l'') = P(x_a | l_{b0}^a) P(x_b | l_{b0}^b)
\]
(A31)

being the simplified state over the relevant subspace of \( x_a \) and \( x_b \) that will be memorized. As the latter is a direct product of 1D PDFs, it turns out that it is sufficient to perform only two 1D updates based on the two marginals

\[
P(x_a | l') = \int_0^1 dx_b P(x_a, x_b | l')
\]
and
\[
P(x_b | l') = \int_0^1 dx_a P(x_a, x_b | l')
\]

This is because the 2D KL of the joint update on agents a and c separates into two 1D KLS for the marginal distributions of \( x_a \) and \( x_b \).

Thus, the belief state \( P(x_a, x_b | l'') \) over the subspace of both agents is approximated as

\[
P(x_a, x_b | l'') = \text{Beta}(x_a | l_{b0}^a) \text{Beta}(x_b | l_{b0}^b)
\]
(A32)

and these can be minimized individually with respect to \( l_{b0}^a \) and \( l_{b0}^b \). Constant terms with respect to \( l_{b0}^a \) and \( l_{b0}^b \) can be reparametrized.

For calculating these single agent marginal KLS, \( KL_{\text{b0}}(l', l'') \) and \( KL_{\text{ba}}(l', l'') \), we need expressions for the marginal updates on speaker and topic, \( P(x_a | l') \) and \( P(x_b | l') \) as given by Equations (A33) and (A34). The involved integrals can be calculated analytically and the results for the different cases unify and generalize to a single expression of the marginal update for any agent \( i \in A \).

\[
P(x_i | l'') = y_i \text{Beta}(x_i | l_{b0}^i) + (1 - y_i) \text{Beta}(x_i | l_{b0}^i)
\]
(A36)

with

\[
l_{bi} := l_{bi} + \{1, 0\}_i \text{ speaker } + \Delta I^i \text{ topic}
\]
(A37)
changes after receiving the message $J_{ab} = (23, 1)$ (black dotted line) by an amount that depends on whether agent $b$ trusts the message fully ($y_j = 1 \Rightarrow I'' = (3, 6)$, blue), with the sender’s reputation $y_j = 0.57 \Rightarrow I'' = (4.0, 1.2)$, orange) or only a little ($y_j = 0.1 \Rightarrow I'' = (4.6, 3.3)$, green). For these cases, the correct posteriors are shown with dashed lines and the memorized PDFs as solid lines in the corresponding colors. The perceived honesty of the message is included in the updates shown in color, but not in the naive update (black dashed line). Left: Linear scale. Right: Logarithmic scale.

Figure A4. Like Figure A3, just with the initial belief state of the receiver being $I_{ba} = (1, 23)$ (solid black line) and the trusts in the message being full ($y_j = 1 \Rightarrow I'' = (25, 24)$, blue), undecided ($y_j = 0.5 \Rightarrow I'' = (0, 1.5)$, orange line), or poor ($y_j = 0.08 \Rightarrow I'' = (0.68)$, green). As the initial belief and the message contradict each other strongly, the last two updates (with $y_j < 1$) can only coarsely capture the bimodal posterior for the price of getting closer to the uninformative state $I_{ba} = (0, 0)$. The displayed updates should only be expected for naive (blue line) to uncritical (green line) agents, as critical and smart agents would put far less trust in a so strongly diverging opinion, as detailed in Section B.

\[
I_{bi}^{\text{th}} := I_{bi} + (0, 1) | \text{speaker}, \quad \text{and} \quad I_{i|\text{condition}} := \begin{cases} I & \text{condition is true} \\ I_0 & \text{condition is false} \end{cases} \text{ (A38)}
\]

an information that only is taken into account in case the condition is true. Equation (A36) is valid for all agents $i \in A$, including the topic $c$, the speaker $a$, the receiver $b$, or anybody else. In case $i \notin \{a, c\}$, Equation (A36) states that for agent $i$ the initial belief is to be kept, $P(x_i|I') = \text{Beta}(x_i|I_{bi}) = P(x_i|I_{bi})$, as no information about $i$ was revealed. The single agent’s marginal KLSs are then

\[
\text{KL}_{x_i}(I', I'') = y_j \text{KL}_{x_i}(I_{bi}', I_{bi}'') + (1 - y_j) \text{KL}_{x_i}(I_{bi}, I_{bi}'') + \text{const, with} \quad \text{const} = \left(\begin{array}{c}
(\lambda - \lambda'') [\psi (\mu + 1) - \psi (\mu + \lambda + 2)] \\
+ \ln \frac{B(\mu' + 1, \lambda' + 1)}{B(\mu + 1, \lambda + 1)}.
\end{array}\right) \text{ (A40)}
\]

\[
\psi(a) = \frac{d \ln \Gamma(a)}{da} \quad \text{(A42)}
\]

the digamma function and const an $I''$ independent constant.\cite{121,122} These KLSs, $\text{KL}_{x_i}$ for speaker $a$ and $\text{KL}_{x_i}$ for topic $c$, then have to be minimized numerically with respect to $I'' = I_{bi}'' = (\mu''_{bi}, \lambda''_{bi})$ for $i \in \{a, c\}$. Details of the numerical implementation are given in Appendix A.5. The parameters obtained by minimizing $I''$ are stored as the updated belief $I_{ba}(t + 1)$ of agent $b$ about agent $i$. Examples of such updates are shown in Figures A3 and A4.

A.5. Numerical Details

Now, we detail how the KL minimization introduced in Section A.4 is performed numerically. We use the Python package acipy\cite{123} to implement and minimize the KLSs with the second order schemes trust-exact and trust-nag\cite{124,125} in this sequence. In our experience, the former scheme seems to be more robust, and therefore provides the starting point for the latter scheme, which seems to be more accurate. Furthermore, we use the machine learning package jax\cite{126} configured for 64 bit calculations to auto-differentiate the KLSs to obtain their required Jacobians and Hessians as well as to speed up all KL-related computations via just-in-time compilation, which accelerates them substantially. Unfortunately, we found that the numerical results of the KL minimization do not exactly agree if executed on different computers. Since the game dynamics is chaotic, such
tiny numerical differences can grow and result in differing game evolution in the later parts of some runs (visible to the eye typically after $t = 1000$ in some of the runs). We verified that the statistical results are not significantly affected by this. Furthermore, to ensure $\mu'', x'' > -1$ in every optimization step the KL divergence $K_L(x', x'')$ is modified to the objective function

$$K_L(x', y(x')) = |x' - y(x')|^2 + |(y'' - y(x''))|^2$$

with $y(x') = \max(x, y_0), y_0 = -1 + 10^{-10}$, and

$$\text{ReLU}(x) = \begin{cases} 0 & x < 0 \\ x & x \geq 0 \end{cases}$$

the rectified linear unit function. This way, the correct minimum is found and the KL divergence $K_L(x', x'')$ can be sufficient small to go unnoticed by the receiver. These are opposite requirements and the optimal scale depends on the lie detection abilities of the receiver. It can therefore be assumed that lie construction and detection strategies should be the result of an antagonistic co-evolution. Here, we follow some imagined first steps of such an evolution by first constructing some basic lie detection strategies in Section B.1, then introduce an adaptive lie construction strategy in Section B.2, and finally a smart lie detection strategy adapted to this in Section B.3. Finally, we explain how the Theory of Mind (or auxiliary) variables used by agents in lie construction and detection are maintained in Section B.4. An overview on the different receiver strategies is given in Table B1.

### Appendix B: Detailed Receiver Strategies

In our reputation game, a speaker tries to construct effective lies when deceiving. An effective lie should on the one hand be as big as possible (as measured in bits) to pursue the speaker’s agenda, and on the other hand sufficiently small to go unnoticed by the receiver. These are opposite requirements and the optimal scale depends on the lie detection abilities of the receiver. It can therefore be assumed that lie construction and detection strategies should be the result of an antagonistic co-evolution. Here, we follow some imagined first steps of such an evolution by first constructing some basic lie detection strategies in Section B.1, then introduce an adaptive lie construction strategy in Section B.2, and finally a smart lie detection strategy adapted to this in Section B.3. Finally, we explain how the Theory of Mind (or auxiliary) variables used by agents in lie construction and detection are maintained in Section B.4. An overview on the different receiver strategies is given in Table B1.

### B.1. Basic Lie Detection

A lie detection strategy of an agent is a recipe for how to choose the weight $y_j := P(d|a)$ of a message $j$ in a communication $a \rightarrow b$, that is how to judge the trustworthiness of a received message. For example, naive agents always assign $y_j = 1$ irrespectively of the data. This is obviously a poor strategy. It already is problematic in case of non-deceptive agents\cite{127} for the strong echo chamber effect it allows, which leads to a too rapid convergence of premature opinions.

The message weight $y_j$ should best be assigned according to Bayes theorem, yielding

$$y_j = \frac{P(d|h)P(h)}{P(d)}$$

the likelihood ratio, $d = (a \rightarrow b, j, o)$ the data available to $b$, and

$$P(h) = \int dx_0 P(x_0|\xi_{ba}) = (\xi_{ba})_{(x_0|x_{ba})} = \xi_{ba}$$

the prior probability that $b$ assigns to $a$ for being honest. Thus, a receiver strategy is fully specified as soon as the likelihood $P(d|h)$ and $P(d|h)$ are given or even just their lie-to-honest likelihood ratio $R(d) = P(d|\neg h)/P(d|h)$. The reputation of a speaker has a strong influence on whether their potentially outrageous statements will be believed or not. If we set $y_j = 1/2$ to investigate which statements are at the margin to being trustworthy and solve Equation B3 for the likelihood ratio

$$R = \frac{\xi_{ba}^{-1} - 1}{\xi_{ba}^{-1} - 1} = \frac{\xi_{ba}}{1 - \xi_{ba}}$$

we see that three agents with reputations $\xi_{ba} = 0.1, 0.5$, and $0.9$ reach $y_j = 1/2$ for $R = 1/2, 1$, or $0$, respectively. Thus, the lie-to-honest likelihood ratio of a statement can be 81 times larger for the most reputed agent $\xi_{ba} = 0.9$ compared to a statement by the least reputed of those agents $\xi_{ba} = 0.1$ before it is perceived as only half trustworthy. Statements of reputed agents are much more trusted.

We assume in the following that these likelihoods are given by independent probabilities for a number of data features $f_j(a)$ with $j$ labeling the different features. Thus, for the honesty state $\epsilon \in \{h, \neg h\}$ we have

$$P(d|\epsilon) = \prod_j P(f_j(d)|\epsilon)$$

The features used in basic lie detection are naive trust, speaker reputation, blushing, confessions, and message surprise. Smart lie detection will
additionally use expectation matching. These features will be explained in the following. The assumption of their independence is not entirely realistic, however, our aim is to set up a reasonably functioning lie detection, but not necessarily the best possible. The independence assumption permits to write

\[ R(d) = \prod_j R_j(f_j(d)) = \prod_j \frac{P(f_j(d)|\neg h)}{P(f_j(d)|h)} \quad (B8) \]

To calculate the likelihood ratio, naive agents use only naive trust, uncritical agents use additionally the speaker reputation and blushing, critical agents use further confessions and surprise information, whereas smart agents exploit expectation matching in addition to the former features, which is whether a message looks more like what the speaker seems to believe, or what the speaker apparently wants them to believe. We also introduce deaf agents, who only use blushing information to learn about others, as an illustrative reference. Deaf agents are also uncritical, as they do not inspect the message content, neither for deciding about its honesty, not for updating their beliefs.

B.1.1. Naive Trust

Naive agents always trust the speaker and set \( y_J = 1 \). This implies that for them

\[ R(d) = R_{naive}(d) = 0 \quad (B9) \]

or \( P(d|\neg h) = 0 \), meaning that they assume a lie would never have reached them.

B.1.2. Speaker Reputation

Let us first inspect the case that no feature beyond the message existence is used at all, and that this existence does not imply any information on the honesty, \( P(d|h) = P(d|\neg h) \). Therefore, \( R(d) = 1 \) and \( y_J = \bar{R}_{ba} \). Thus, without inspecting the message data agent \( b \) assigns the prior average belief on the honesty of \( a \) to the message being honest. This already provides some amount of defense against liars, since if identified as such, they get their messages down weighted.

B.1.3. Blushing

The blushing feature \( f_b(d) \) = \( a \in \{ \text{blush, no blush} \} = \{ \neg b \} \) has the likelihood

\[ P(b|\neg h) = f_b \quad (B10) \]

\[ P(b|h) = 0, \quad \text{and} \quad (B11) \]

\[ P(\neg b|\text{state}) = 1 - P(b|\text{state}) \]

Therefore, \( R(b) = \infty \) and \( R(\neg b) = 1 - f_b \). Thus, the uncritical agent assigns

\[ R_{uncritical}(d) = R_b(a) = \begin{cases} 1 - f_b & \text{for } b \\ 1 - f_b & \text{for } \neg b \end{cases} \quad (B13) \]

where \( P(\neg b|o) \) := \( P(o = \neg b|o) \in (0, 1) \) is the logical theta function that is unity in case of no blushing, and otherwise zero. The uncritical agent, who uses only blushing information, assigns \( y_J = 0 \) in case the speaker blushes, otherwise \( y_J = \bar{R}_{ba}[(1 - f_b) + f_b\bar{R}_{ba}]^{-1} = \bar{R}_{ba}[0.9 + 0.1\bar{R}_{ba}]^{-1} \approx \bar{R}_{ba} \), since \( f_b = 0.1 \). The small enhancement of \( y_J \) with respect to \( \bar{R}_{ba} \) is due to the weak indication of honesty implied by non-blushing, see Equation (B3) with \( R(d) = R_b(\neg b) = 1 - f_b = 0.9 \) inserted.

B.1.4. Confession

As agents rather overstate their honesty than understate it, a self-statement of a currently non-blushing agent \( a \) indicates an honesty \( \bar{R}_{ja} \) below the agent's reputation \( \bar{R}_{ba} \) to \( b \) must be an honest confession.

Whether a confession is present is given by

\[ f_c(d) := c = (\bar{R}_{ja} < \bar{R}_{ba}) \in \{ \text{true, false} \} \quad (B14) \]

and we have \( P(c|\neg h) = 0 \), such that

\[ R_c(c, \neg b) = \frac{P(c \land \neg b|h)}{P(c \land \neg b)} = 0 \quad (B15) \]

and therefore \( y_J = 1 \) if a confession is present. The absence of a confession does not bear much information, as it could be caused by a lie or by agent \( b \) being misinformed about the true honesty of \( a \). The former has a probability of \( 1 - x_b \), but the probability of the latter is hard to estimate accurately. Thus, it is safer to set the likelihood ratio for all other cases to be uninformative,

\[ R_c(c \land \neg b) = 1 \quad (B16) \]

than to risk to get misleading hints. We collect all these cases in

\[ R_c(c, o) = P(\neg c \lor b|c, o) \quad (B17) \]

again using the probability notation to express a logical theta function.

B.1.5. Message Surprise

Critical agents use in addition to the blushing and confession information the cognitive dissonance the message generates if taken for true, which we associate to the surprise of a message \( f_a \rightarrow c \), with respect to their own beliefs. This surprise is \( s_J = KL_{x_a} (\mu_{x_a, b} \rightarrow I_a) \), the number of nits a plain adaptation of the message would cause in \( b \)'s mind. This gets compared to an agent specific and learned reference scale \( x_b \) to form the normalized surprise data feature

\[ f_s(d) := s_J \equiv \frac{KL_{x_a} (\mu_{x_a, b} \rightarrow I_a)}{x_b} \quad (B18) \]

Here, we make the ad-hoc assumption that critical agents implicitly assume the distributions of \( s_J \in R_b^0 \) to be

\[ P(s_J|h) := e^{-s_J} \quad (B19) \]

\[ P(s_J|\neg h) := \frac{s_J^2}{2} e^{-s_J} \quad (B20) \]

such that for them

\[ R_{critical}(d) = R_s(s_J) R_c(c, o) R_b(o) \quad (B21) \]

\[ = \frac{s_J^2}{2} P(\neg c \lor b|c, o) \frac{1 - f_b}{P(\neg b|o)} \quad (B22) \]
This means critical agents assume the surprises of honest messages to be distributed exponentially, with a clear peak at zero surprise, whereas that of lies to have a typical surprise $s_t$ of at least $\sqrt{2}k_h$, the surprise level above which the lies should dominate. The assumed surprise likelihood functions are depicted in Figure B1. They allow for a more critical discrimination of lies from honest statements than blushing, confession, and the speaker’s reputation alone. Tuning their auxiliary parameters $\kappa$ allows agents to adapt the absolute surprise distribution functions $P(s_j|\text{state})$ to the social situation they find themselves in. This will be detailed later in Section B.4.

B.2. Lie Construction

With the basic receiver strategies to detect lies in place, the question can be addressed how agents should construct their lies.

Lies toward naive and uncritical agents can be arbitrarily big, as these do not inspect the messages closely. Thus, these agents are very vulnerable to propaganda. Lies toward critical as well as smart agents need to balance the push for the speaker’s agenda, favoring larger lies, and the risk to get caught, which increases with the size of the lie (where the size is measured by the receiver in units of bits).

As a statement toward a critical or smart agent gets judged on the basis of how much it diverges from the receiver’s own opinion, it better stays close to this opinion and deviates only so little in the desired direction that it can go unnoticed. In order not to be too predictable in this, lies are designed such that their surprises approximately match the assumed surprise distribution of honest statements, Equation (B19).

A liar $a$ proceeds in the following way when talking to an enemy or a friend. The agent takes $I_{abc}$, the assumed belief of the recipient $b$ on the topic, decides on the direction $D \in \{(1, 0), (0, 1)\}$ of the bias to be applied according to whether $c$ is a friend to $a$ or an enemy, respectively. The lie will be constructed as

$$J_{a \leftarrow b} = I_{abc} + \alpha D$$  \hspace{1cm} (B23)

with $\alpha \in \mathbb{R}^+_{0}$ such that the receiver is expected to experience only a certain surprise by the lie. This is achieved by drawing randomly a target normalized surprise $S_J \sim P(S_j|h)$, multiplying it with $\kappa_{J_{\text{caution}}}$, where $\kappa_J$ is agent $a$’s substitute for $\kappa_h$, unknown by $b$ and $f_{\text{caution}} = 0.3$ is a caution factor to compensate for the mistake thereby done, and choose $\alpha$ via a numerical line search such that

$$KL_{\mu_x}(I_{abc} + \alpha D, I_{abc}) = \kappa_{J_{\text{caution}}^{-1}}$$  \hspace{1cm} (B24)

For an agent being a topic, who is neither a friend or an enemy, a white lie is used by setting $J_{a \leftarrow b} = I_{abc}$. White lies do not necessarily bias the recipient’s opinion on $c$, however they let the speaker appear honest without revealing the speaker’s true opinion.

B.3. Smart Lie Detection

A more efficient, smart lie detection takes into account the way lies are constructed. The agent’s lies are constructed as biased copies of what the speaker $a$ thinks the receiver $b$ believes on the topic. This opens the possibility for a smart agent $b$ to discriminate messages by matching them up against expected honest and dishonest statements of the speaker. For this $b$ needs an idea of what $a$ believes on topic $c$, denoted as $I_{bac}$ (agent $b$’s guess for $a$’s belief on $c$), as well as an idea of what $a$ wants $b$ to believe on that topic, denoted as $\tilde{I}_{bac}$ (b’s guess for what $a$ wants $b$ to think about $c$). Which of those matches better to the message $J_{a \leftarrow b}$ is then an indicator of the message’s honesty. The data features used by smart agents are the surprisal distributions with respect to $I_{bac}$ and $\tilde{I}_{bac}$, $\tilde{\kappa}_\text{h} := KL_{\mu_x}(J_{a \leftarrow b}, I_{bac})$ and $\kappa_h := KL_{\mu_x}(J_{a \leftarrow b}, \tilde{I}_{bac})$, respectively. The corresponding normalized surprisal distributions $S_{\text{state}} := S_{\text{state}}/\kappa_h$ (with state $e \in \{h, \neg h\}$) are again assumed to be zero peaked exponential distributions,

$$P(S_{\text{state}}|\text{state}) := e^{-S_{\text{state}}}$$  \hspace{1cm} (B25)

with the lie detection scale parameter $\kappa_h$. This specifies the distribution of $S_{\text{h}}$ in case $h$, as well as of $S_{\neg h}$ in case $\neg h$. The distribution of $S_{\text{h}}$ in case $\neg h$ and that of $S_{\neg h}$ in case $h$ are not needed in detail, we only assume them to be identical,

$$P(S_{\text{h}}|\neg h) = P(S_{\neg h}|h)$$  \hspace{1cm} (B26)

Furthermore, we assume these two features to be independent of each other, so that their lie-to-honest likelihood ratio becomes

$$R_{\text{em}}(S_{\text{h}}, S_{\neg h}) := \frac{P(S_{\text{h}}|S_{\neg h}|\neg h)}{P(S_{\text{h}}|S_{\neg h}|h)} = \frac{P(S_{\text{h}}|\neg h)}{P(S_{\text{h}}|h)}$$  \hspace{1cm} (B27)

$$R_{\text{h}}(S_c, o) := \frac{P(S_c|\neg h)}{P(S_c|h)}$$  \hspace{1cm} (B28)

$$R_{\text{\neg h}}(S_c, o) := \frac{P(S_c|h)}{P(S_c|\neg h)}$$  \hspace{1cm} (B29)

For the smart lie detection, this likelihood ratio is just multiplied to the likelihood ratio critical agents use

$$R_{\text{smart}}(\alpha) = R_{\text{em}}(S_{\text{h}}, S_{\neg h}) R_{\text{h}}(S_{\neg h}) R_{\text{\neg h}}(S_{\text{h}}) R_c(\{1, 0\}) R_o(o)$$  \hspace{1cm} (B30)

$$= e^{\kappa_{h^{-1}} S_{\text{h}}} \frac{\kappa_{\neg h^{-1}} S_{\neg h}^{-\alpha} \mathbb{I}(c \lor b \lor o) \frac{1 - f_b}{P(b|\neg b)}}{2}$$  \hspace{1cm} (B31)
Special deception strategies, which circumvent or even exploit smart lie detection, can be imagined as well. These are beyond the scope of this work. The above strategies are sufficient to illustrate what kind of strategies might be used by real humans. Note that we do not claim that the ones chosen here are exhaustive.

### B.4. Auxiliary Parameters Update

We now summarize how all the auxiliary parameters forming the Theory of Mind knowledge are maintained. After receiving the communication \( J = f^J_{a → b} \) (and eventually having responded), agent \( b \) performs updates of the following parameters: Lists of friends \( F_b \) and enemies \( E_b \), guesses for agent \( a \)’s belief on and intention for \( c \), \( I_{bac} \) and \( \tilde{I}_{bac} \), respectively, as well as the reference surprise scale \( K_b \).

#### B.4.1. Friends and Enemies

Agent \( b \) updates the list of friends \( F_b \) and that of enemies \( E_b \), where \( F_b = \{ b \} \) and \( E_b = \{ \} \), initially. An agent in none of these lists is regarded by \( b \) as being neutral to \( b \).

In case agent \( a \) made a statement \( J \) about \( a \) to \( b \), agent \( b \) memorizes how much respect \( r_{bac} \) \( \rightleftharpoons \) \( \tilde{r}_{bac} \) agent \( a \) thereby expresses for \( b \), where we define respect as the communication stated honesty of an agent. Then the median \( \overline{r}_b = \text{median}(\{r_{bac} \mid c \in A(a,b)\}) \) of the memorized respect values of all other agents is calculated and compared to this updated one. If \( r_{bac} > \overline{r}_b \) agent \( a \) is added to the set \( F_b \) of \( b \)'s friends and removed from \( E_b \), the list of b’s enemies (if listed there). If \( r_{bac} < \overline{r}_b \) agent \( a \) will be added to the enemy list and removed from the friendly list. In case \( r_{bac} = \overline{r}_b \), these lists stay as they are.

In summary, an agent \( a \) is regarded as a friend by \( b \) whenever \( a \)'s last statement about \( b \) was more positive than the median of other agents' last statements at that point in time and \( a \) is regarded as an enemy, if this was less positive.

#### B.4.2. Other’s Beliefs and Intentions

Agents maintain an image of the opinions and intentions of the other agents. Agent \( b \) does not have direct access to the beliefs of agent \( a \), but only to the received message \( J = f^J_{a → b} \). This message has to be analyzed to determine \( a \)'s beliefs.

Agent \( b \) extracts from the message what \( a \) seems to believe on topic \( c \), whenever \( a \) seems to be honest, and stores this as \( I_{bac} \) (agent \( b \)'s best guess for \( I_{bac} \)). Similarly, agent \( b \) can also determine the intention of \( a \) when \( a \) is lying. In that case the message contains what \( a \) wants \( b \) to believe about \( c \). This intention is stored by \( b \) as \( \tilde{I}_{bac} \) (agent \( b \)'s best guess for \( \tilde{I}_{bac} \)).

The updates for \( I_{bac} \) and \( \tilde{I}_{bac} \) are done by blending the message \( J \) into the present value of these variables with a weight according to how much the message seems to be honest (weight \( \gamma_J \)) or dishonest (weight \( 1 - \gamma_J \)), respectively:

\[
l_{bac}(t) \rightarrow l_{bac}(t + 1) = \gamma_J l_{bac}(t) + (1 - \gamma_J) J_{bac}(t)
\]

\[
\tilde{l}_{bac}(t) \rightarrow \tilde{l}_{bac}(t + 1) = (1 - \gamma_J) l_{bac}(t) + \gamma_J J_{bac}(t)
\]

These update rules can be regarded as modified DeGroot learning, which is often treated as the counterpart to fully Bayesian updates that have been used for the direct observation of others’ opinions in this work.\[^{1129–131}\] The only difference to classical DeGroot updates is the variable trust matrix, which here always adapts to the presumed trustworthiness of the message at hand. Similar rules are also used for agent based simulations on trust networks.\[^{135}\] These updates should provide guesses of \( b \) for \( I_{bac} \) and \( \tilde{I}_{bac} \) (modified by the bias of the lie), respectively. The corresponding guesses, \( l_{bac} \) and \( \tilde{l}_{bac} \), become accurate whenever the speaker \( a \) reveals to be honest \((y_j = 1 \Rightarrow l_{bac} = \tilde{l}_{bac})\) or to be lying \((y_j = 0 \Rightarrow l_{bac} = \tilde{l}_{bac})\), respectively. Hopefully for \( b \), these guesses should stay reasonably accurate at other times.

#### B.4.3. Typical Surprises

Agent \( b \)'s lie detection relies on the surprise reference scale \( K_b \). This determines the assumed PDFs for message surprises \( s_j = K_j \). \( J \) is evaluated on the mean surprise scale \( K_j \). No static value can be assigned to \( K_j \). The surprise PDFs \( \{P(s_j \mid h)\} \) and \( \{P(s_j \mid \neg h)\} \) differ in different social situations and usually also evolve as a function of time. A simple heuristic is used to update \( K_b \).

Initially, we set \( K_b = 1 \). For the update of \( K_b \), it will be used that given the assumed surprise distributions for honest and dishonest statements, Equations (B19) and (B20), respectively, and given that half of the statements are a priori expected to be honest and half to be dishonest (as implied by \( P(K_b = 1) = 1 \)). The median value for message surprises \( J \) (with respect to \( K_b \)) should be located at \( \sqrt{K_b} \). This is the expected median of the assumed surprise distribution and marks the expected transition from mostly honest to mostly dishonest statements. Thus, agent \( b \) just maintains a tuple \( K_b \) with the \( N_b \) last non-zero surprises received and sets

\[
k_b = \frac{\text{median}(K_j)}{\sqrt{N_b}} \quad \text{(B34)}
\]

whenever a new message arrives. The size of \( N_b \) determines how quickly or slowly agent \( b \) adapts to a changing social atmosphere, and is set to \( N_b = 10 \) in our simulations. We initialize \( K_b \) with \( (\sqrt{N_0}, \ldots, \sqrt{N_0}) \) to be consistent with the initial \( K_b = 1 \).

### Appendix C: Detailed Communication Strategies

As a supplement to Section 5, the basic communication strategies are explained more rigorously here once again.

The **ordinary agent** \( a \) picks the communication partner \( b \) randomly and uniformly from all other agents, \( b \leftarrow A(a) \), the topic \( c \) randomly and uniformly from all agents, \( c \leftarrow A \), communicates honestly with the frequency \( x_{ac} \), promotes friends and demotes enemies when lying, and uses a critical receiver strategy.

The **strategic agent** \( a \), however, picks communication partners according to their reputation, by setting

\[
P(a \rightleftharpoons b \mid \text{a strategic}) = \frac{x_{ab}}{\sum_{c : A(a)} x_{ab}} (1 - \delta_{ab}) \quad \text{(C1)}
\]

By concentrating communications on presumably reputed, if not even really honest agents, the strategic agent’s opinions, if adapted by \( b \), might propagate more efficiently into third agents. This is because the communicated opinion benefits from the reputed agents being more influential and the higher frequency with which honest agents express their true beliefs. Strategic agents therefore target optimal multipliers for their communications. Being strategic will be part of the dominant and the destructive strategies.

We call an agent preferring low reputed agents as communication partners an **anti-strategic** agent:

\[
P(a \rightleftharpoons b \mid \text{a anti-strategic}) = \sum_{c : A(a)} (1 - x_{ab}) (1 - \delta_{ab}) \quad \text{(C2)}
\]
Table C1. Summary of agents’ communication strategies, which determine how an agent a picks (if being initiator of a conversation a ↦ b) the partner b, topic c, whether (in any communication a ↦ b) a is honest (h) or lies (¬h), whether a blushes (b), how a lies about a, about a friend (fr.), and how a receives messages. “↑” means that the testimony in a lie is biased positively (with \( \delta_{ab} \mu, \delta_{ab} \lambda = 1 - \delta_{ab} \alpha(1, 0) \)) and “↓” means negatively (\( \delta_{ab} \mu, \delta_{ab} \lambda \alpha(0, 1) \)) w.r.t. to \( \lambda_{abc} \), the by-a-assumed opinion of b about c. “Ω” means white lies, in which a tries to tell b exactly what b believes about c \( |\lambda_{abc}| = 1 \). Differences in behavior with respect to an ordinary agent are marked in blue.

| Agent a       | P(a ↦ b | a ↦ b) \( \alpha(1 - \delta_{ab}) \times \) | P(a ↦ b | a ↦ b) = | P(h(a ↦ b) = h) = | P(b|h(a ↦ b) = h) = | Deception strategy | Receiver strategy |
|---------------|-----------------------------------------------|---------------|-----------------|-----------------|-------------------|------------------|
| Deaf          | 1                                             | 1/2           | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | deaf             |
| Naive         | 1                                             | 1/2           | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | naive            |
| Uncritical    | 1                                             | 1/2           | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | critical         |
| Ordinary      | 1                                             | 1/2           | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | critical         |
| Strategic     | \( \tau_{ab} \)                              | 1/2           | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | critical         |
| Anti-strategic| \( 1 - \tau_{ab} \)                           | 1/2           | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | critical         |
| Flattering    | 1                                             | 1/2 \( \delta_{ab} + 1/2 \) | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | critical         |
| Aggressive    | 1                                             | 1/2 \( \delta_{ab} + 1/2 \) | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | critical         |
| Shameless     | 1                                             | 1/2           | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | critical         |
| Smart         | 1                                             | 1/2           | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | smart            |
| Deceptive     | 1                                             | 1/2           | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | smart            |
| Clever        | 1                                             | 1/2           | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | smart            |
| Manipulative  | \( 1 - \tau_{ab} \)                           | 1/2           | \( \delta_{ab} \) | \( \delta_{ab} \) | a, b, fr.; en.; n. 0 | smart           |
| Dominant      | \( \tau_{ab} \)                              | 1/2 \( \delta_{ab} + 1/2 \) | \( \delta_{ab} \) | \( \delta_{ab} \) | a, b, fr.; en.; n. 0 | smart           |
| Destructive   | \( 1 - \tau_{ab} \)                           | 1/2 \( \delta_{ab} + 1/2 \) | \( \delta_{ab} \) | \( \delta_{ab} \) | a, fr.; en.; n. 0 | smart           |

Being anti-strategic may pay off for flattering agents, who always lie positively when their conversation partner is the topic, and pick the conversation partner as topic whenever they have the opportunity to initiate a conversation,

\[
P(a ↦ b | a ↦ b) = \delta_{bc} \tag{C3}
\]

Flattering agents should be efficient in befriending others. Being an agent b’s friend pays off for a whenever b lies about a. Thus, flattering agents are best advised to be anti-strategic as well, in order to achieve the friendship of the most frequent liars they can identify. Being flattering and anti-strategic will therefore be part of the manipulative strategy.

Egocentric agents prefer to speak about themselves. In half of the cases in which they initiate a conversation, they directly pick themselves as topic, in the other half, they pick randomly and uniformly from the set of all agents A,

\[
P(a ↦ b | a ↦ b, a \text{ egocentric}) = \frac{1}{2} (\delta_{ac} + \frac{1}{n}) \tag{C4}
\]

Thus, they present themselves in more than half of the conversations they initiate. Egocentric agents can benefit from being strategic, as this should increase their reach. For this reason, being anti-egocentric in addition to being strategic will be part of the dominant strategy.

Aggressive agents only speak about enemies when initiating a conversation,

\[
P(a ↦ b | a ↦ b, a \text{ aggressive}) = \frac{\delta_{ac} \delta_{ab}}{1 + \alpha(1 - \delta_{ab})} \tag{C5}
\]

and neither praise friends nor themselves. The aggressive agent’s destructiveness with respect to other agents’ reputations can unfold best if the agent is also strategic and therefore the destructive agent will be both, aggressive and strategic.

A shameless agent a lies without blushing, which gives a clear advantage if lying frequently and we will assume the destructive agent also to be shameless.

Finally, a (fully) deceptive agent a lies without exception, \( x_{a} = 0 \), and therefore does not risk to make any confession or to be caught lying due to contradictions between expressed true beliefs and lies.

All special agents, the clever, the manipulative, the dominant, and the destructive agent, are combinations of different basic strategies as explained in Section 5. Thus, since the single basic strategies that have been put together never contradict each other, the basic characteristics presented above can simply be combined for all remaining special strategies.

For an overview, see Table C1.

Appendix D: Detailed Figures

We show here a number of figures that permit the inspection of further details of the simulation runs, but which are too crowded to be discussed in the main text.

Figure D1 shows the communication patterns for the basic communication strategies for random sequences No. 1 and Figure D2 for special strategies for random sequences No. 1 and No. 2. Figure D3 shows 2D reputation distributions for different agent types for simulation runs with three to five agents, respectively.

Figure D4 shows the run averaged relation of reputation and friendship between agents in the four and five agent simulations, respectively.
Figure D1. Communication patterns as in Figure 5 of the simulations of basic communication strategies with agent red being here strategic (top left), egocentric (top right), and flattering (middle left), shameless (middle right), aggressive (bottom left), and deceptive (fourth row). The used random sequences No. 1 are also identical to the simulations shown in Figure 5.

Figure D5 displays the relation between the run averaged reputation of an agent and the level of social chaos.

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Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.
Figure D2. As Figure D1, just for agent red being clever (first row), manipulative (second row), dominant (third row), and destructive (fourth row). The left column shows simulations with the random sequences No. 1, and the right with No. 2.
Figure D3. Like Figure 14, just for agent red being deceptive, clever, manipulative, and destructive from top to bottom, respectively.
Figure D4. Like Figure 17, just for simulations with four (upper rows) and five (lower rows) agents.
Figure D5. Like Figure 18, just for simulations with four (upper rows) and five (lower rows) agents.
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Inhuman psychology, however, additional criteria might be relevant that can lead to deviations from a pure KL based data compression. Recognizing liars might be more essential than differentiating between mostly honest people. Consequently, a positive-negative asymmetry of diagnosticity of information seems to be used by human minds when deciding how to store morality related information (e.g. honesty-honesty). In this first incarnation of our reputation game, we ignore such subtleties.

In psychology, however, additional criteria might be relevant that can lead to deviations from a pure KL based data compression. Recognizing liars might be more essential than differentiating between mostly honest people. Consequently, a positive-negative asymmetry of diagnosticity of information seems to be used by human minds when deciding how to store morality related information (e.g. honesty-honesty). In this first incarnation of our reputation game, we ignore such subtleties.

As agents have unspecified genders we use the singular they and them to refer to them individually. We denote probabilities with $P$ and PDFs with $p$. They are related via integration: $P(x \in [x_1, x_2]) = \int_{x_1}^{x_2} dx \, p(x)$. Note that probabilities take values in $P \in [0, 1]$, whereas PDFs $P \in \mathbb{R}^+$. Bayes' theorem applies to both, so that a strict discrimination between those is not always necessary. We therefore use the word “probability” for both, probabilities and PDFs.

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Non-deceptive agents would even communicate honest statements when they should lie according to their lie-frequencies $1 - x_a$.

In the current version of our game, this would not be fully exploited by malicious agents, as agents do not infer the character of other agents except for the level of their honesty.

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