An Agent Architecture for Simulating Communication Dynamics in Social Media

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Abstract. Social media like Facebook, Twitter, or Google+ have become important communication channels. Nonetheless, the distribution and dynamics of that communication make it difficult to analyze and understand. To overcome this, we propose an agent architecture for modeling and simulating user behavior to analyze communication dynamics in social media. Our agent decision-making method utilizes sociological actor types to represent motivations of media users and their impact on communicative behavior. We apply this concept to a simulation of real world Twitter communication accompanying a German television program. Our evaluation shows that the agent architecture is capable of simulating communication dynamics in human media usage.

Keywords: Agent architecture · Social actor types · Social media communication · Agent-based social simulation

1 Introduction

Within the last decade, *social media* like Facebook, Twitter, or Google+ have become predominant means of communication for both private and professional users. They are used for purposes as various as casual smalltalk, commercial marketing campaigns, and the shaping of political opinion [19,23].

However, the inherent distribution of social media and the dynamics of user interactions therein make it difficult to analyze and comprehend that communication. Agent-based social simulations (ABSS) [11] are a promising technique for understanding complex dynamics of interrelated communication activities. For instance, viral dynamics of mass phenomena in social media like the *harlem shake* [6] can be reproduced by representing media users with artificial agents [21]. The interrelated activities of these agents within a simulation lead to emergent dynamics. Exploring various user populations and agent decisions in a controlled experiment helps understand these dynamics in real world social media [33].

Nevertheless, there is a discrepancy between the majority of agent-based models for social media analysis on the one hand and the available agent architectures based on sociological, philosophical, and psychological theories on the other. While the ABSS community has recognized these architectures for agent

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decision-making [1], agent-based social media simulation focuses largely on simple reactive agents (e.g., threshold models of information diffusion) without accounting for elaborate decision-making [10,18,36]. That is, these models only address the question, *whether or not* users communicate in a social network.

In this paper, we complement the aforementioned approaches with a sociologically inspired agent decision-making architecture for simulating user motivations and the resulting behaviors. In particular, we aim at modeling *when* and *why* users communicate in *which* way. This requires more differentiated models of agent decision contexts, their available activities, and their action selection mechanisms. Only if the agents in a social simulation experiment are complex enough in these respects, it is possible to reproduce realistic communication processes and to explain why and how these processes emerge.

The remainder of the paper is structured as follows. Section 2 provides an overview of social media communication, sociological and psychological models, as well as agent-based approaches to social simulation. Subsequently, Sect. 3 describes our agent decision-making concept for modeling communication dynamics. This concept covers the decision-making of individual social actors as well as populations of media users. Section 4 applies the concept to an example of communication processes on Twitter which accompany a German television program. In Sect. 5 we evaluate the agent architecture by simulating communication in that scenario and by comparing our results to a real world dataset. Finally, Sect. 6 provides a concluding summary and an outlook on future work.

2 Foundations

Agent-based social simulation models consist of three main components: The agents' decision-making *context*, their decision *mechanisms*, and their available *activity options* in a specific context. An agent observes a situation which provides the context for its decision. The decision itself is made by selecting an activity by means of its agent function (i.e., the decision mechanism). While context and activities depend on a particular application domain, there are domain independent theories and architectures for the actual decision-making. Thus, the following sections first introduce the application domain of social media communication to provide a scenario for agent-based social simulation. Subsequently, they discuss sociological and psychological theory and techniques for modeling decisions as well as the underlying motivations in such a setting.

2.1 Social Media Communication

Human communication can be considered as a sequence of actions by individuals, where the behavior of a sender influences the behavior of a receiver [3]. The sender uses a set of characters to encode a message, which is transmitted using an information medium. The receiver uses an own set of characters to decode and interpret the message and returns a feedback using the same mechanism [31]. The formulation and transmission of messages by the sender as well as the corresponding reaction by the receiver form the communicative activities available to users of social media.

Social media provide options to their users to connect and communicate with each other. In terms of graph theory, such a structure can be described by a set of users (nodes) and relationships between the users (edges) [35]. For instance, the online social network Twitter can be modeled as a directed graph. Twitter distinguishes between *followers* and *followees*. A user actively and voluntarily decides which other users to *follow* for receiving their status updates (Tweets). Being followed by another Twitter participant makes a user become a *followee*. However, the user being followed does not need to follow its *followers*.

When a user publishes a message on Twitter, all of that person's followers become notified. However, it is also possible to address other users directly in order to reply to a message and to forward messages to others. Using the @-symbol followed by the name of a user or putting the prefix *"RT"* (retweet) at the beginning of a Tweet establishes sequences of messages. These sequences form dialogs and conversations between two or more users [8]. In addition, Twitter provides another operator for classifying the content of a message. To that end, the #-symbol (hashtag) is used for categorizing messages and for marking keywords that describe the topic of a conversation.

Twitter has been widely used for conducting studies of certain subjects or events, e.g., spread of news and criticism [20,33], the activity of diseases [32], or political communication [23]. In an agent-based social simulation of such phenomena, the agents' activities comprise publishing messages. Their options among which to choose are given by the aforementioned operators. They can introduce new messages, retweet existing ones, address particular users, and cover specific topics. In addition, further content descriptors can cover the tonality and style of messages. This leads to a variety of possible agent activities.

Moreover, in a simulated conversation, an agent's previous messages as well as other agents' Tweets about the same topic form the context of the agent's decision-making. The agent observes the preceding sequence of messages and decides whether and how to react to it. Consequently, it requires a mechanism to process the conversational context and to select a response. In order to obtain a realistic simulation, it is desirable take sociological and psychological analyses into account for developing agent decision-making mechanisms. Such theory can provide deeper insights into the dynamics of communication processes and the underlying motivations of social actors from which they emerge.

2.2 Sociological and Psychological Models

Communication is inherently social. In fact, sociality can be considered to consist entirely of communication [22]. Social systems emerge from interconnected communicative activities being selected by social actors [15]. Those actors are influenced by an observed social situation and decide about their reactions to that situation which results in observable behaviors that lead to the emergence of a new situation (cf. Fig. 1). For example, a Twitter user can observe an ongoing conversation about a specific topic (1). She may decide to utter a controversial opinion about that topic (2) which becomes observable to other users in the form of her respective Tweet (3). This changes the conversation and provokes further reactions. Thus, the conversation on the macro-social level (4) both influences individual behaviors on the micro-social level and emerges from them.

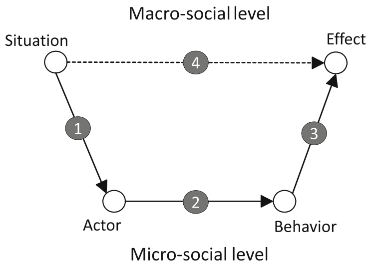

Fig. 1. Emergence of macro-social effects from micro-social behavior [15].

For explaining macro-level communication dynamics by means of the aforementioned model, it is necessary to understand the behaviors of participating actors on the micro-level. As discussed in the preceding section, in social media, the visibility of the situational context (1) is given by the social network platform. That platform also provides the activity options and publishes the selected action for other users to observe (3). However, given a specific situation, the user behavior (2) depends on various attributes and dispositions like static personal and demographic traits as well as dynamic motivations. Psychologically and sociologically grounded analyses identify these traits and motivations in order to derive their impact on the decision-making from empirical evidence.

There are several analyses of user behavior in social media available. For instance, activity frequencies on Twitter have been related to user attributes and traits such as gender, age, region, and political opinion [27]. While such an analysis reveals *how* social media users interact with each other, it cannot explain *why* they do it. To answer that question, other studies cover motivations for communication. These motivations can be categorized into groups like *smalltalk*, *entertainment*, or *information and news sharing* [17]. Additionally, they can be derived from psychological personality traits [21,34]. Such approaches provide insights into the decision-making of social actors in diverse situations ranging from casual comments on a television series [29] to crisis communication [16].

In addition to social media specific and psychologically founded motivations, there are also theoretical foundations for describing actor behaviors in sociology. Sociologists distinguish between four basic social actor types which differ in their behavior [12]. Firstly, a *homo economicus* is a rational decision-maker who strives to maximize her personal utility. Such an actor attempts to reach personal goals as efficiently as possible, whereas such a goal does not need to be monetary. Secondly, a *homo sociologicus* obeys social norms and obligations. This actor type tries to conform with expectations in order to avoid negative sanctions.

Thirdly, an *emotional man* is driven by uncontrollable emotions such as love, anger, respect, or disgust. This leads to affective behavior in response to, e.g., unfulfilled expectations [14]. Finally, an *identity keeper* tries to establish and maintain a desired social role. Such an actor seeks social acknowledgment by provoking positive reactions toward stereotypical behaviors. These basic types are theoretically well-founded and can be utilized to describe basic as well as mixed social motivations of humans [12].

2.3 Agent Architectures for Social Simulation

Communication processes in social media emerge from individual activities of the participating users. For experimentally analyzing such emergent phenomena, agent-based computer simulation has been established as a standard means. By modeling real world actors as software agents, individual behavior and anticipation of behavior on the micro level can be simulated resulting in emergent effects on a macro level [4,7]. In terms of social sciences, this is referred to as agent-based modeling and agent-based social simulation [11].

The majority of agent-based models in social media analysis focuses on *information propagation*. These models aim at identifying the optimal group of users to spread information to as many others as possible [36]. The users are frequently modeled as reactive agents with behavioral rules that fire if an activation threshold is reached. The threshold denotes the required strength of influence (e.g., a number of received messages) on an agent until it becomes active itself. This method is particularly relevant for planning marketing campaigns in social media which make use of information propagation effects [10,18].

While threshold models are usually investigated by means of simulation studies, there are also *analytical approaches* to agent-based modeling of opinion formation. These focus on the interactions among agents which lead to the diffusion and adoption of opinions in a process of compromising [25]. They model these interactions by means of thermodynamics [30] or the kinetic theory of gases [24]. These methods describe the emergence of macro-social phenomena from micro-social interactions using differential equations. This allows for analyzing the resulting opinion dynamics mathematically.

However, there is a discrepancy between threshold and analytical models on the one hand, and sociological perspectives on decision-making on the other. While these methods describe *how* opinion and communication dynamics occur in agent-based social simulations, they lack the descriptive power to analyze *why* this happens. That is, they focus on the dynamics between interacting agents and treat the agent population as a homogeneous mass. For instance, in kinetic theory, gas molecules behave solely according to their current states and their mutual influences without having individual habits. As a result, the discussed approaches largely leave the communication content as well as the participating users' underlying motivations out of account.

Thus, to understand human behavior, more elaborate agent decision approaches are necessary. In fact, a wide range of agent architectures based on philosophy, psychology and cognitive science is readily available [1]. The most prominent of those is the *belief-desire-intention* (BDI) architecture of practical reasoning [9,28]. BDI agents are well-suited for modeling motivations in terms of *desires* and for deriving *intentional* behavior from them according to *beliefs* about the current situational context.

Nonetheless, BDI agents are more complicated to apply than reactive architectures. They are especially suitable for modeling strategic and goal-directed behavior. By contrast, social media communication is often governed by affective and spontaneous contributions [33]. Hence, there is no need for modeling persistent intentions to satisfy communicative desires in such a setting. Consequently, we propose to strike a balance between cognitive and reactive agents which utilizes the aforementioned sociological foundations for modeling complex agent behaviors based on social actor types.

Sociological theory and agent technology have been combined in the interdisciplinary field of *socionics* [13]. In that context, Dittrich and Kron model social characters by means of actor types and combinations between these types [12]. They simulate the "bystander dilemma" in which persons must decide whether or not to help a victim of physical violence. In their model, agents with the *homo sociologicus* and *identity keeper* roles feel obliged to help while *homo economicus* and *emotional man* flee the situation. Combining these dispositions on both the individual and population levels leads to complex macro-social behaviors.

As social actor types provide a simple method for modeling complex agent motivations, they are a promising concept for simulating other human interaction dynamics. However, it is unclear, how they can be transferred to other applications. Therefore, we provide an agent decision-making architecture based on these actor types and show its applicability for simulating communication dynamics in social media in the remainder of this paper.

3 Agent Decision-Making Concept

In this section, we adapt the agent decision-making approach by Dittrich and Kron [12] to modeling communicative user behavior in social media. In particular, we model the selection of messages about a specific topic to be published on a social media platform within a limited time frame [2].

Our modeling and simulation concept is structured as depicted in Fig. 2. Each decision-making situation receives an input of one or more keywords to

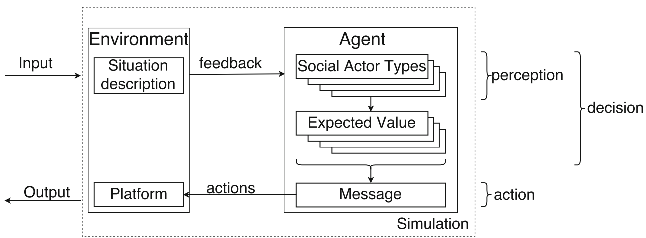

Fig. 2. Agent-environment interaction and agent decision-making concept.

describe that situation (e.g., a list of hashtags or abstract topic description). The respective output consists of messages being published at the social media platform by the population of agents. In order to produce that output, each agent observes the situation and calculates expected values for its potential reactions according to its respective social actor type and depending on the activities of other agents. It then selects its next message (or chooses not to publish any message) with respect to these expected values. The following sections describe the actor types, their combinations, and the resulting agent populations.

3.1 Social Actor Types and Decision-Making

According to Fig. 2, the agent decision-making maps a perceived situation description to a communicative action. Given a set S of possible situations and a set A of available actions, the agent function has the following structure.

$$action : S \rightarrow A$$

Besides the current situation $s \in S$, its social actor type determines an agent's decision-making. To that end, we model each type by means of a function EV that returns an expected value for each available activity option. For a *homo economicus* (HE), this amounts to a standard utility function. Contrastingly, a *homo sociologicus* (HS) prefers socially adequate behaviors over controversial actions. Such an agent makes its behavior dependent on contributions to a conversation by other agents. In addition, while the *identity keeper* (IK) has a genuine desire to further any kind of discussion, the *emotional man* (EM) only becomes active when being emotionally affected by the situation.

All of the expected value functions should cover the same range of values to make them comparable with each other. That range depends on the number of available activity options and their effects in a particular application scenario. Each option can either have a positive, neutral, or negative effect on an agent's motivations. For instance, a scenario with five possible messages can be encoded through the following set of values: $\{-1, 0, 1, 2, 3\}$. In this case, a message is either detrimental to an agent's goals (-1), it can be neutral towards them (0), or it furthers its motivations to different extents (1–3). Then, the agent can select its next action $a \in A$ depending on the situation s as follows.

$$action_i(s) = \arg\max_a EV_i(s, a)$$

Each actor type $i \in \{HE, HS, EM, IK\}$ maximizes its expected value for all available actions a in the situation s. If there are several options with the same value, an agent decides randomly among them. This results in a specific message (i.e., Tweet) being selected and published at the simulated social network platform for all other agents to observe.

3.2 Actor Type Combinations and Populations

According to the preceding decision-making model, each agent can implement one of the four available actor types. However, these are only prototypical examples for categorizing motivations. In fact, an actor's motivational disposition will often be more adequately described by a mixture of several basic motivations [12]. Consequently, we allow for combinations of actor types within individual agents to represent that phenomenon.

For mixing several actor types, each agent is defined by four weights w_i, one for each actor type i, with $\sum_i w_i = 1$. Those weights denote the ratio with which those types contribute to its decision-making. Then, an agent with mixed types selects its activities by maximizing the weighted sum of the respective expected values (with a randomized selection in case of several maxima).

$$action(s) = \arg\max_a \sum_i EV_i(s,a)\; w_i$$

In addition to combining actor types within an individual agent, it is also possible to mix different agents within the overall agent population. That is, a population can either consist of homogeneous agents that all implement the same actor type combination, or it can comprise different agents. Homogeneous populations are particularly useful for model validation and calibration. They make the effects of different value functions easily observable and adjustable. Contrastingly, heterogeneous populations are more realistic. They lead to complex interaction dynamics which are necessary for replicating and explaining user behaviors in social media as described in the following sections.

4 Application to Social Media Communication

The preceding section has outlined the general agent decision-making behavior without specifying the application-dependent expected value functions for the four actor types. In this section, we complement that description by applying our modeling concept to an analysis of user behavior in communication processes on Twitter. In particular, we model live-tweeting behavior during an episode of the German television series "Tatort" (meaning *crime scene*). Running since 1970, "Tatort" is the most popular German TV series which attracts a broad audience across all social groups, genders, and ages. We use a dataset of Tweets about the episode "Alle meine Jungs" (*all my boys*), of May 18, 2014. The dataset has been obtained through the Twitter-API and contains 7448 Tweets. Out of these, 192 original Tweets (excluding Retweets) form eight distinct phases of Twitter activity which correspond to specific scenes of the episode. These scenes provide the situation for the agents in our model to react to. Each of them is described by one or more out of five attributional categories as shown in Table 1. The categories are described by

$$C = \{\text{thrilling, funny, music-related, emotional, judgmental}\}.$$

Each scene in this model is represented by a subset of C. Hence, $S = 2^C$ is the set of all possible scene descriptors.

The agents can act repeatedly during each scene. At the beginning of a scene, they base their actions only on the respective description; subsequently, they

Table 1. Situation descriptions.

Scene	Description
0	Thrilling
1	Funny, music-related
2	Funny, music-related
3	Funny, music-related
4	Funny
5	Thrilling, emotional
6	Thrilling
7	Judgmental

can also react to other agents' Tweets. Thus, a dynamic communication system emerges from these interrelated activities. In the following, we particularize the available actions and the decision-making of the four actor types.

4.1 Agent Activity Options and Auxiliary Functions

The Tweets in our data set can be classified by their sentiment and tonality along two different dimensions. They are either positive or negative and they are either joking or not joking (i.e., serious). The possible combinations of these categories result in four different message types available to the agents. However, since not all users reply to every message, an agent also has the option not to tweet. Nevertheless, it can still decide to participate in the conversation about the current scene at a later time after observing Tweets by other agents. This results in the following set A of five activity options.

$$\begin{aligned} A = \{&\text{No tweet, Tweet}-\text{positive}-\text{joking, Tweet}-\text{positive}-\text{not joking,} \\ &\text{Tweet}-\text{negative}-\text{joking, Tweet}-\text{negative}-\text{not joking}\} \end{aligned}$$

Which option $a \in A$ an agent selects at what time depends on its underlying combination of actor types as well as on the activities of other agents. To include the latter into the decision-making, we define two auxiliary functions φ_s and $tweets_s$ which count published messages in the original data set as well as in the simulated communication process, respectively. The function $\varphi_s : A_{s \in S} \rightarrow \mathbb{N}$ returns the absolute number of each action a in scene $s \in S$ as contained in the data set. Analogously, the numbers of different Tweets being published at the time of decision in the agent-based simulation is given by $tweets_s : A_{s \in S} \rightarrow \mathbb{N}$. Those functions are necessary to take the activities of other agents into account in the agent decision-making process.

4.2 Agent Decision-Making

In our application example, the four actor types represent typical behavioral roles and motivations in social media communication. These include the maximization of publicity, a desire for serious discussion, the expression of anger, as well as genuine content production. These motivations are represented by the *homo economicus*, *homo sociologicus*, *emotional man*, and *identity keeper*, respectively. For all actor types, we evaluate the available activity options with respect to those motivations in each situation in order to identify expected values for the agents' decisions. Table 2 summarizes the criteria and values for that evaluation.

Table 2. Agent decision-making by social actor types (expected values).

Homo economicus	Homo sociologicus	Emotional man	Identity keeper
No tweet (0)	Must (3)	Unchanged (0)	Strengthened (3)
Utility function	Should (2)	Increased (−1)	Weakened (−1)
(0 to 3)	Can (1)	Decreased (2)	
Conversation size	Should not (−1)	Strongly	
Threshold (−1)		Decreased (3)	

In social media communication, a *homo economicus* agent tries to maximize the impact of its contributions on the conversation. Such an agent gains the highest utility by reaching agreement with as many others as possible. Thus, its underlying utility function anticipates probable majority opinions. Actions supporting these are rated higher than less popular or controversial contributions according to the ratio of actions in the original dataset. This agent type will maintain its ratings during a conversation regardless of other agents' behaviors. In addition, we use a threshold of a minimal number of Tweets by other agents for the agent to become active itself. The threshold is the mean number of Tweets across all scenes. Until this threshold is reached, an agent will not participate in the conversation which leaves its utility unchanged. Thus, the *homo economicus* represents a casual media user who only joins ongoing conversations to represent common sense opinions shared by the expected majority of recipients.

The corresponding expected value function depends on the Tweets published in the current scene s so far as given by $tweets_s$. If the overall number of Tweets in $\sum_{a' \in A} tweets_s(a')$ does not exceed the threshold, the *homo economicus* has a value of -1 for all other actions than the no Tweet option. The threshold $\frac{1}{|A|} \sum_{a' \in A} \varphi_s(a')$ is the arithmetic mean of all Tweets throughout the scenes in the entire original data set. Otherwise, the agent selects its actions according to their share in the real world data set given by $\varphi_s(a)$ The prevalent action is yielded by the term $\max_{a' \in A}(\varphi_s(a'))$ which iterates over all possible actions in the respective scene. Moreover, the utility values for a *homo economicus* are normalized and rounded to natural numbers between 0 and 3.

$$EV_{HE}(s,a) = \begin{cases} -1 & \text{, if } \sum_{a' \in A} tweets_s(a') < \frac{1}{|A|} \sum_{a' \in A} \varphi_s(a') \\ \left\lfloor 3 \frac{\varphi_s(a)}{\max_{a' \in A}(\varphi_s(a'))} \right\rceil & \text{, otherwise} \end{cases}$$

Contrastingly, a *homo sociologicus* agent rates the available actions according to both general social norms as well as other agents' behaviors. Its expected value function evaluates these options by their perceived strength of obligation. For instance, an agent *should not* joke about an emotional scene. However, if the majority of other agents has deviated from such norms before, the *homo sociologicus* will mimic these previously observed activities in order to gain acceptance by other agents. Hence, that type of agent represents a both morally concerned and opportunistic user who joins the dominant group as soon as one emerges. This behavior is typical, e.g., in massive online protests [33].

The expected value of a *homo sociologicus* agent depends on the norm for the current situation and the predominant action so far. The function $norm(c, a)$ returns a value of -1 for an action it *should not* select, 1 if the agent *can* execute an activity, 2 if it *should* do it, and 3 if it *must* choose the respective action. Table 3 shows the norms that affect an agent for each attributional category in the current scene description.

$$EV_{HS}\,(s, a) = \begin{cases} 3 & \text{, if a = } \arg max_{a' \epsilon A}(tweets_s(a')) \\ \sum_{c \in s} norm(c, a) & \text{, otherwise} \end{cases}$$
$$\text{with } norm: \; C \times A \rightarrow \{-1, 0, 1, 2, 3\}$$

The *emotional man*, on the other hand, represents an outright dissatisfied and angry user. Such an agent strives to express that anger which leads to predominantly negative and sometimes sarcastic (i.e., joking) contributions. By publishing negative Tweets, the agent decreases its anger until it no longer feels the need to communicate. Consequently, that behavior produces isolated criticism without any intention of engaging in an actual discussion.

The expected value for the *emotional man* depends on the output of an *anger*-function. That function evaluates the current attributional categories of the situation description according to their emotional implications for the agent. If an action *decreases* the agent's anger, its expected value is 2. If the agent can even *strongly decrease* it, the value is 3. In case an action would *increase* its anger instead, the *anger*-function returns -1 and if an action does not affect the anger at all, the yielded value is 0. Table 3 shows the results of the *anger*-function.

$$EV_{EM}(s, a) = \sum_{c \in s} anger(c, a), \;\; \text{with} \;\; anger: \; C \times A \rightarrow \{-1, 0, 1, 2, 3\}$$

Finally, the *identity keeper* is a genuine content producer. This type of agent has the goal of bringing forward any kind of discussion in order to maintain its participation in it. That is, the agent can strengthen its identity by providing arguments for other agents to react to. For that purpose, any kind of Tweet can be appropriate, especially controversial ones if they provoke reactions. Only remaining inactive weakens that identity. As a result, the *identity keeper* represents a user who enjoys a conversation for the sake of the conversation and

Table 3. Values of $anger(c, a)$ and $norm(c, a)$ for categories and actions.

Category $c \in C$	Action $a \in A$	$norm(c, a)$	$anger(c, a)$
Thrilling	No tweet	1	0
	Tweet - positive - joking	2	−1
	Tweet - positive - not joking	2	−1
	Tweet - negative - joking	−1	3
	Tweet - negative - not joking	1	2
Funny	No tweet	1	0
	Tweet - positive - joking	2	−1
	Tweet - positive - not joking	3	−1
	Tweet - negative - joking	−1	2
	Tweet - negative - not joking	−1	3
Music-related	No tweet	1	0
	Tweet - positive - joking	2	−1
	Tweet - positive - not joking	3	−1
	Tweet - negative - joking	−1	2
	Tweet - negative - not joking	1	2
Emotional	No tweet	2	0
	Tweet - positive - joking	−1	−1
	Tweet - positive - not joking	1	−1
	Tweet - negative - joking	−1	0
	Tweet - negative - not joking	1	0
Judgmental	No tweet	−1	0
	Tweet - positive - joking	1	−1
	Tweet - positive - not joking	3	−1
	Tweet - negative - joking	−1	3
	Tweet - negative - not joking	2	2

who ensures a certain diversity of perspectives on the discussed topic. Thus, the expected value for the *identity keeper* is expressed as follows.

$$EV_{IK}(s, a) = \begin{cases} -1 & \text{, if a } = \text{no tweet} \\ 3 & \text{, otherwise} \end{cases}$$

The described actor types explain different motivations that cause particular behaviors in decision-making. Combining these actor type models within individual agents creates complex agent behaviors. In the following section we evaluate this modeling approach by reproducing the behavior recorded in the real world data set in an agent-based simulation experiment.

5 Evaluation: Simulation of Social Media Usage

In this section, we evaluate the capability of our agent decision-making approach to reproduce realistic communication dynamics in social media. From a previous experiment [5], we know that the composition of the agent population in this kind of model has a large impact on the overall communication dynamics in the simulation. In that experiment, we evaluated two different settings to analyze the interplay of several actor types on the individual level and the population level. The first setting examined a homogeneous agent poulation ofpopulationall four actor types in equal shares. The second setting consisted of a heterogeneous agent population in which every agent implemented one of the four basic actor types. These experiments gave us an impression of the interplay of different actor types both within and between agents. In the following, we complement these findings with an analysis of whether the agent architecture is also capable of producing realistic simulation results.

5.1 Experiment Setup and Results

We implemented the four agent types in a *JAVA* program to imitate the behavior of 165 human Twitter users as represented in the aforementioned data set in a simulation experiment. Consequently, our experiment confronts a population of 165 agents with each of the eight scene descriptions shown in Table 1. This population comprises equal numbers of three different actor type combinations, each of which contains all four basic types to various extents. In particular, each agent includes all motivational descriptions for at least 10% and at most 70% to add up to a total of 100%. In our simulation, we vary the ratios of these combinations in steps of 10% in order to evaluate whether the resulting simulated communication accurately replicates the original conversation.

Iterating the percentages of the motivational descriptions results in 80 different actor type combinations. As the overall agent population consists of three of these combinations, our experiment covers 512 thousand different populations ($80 \times 80 \times 80$). Each of these populations is simulated 100 times to account for stochastic decisions. The arithmetic mean of those repetitions is used to evaluate the accuracy of the simulated data. To that end, the communication in each scene of the experiment is compared to that of the matching scene of the real world data set.

Throughout the experiment, the population of interacting agents does not have to remain stable across all scenes. In fact, in real world social media communication, users enter and leave the conversation. Furthermore, the composition of the four actor types within an agent is perceived as a current set of motivations. These motivations can vary depending on the situational context or other external or internal stimulations. Therefore, we treat each scene seperately in our search for a fitting agent population to reproduce real world communication dynamics. Table 4 presents the actor type combinations which lead to the most accurate simulation results for each scene.

Table 4. Agent population (actor type combinations) for the different scenes.

Scene	Combination 1				Combination 2				Combination 3			
	HE	HS	EM	IK	HE	HS	EM	IK	HE	HS	EM	IK
0	10	50	20	20	20	30	20	30	10	20	30	40
1	20	10	10	60	20	20	20	40	10	50	20	20
2	70	10	10	10	30	20	20	30	30	20	20	30
3	40	10	40	10	50	30	10	10	10	60	10	20
4	20	30	30	20	30	20	10	40	10	30	40	20
5	20	30	40	10	40	10	30	20	30	50	10	10
6	10	20	30	40	30	10	20	40	20	20	50	10
7	30	10	10	50	20	50	20	10	10	10	60	20

Figure 3 shows the outcomes of the expriment (except for the "No Tweet" option) for the populations listed in Table 4. The upper barplot represents the total numbers of Tweets taken by the different agents in the eight scenes. The numbers show the arithmetic mean of all 100 iterations of the simulation (omitting the standard deviation which never exceeds a value of 0.2). The lower barplot shows the relative ratio of the actions executed by the agent-population. The error bars depict the distance of the simulation output to the original real world data. Due to the small absolute number of Tweets in some scenes, a slight distance in individual actions leads to a more pronounced error bar in the relative ratio.

We define the distance $dist_{a,z}$ as the absolute difference between the numbers of occurrences of action a in the simulation and the real world data for any

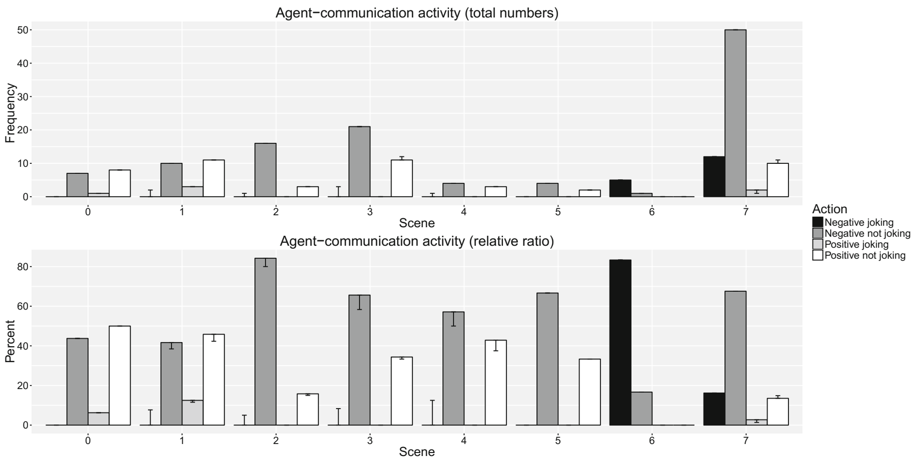

Fig. 3. Agent-communication activity.

scene $z \in \{0, \ldots, 7\}$. To calculate that distance, we count the occurrences of each particular action: $count_{sim,r}(a, z)$ in simulation run r and $count_{real}(a, z)$ in the data set. Then, we use the arithmetic mean of $count_{sim}$ for the $n = 100$ simulation runs and subtract $count_{real}$ to obtain our distance measure.

$$dist_{a,z} = \left| \left(\frac{1}{n} \sum_{r=1}^{n} count_{sim,r}(a, z) \right) - count_{real}(a, z) \right|$$

True to the real world data set, the results show a majority of negative not joking Tweets. Responsible for this are the actor types of *homo economicus*, *identity keeper*, and *emotional man* that consider this action either as the best or as one of their favorite activities. Moreover, while a *homo sociologicus* generally prefers positive and serious (not joking) Tweets, it imitates the dominant behavior. Only scenes 1 and 2 produce a majority of positive outputs. Scene 2 is described as being funny and music-related and scene 1 is characterized as thrilling. This leads to positive not joking actions being favored by three of the actor types which outrival the negative option selected by the *emotional man.* Furthermore, thrilling scenes reduce the overall number of Tweets. In the simulation, this is accomplished by the *homo economicus* needing to reach a threshold of 24 existing contributions to join a conversation.

Due to those effects, the absolute number of agent activities in the simulation deviates only slightly from the original user behavior. The maximum distance (in scene 3) amounts to a total of four Tweets. Here, the two major options selected by the agents are negative not joking and positive not joking Tweets. The former message option is favored by the first actor type combination, predominantly consisting of *homo economicus* and *emotional man.* The second form of Tweet is mainly chosen by the *homo sociologicus* in third combination of actor types. These actions are balanced out by the second actor type combination which is dominated by the *homo economicus.* When the threshold is reached, those agents decide for a negative Tweet. Otherwise, they do not participate in the conversation which boosts the relative ratio of positive contributions.

5.2 Experiment Discussion

The presented results show that our agent architecture allows for simulating realistic dynamics of social media communication in an agent-based setting. However, there are still some minor inaccuracies in the emergent agent behavior. In particular, the small percentage of *identity keeper* behaviors in the agent population leads to a slight under-representation of positive joking Tweets in scene 3. In order to reproduce the real data behavior exactly, a fourth combination of actor types would be required. By extending the experiment design with more actor types in each experiment, a more diverse activity-pattern can be achieved. This would facilitate further minimizing the distance between the simulated and the original behavior. Nevertheless, our results show that even a population of only three different actor type combinations is able to approximate real world social media communication in an agent-based simulation.

In addition, our experiment has analyzed the model behavior on the macro-social level. We have concentrated on evaluating the aggregated effects of the agents‘different decision making strategies. While this allows for concluding on the emergence of communication dynamics, further experiments will provide deeper insights into micro-social behaviors that bring about these results. In this context, both the capability of our agent architecture to simulate individual media users and the interplay between their activities over time are of interest.

Firstly, the behavior of individual agents within a population should be compared to the real world behavior of actual media users. This amounts to evaluating the simulated behavior on the micro-social level with respect to the frequency of activity and the tendencies to react to a scene description and other agents' communication. This will then allow for examining which agents in the simulation are more important than others for the emergence of specific communication dynamics. In other communication contexts (e.g., massive online criticism), the conversation is frequently driven by few particular users [33]. Therefore, an accurate representation of such users in the simulation will be useful for analyzing communication strategies in such a situation.

Secondly, the discourse dynamics between different agents within the frame of each scene is a relevant aspect to evaluate. For deriving the aforementioned strategies, it is necessary to observe the impact of possible interventions on the communication. To that end, the agents' mutual reactions to each other's communicative acts must be understood. Hence, a next step in our future experiments will include a detailed analysis of trajectories and their stability within the dynamic multiagent communication system.

6 Conclusions and Future Work

In this paper, we have developed an agent architecture for modeling user behavior in social media. Our model utilizes well-established sociological foundations for representing actors that communicate about a specific topic. In particular, we have presented a concept for representing and combining motivational causes for user behaviors by means of four different social actor types in agent-based simulations. We have applied this concept to model and analyze Twitter communication about a German television program. Our evaluation shows that even few combinations of different motivations within individual agents are sufficient for near accurate replications of real world user behavior. Thus, we conclude that our agent architecture provides a promising approach toward more elaborate agent-based simulation studies of social media usage than existing information propagation models [36]. Such a simulation can serve as a useful decision support tool for planning communication strategies in social media [33].

Nonetheless, there are several extensions of our agent architecture we consider for future work. Firstly, we are interested in comparing this method with existing information diffusion approaches. This will provide further insights into which level of complexity is necessary for simulating meaningful social media communication. Moreover, integrating both approaches will extend our architecture with a representation of the social network in which an agent is connected with others. This network restricts an agent's ability to perceive other agents' activities. In addition, such an integration will complement information propagation methods with motivational aspects of *why* information is spread within a social network.

Secondly, it will also be necessary to represent the activity options and situation descriptions for the agents in more detail. In order to simulate, e.g., the shaping of opinions in political discourses, a classification of communication contents and their impact on the interaction is required. To achieve this, we plan to utilize content modeling and annotation techniques from media and communication studies [26] for encoding discourses in agent-based social simulations.

Finally, a more detailed decision context and activity representation enables more strategic decision-making. As developing behavioral rules for an increasing number of options quickly becomes complicated, we plan to re-implement the four social actor types as BDI agents. How these types can influence the adoption of communicative intentions by such agents will be subject of our future research.

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