Modeling User Behavior in Social Media with Complex Agents

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***Abstract*—Social media like Facebook, Twitter, or Google+ have become predominant means of communication. However, their distributed structure and dynamic interaction processes make it difficult to analyze and understand that communication. Thus, we propose agent-based modeling and simulation of user behavior for analyzing communication dynamics in social media. We develop an agent decision-making method that models motivations of media users and their impact on behavior by means of social actor types. Moreover, we apply this model to Twitter communication accompanying a German television program. Our evaluation shows that different actor constellations within a population of agents drastically impact the dynamics of this communication.**

***Keywords*–Agent-Based Modeling; Social Actor Types; Social Media Analysis; User Behavior; Social Simulation.**

I. Introduction

One of the most noticeable advances of this century is the omnipresence of information and communications technology. The establishment of computer systems in our daily life and the connection of private households to the Internet has initiated and still promotes the *digital revolution* [1]. In particular, *social media* like Facebook, Twitter, or Google+ have become predominant means of communication for both private and professional users. They are widely used for various purposes, ranging from casual smalltalk to commercial marketing campaigns and the shaping of political opinion [2] [3].

Understanding these communication processes is important in both commerce and politics to derive communication strategies for social media. For example, marketing campaigns can reach a vast target audience through viral communication dynamics [4]. However, if the same dynamics distributes negative opinions, emerging mass criticism can endanger a company's commercial success. Therefore, it is crucial to anticipate likely reactions of social media users to such campaigns to avoid unintended effects or to develop appropriate counter strategies to those effects [5].

Nonetheless, the inherent distribution of social media and the dynamics of user interactions therein make it difficult to analyze and understand that kind of communication. Thus, manual analysis has been complemented with computational linguistics, data mining, and simulation methods [6]. These methods help recognize conversation topics, discern user communities, and model information diffusion in social networks.

Especially agent-based social simulations [7] are a promising technique for understanding complex dynamics of interrelated communication activities. They model behaviors of humans by means of artificial agents in order to explore the effects of different social actor constellations and various situations in an experimental environment. For instance, viral dynamics of mass phenomena in social media like the *harlem shake* [8] can be reproduced by using artificial agents for representing media users [9]. Each agent can react to other agents' communication activities in a simulated media environment. This interaction leads to complex dynamics. Exploring various user constellations and agent decisions in a controlled experiment helps understand these dynamics in real world social media.

However, agent-based simulation for social media analysis requires a model of user motivations and resulting behaviors to yield realistic results. Agents must be complex enough to explain *why* particular communication processes emerge and which effects potential reactions to them will provoke. Thus, in this paper, we develop an agent-based model of user behavior for analyzing communication dynamics in social media. This is a first step toward a simulation-based decision-support method for developing and testing social media communication strategies as proposed by Berndt et al. [5].

The paper is structured as follows. Section II provides an overview of the foundations of social media analysis, social actor theory, and agent-based modeling as a technique for dynamic analysis. Subsequently, Section III describes our concept of complex agents for modeling user behavior. This concept covers individual social actors, their respective decision-making, as well as populations of media users. Section IV applies that concept to communication processes on Twitter which accompany a German television program. In Section V, we evaluate our model by simulating user behaviors in that scenario. Finally, Section VI concludes on our findings and gives an outlook on possible future work.

II. Foundations

To analyze, model, and simulate user behavior in social media, it is necessary to understand communication processes within those media. These processes depend on the underlying platforms that structure possible communication, the observable communicative activities, as well as the social actors performing these activities. Thus, the following sections discuss approaches and theories for analyzing and modeling these aspects. In addition, we give an overview of the state of research in agent-based modeling of human behavior to provide a foundation for our approach to user behavior analysis.

A. Social Media

Social media structure communication processes by providing options to their users to connect 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)

[10]. Graphs can be unidirectional, defining the direction of the relationship, or bidirectional, connecting two nodes without providing information regarding that direction.

For instance, the online social network Twitter can be modeled as a directed graph. In contrast to most other platforms, which consist of bidirectional relationships between users, a distinction between *followers* and *followees* is made on Twitter. That is, a user actively and voluntarily decides which other users to *follow* for receiving their status updates. Following another Twitter participant makes the following user become a *follower*. However, a *followee*, i.e., the user being followed, does not need to follow his or her followers.

When analyzing the structure of social media, a typical task is to identify and assess the importance of the most influential users by means of centrality measures [11]. The *degree* of centrality corresponds to the total number of edges a node has. Hence, it is a measure of a node's interconnectedness in a graph. Nodes having a high *degree* (compared to other nodes) act as hubs for information diffusion within a social network.

By contrast, a graph's *density* denotes the interconnectedness of an entire network. It is used for comparing different network structures and their impact on information propagation. The *density* is defined by the ratio of the number of existing edges and the maximum number of edges in case every pair of nodes would be connected by an edge (complete graph).

B. 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 [12]. 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 [13]. 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.

However, the shift of communication into technical media is accompanied by a loss of information. The transmission of messages is ensured, yet, the receiver does not know whether a message was interpreted correctly. On Twitter, communication results can only be returned by replying to a Tweet using another Tweet. Consequently, conversations are formed as sequences of messages which refer to or forward previous ones [14]. To that end, Twitter provides mechanisms for replying to other tweets and for addressing a tweet to a certain person. Using the @-symbol followed by the name of a user or by putting the prefix *"RT"* (retweet) at the beginning of a tweet, the identification of dialogs or conversations is supported.

In addition to the structuring of dialogs, Twitter users can use another operator for classifying the content of a message. The content provides information about the intention as well as the context of communication. On Twitter, the #-symbol (hashtag) is used for categorizing messages and for marking keywords. This simplifies filtering Tweets according to certain topics, which makes this kind of communication easily accessible to media studies and communication research. In fact, Twitter has been widely used for conducting studies of certain subjects or events, e.g., spread of news and criticism [15] [6], the activity of diseases [16], or political communication [3].

C. Social Actors

Communication is inherently social. In fact, sociality can be considered to consist entirely of communication [17]. Social systems emerge from interconnected communicative activities being selected by social actors. Those actors are influenced by an observed social situation. They decide about their reactions to that situation. This results in observable behaviors that lead to a new situation in effect (Figure 1). For example, a user can observe an ongoing conversation about a specific topic (1). She may decide to utter a controversial opinion about that topic (2). Her utterance 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 and emerges from them on the micro-social level.

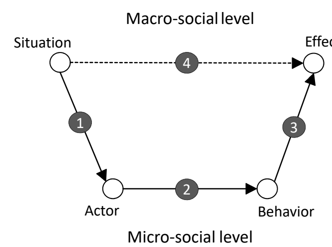

Figure 1. Emergence of macro-social effects from micro-social behavior [18].

There are several analyses of user behavior in social media available. For instance, activity frequencies on Twitter (i.e., Tweets, Responses, Retweets) have been related to user attributes and traits such as gender, age, region and political opinion [19]. 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* [20]. Additionally, they can be derived from psychological personality traits [9] [21]. Such approaches provide valuable insights into the decision-making process of social actors in diverse situations ranging from casual comments on a television series [22] to crisis communication [23].

In addition to social media specific and psychologically founded motivational categories, there are also theories of actor behavior in sociology. Sociologists distinguish between four basic social actor types which differ in their behavior [24]. Firstly, the *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. Secondly, the *homo sociologicus* obeys social norms and obligations. This actor type tries to conform with expectations to avoid negative sanctions. Thirdly, the *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 [25]. Finally, the *identity keeper* has the goal to establish and maintain a desired social role. Such an actor seeks social acknowledgment by provoking positive reactions toward stereotypical behaviors. In the remainder of this paper, we will show how these actor types can be applied to agent-based modeling of user behavior in social media.

D. Related Work: Agent-Based Modeling of Human Behavior

As discussed in the preceding section, communication processes in social media emerge from individual activities of the participating users. For investigating emergent phenomena, agent-based modeling has been established as a standard means. Artificial agents are capable of decision-making, communication, and goal-directed behavior [26]. 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 [27] [28]. In terms of social sciences, using such actor models for simulation studies is referred to as agent-based social simulation [7].

The majority of agent-based models in social media analysis is concerned with *information propagation*. They aim at identifying a group of users which can propagate information, i.e., a message, to as many users as possible [29]. The users are frequently modeled as agents being connected by neighborhood relations in cellular automata [30] or general network graphs [31]. These agents often have particular behavioral rules that fire if a certain activation threshold is reached. Such a 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 advertising strategies since viral marketing campaigns make use of information propagation effects [32] [4].

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 [33]. They model these interactions by means of thermodynamics [34] or the kinetic theory of gases [35]. 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 these threshold and analytical models on the one hand, and the mentioned 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. The same holds for cellular automata in which all cells, i.e., agents, are usually homogeneous and strongly restricted in their neighborhood relations. As a result, the discussed approaches largely disregard modeling individual motivations for decision-making such as described by social actor types.

For utilizing agent-based social simulation to understand human behavior and to develop communication strategies, it is necessary to apply more elaborate agent decision approaches. Agents must have individual motivations to allow for analyzing who participates in communication processes for which reason [5]. Since, in social media, different users react differently to the same message, this should also be the case for artificial agents in a simulation model. In fact, a wide range of agent decision-making architectures based on philosophy, psychology and cognitive science is readily available [36]. In addition, sociological theory and agent-based modeling have been combined in the interdisciplinary field of *socionics* [37]. In that context, the described social actor types can be utilized to explain social behavior in an agent-based simulation.

Dittrich and Kron model social characters by means of actor types and combinations between these types [24]. They simulate the so-called "bystander dilemma" in which persons must decide whether or not to help a victim of physical violence. In their model, agents implementing 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 an individual and on a population level leads to complex macro-social behaviors. This makes that approach a promising candidate for a transfer to modeling user behavior in social media as described in the following section.

III. Concept: Modeling User Behavior

In this section, we adapt the agent-based decision-making approach by Dittrich and Kron [24] to modeling communicative user behavior in social media. That is, we model the selection of messages about a specific topic to be published on a social media platform within a limited time frame [38].

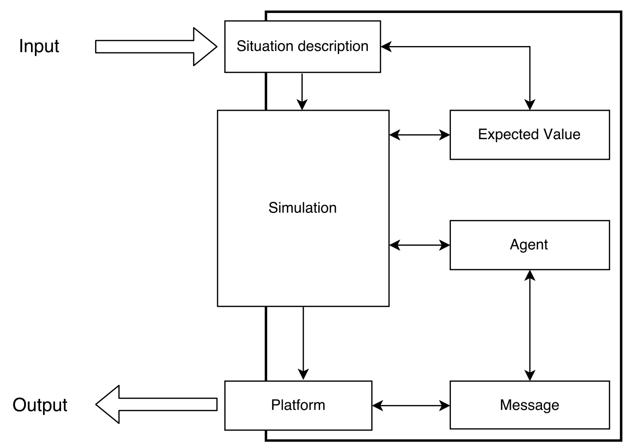

Figure 2. Structure of the user modeling and simulation concept.

Our modeling and simulation concept is structured as depicted in Figure 2. Each decision-making situation receives an input of one or more keywords to describe that situation (e.g., a list of hashtags or abstract topic description). The respective output consists of messages being published at the social network 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.

A. Social Actor Types and Decision-Making

Besides the current situation, 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*, this amounts to a standard utility function. Contrastingly, a *homo* *sociologicus* 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* has a genuine desire to further any kind of discussion, the *emotional man* 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 goals. 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 actions as follows.

$$\arg\max_{a} EV_i(s, a) \tag{1}$$

Each actor type i ($i \in \{$*homo economicus*, *homo sociologicus*, *emotional man*, *identity keeper*$\}$) maximizes its expected value for all available actions a in the current 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.

Using the described value maximization approach to select a message to be communicated leads to a restriction in the amount of behavioral randomness. This is especially useful for evaluating the sensitivity of the resulting emergent effects on the population level to the agent population. Different compositions of agents within a population will lead to different interactions with low variance.

In order to increase the variance of agent behaviors, fluctuating populations can be introduced. Alternatively, a random selection of messages, weighted by their respective expected values, can be introduced. This will then increase the randomness on an individual instead of the population level. However, adding this stochasticity decreases the explanatory impact of modeling social actor types because their respective motivations become less pronounced in the selected communication activities.

B. 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 social disposition will often be more adequately described by a mixture of several basic motivations [24]. 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 $\sum_i w_i = 1$. The 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).

$$\arg\max_{a} \sum_{i} EV_i(s, a)\ w_i \tag{2}$$

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.

IV. Application: Agent-Based Analysis of Social Media Communication

In this section, we apply our agent-based 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 18 May 2014. The dataset contains eight distinct phases of very high or very low 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 attributes as shown in Table I.

TABLE I. SITUATION DESCRIPTIONS.

Scene	Description	Scene	Description
0	thrilling	4	funny
1	funny, music-related	5	thrilling, emotional
2	funny, music-related	6	thrilling
3	funny, music-related	7	judgmental

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

A. Agent Activity Options

The Tweets in our dataset 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 five activity options for the agents.

1) No Tweet
2) Tweet – positive – joking
3) Tweet – positive – not joking
4) Tweet – negative – joking
5) Tweet – negative – not joking

Which of these options an agent selects at which time depends on its underlying combination of actor types, as well as on the activities of other agents as described in the following.

B. Agent Decision-Making

In our application example, the actor types defining the agents' decision-making 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 [39]. Table II summarizes the criteria and values for that evaluation.

TABLE II. DECISION-MAKING BY SOCIAL ACTOR TYPES.

Homo Economicus	Homo Sociologicus	Emotional Man	Identity Keeper
No Tweet (0)	Must (3)	Unchanged (0)	Strengthened (3)
Utility function (0 to 3)	Should (2)	Increased (-1)	Weakened (-1)
Conversation size threshold (-1)	Can (1)	Decreased (2)	
	Should not (-1)	Strongly decreased (3)	

In social media communication, a *homo economicus* agent attempts to maximize the impact of its contributions on the conversation. Such an agent gains the highest utility by provoking agreement with as many other agents as possible. Thus, its underlying utility function anticipates probable majority opinions. Actions supporting these are rated higher than less popular or even controversial contributions according to the distribution of actions in the original dataset. This agent type will maintain its ratings during an actual conversation regardless of other agents' behaviors.

In addition, we use a threshold of a minimal number of Tweets by other agents for this type of agent to become active itself. This threshold equals to the mean number of Tweets across all scenes (24 in the dataset). Until the threshold is reached, an agent will not participate in the conversation, leaving 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.

Contrastingly, a *homo sociologicus* agent rates the available actions according to general social norms as well as other agents' behaviors. With respect to the scene description, 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 [6].

The *emotional man*, on the other hand, represents an outright dissatisfied and angry user. Such an agent strives to express that anger. This 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.

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 who ensures a certain diversity of perspectives on the discussed topic.

By combining the described actor type models within individual agents, it is possible to represent mixed motivations and to implement a wide variety of decision behaviors. Moreover, heterogeneous populations of different agent types will lead to complex interactions of these behaviors. The following section evaluates these effects.

V. Evaluation: Simulation of User Behavior

As a proof of concept for our agent-based modeling approach, we have implemented the aforementioned agent types and decision-making algorithms in a *JAVA* program. In the following, we use that program to simulate user behaviors emerging from different populations of various agents. Such a simulation gives a first impression of the range of effects that the model can (re)-produce. In particular, it allows for analyzing the interplay between several actor types on both the individual and the population level.

In our simulation, we compare two different settings. The first one consists of a homogeneous agent population with mixed actor types. That is, each agent combines all four types with equal weights. By contrast, the second setting comprises a heterogeneous agent population in which every agent implements one of the four basic actor types. Throughout the population, these agents are uniformly distributed. They communicate about all eight scenes. Their respective activity choices depend on the situation description for those scenes as well as on the previous actions of other agents.

For both settings, the population size is set to 164 agents that can join the conversation in each scene (as in the real world dataset). This number is relevant as long as the *homo economicus* uses a fixed conversation size threshold. The more agents there are, the sooner will a *homo economicus* impact the communication dynamics. While the threshold can be scaled up or down according to the population size, we use the realistic one to enable comparisons of our simulation results with that dataset in future studies.

Figure 3 shows the arithmetic mean of our evaluation results together with the respective standard deviations out of 100 simulation repetitions (except for the "No Tweet" option). For the homogeneous population, the results show a majority of negative not joking Tweets. This is due to the fact that both *identity keeper* and *homo economicus* consider this activity as adequate. Moreover, the *emotional man* favors it over all others. Combining these within the agents leads to the observed uniformity which even becomes amplified as the *homo sociologicus* imitates dominant behaviors. Only scene 4 leads to negative as well as positive Tweets. That scene is described as being funny. Hence, the positive actions favored

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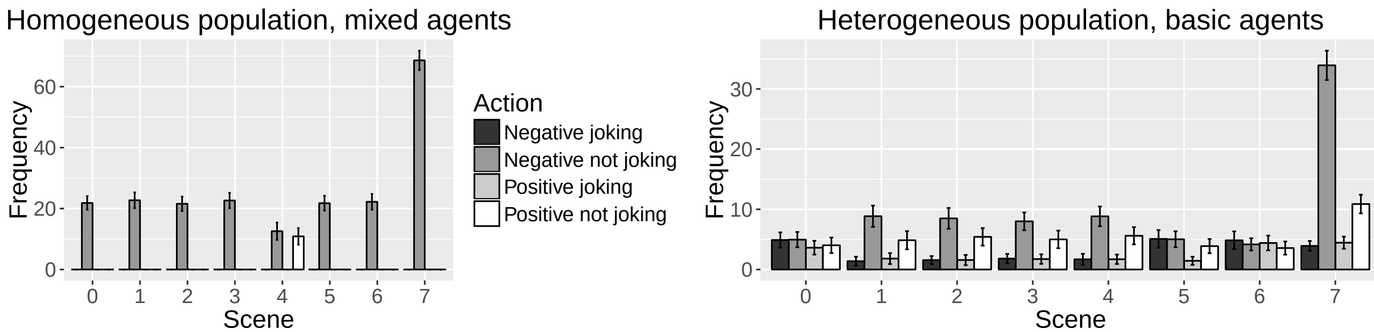

Figure 3. Activity frequencies of a homogeneous population of mixed actors (left) and a heterogeneous population of basic actor types (right).

by all other actor types override the negative option selected by the *emotional man*.

Contrastingly, the heterogeneous population leads to more diverse behavior. In that case, negative Tweets are still prevalent for most scenes. This is caused by the same effects as described: The *homo sociologicus* amplifies the behavior being initially driven by the other actor types, particularly the *emotional man*. However, since these agent types act simultaneously in a mixed population, all other actions are also observable. This leads to realistic effects, such as decisions not to tweet at all in scenes being described as thrilling.

Overall, these results show that the combination of actor types both within individual agents and their mixing in heterogeneous populations drastically impacts the emergent dynamics of simulated social media communication. This demonstrates that modeling motivations of individual agents can produce behavioral heterogeneity, which other models have to introduce artificially, e.g., by means of random noise [35]. In contrast to those approaches, we can directly control which type of agent reacts to which particular communicative situation in what manner. The composition of an agent population then models the affinity or aversion of a user group in social media to certain topics, opinions, and communication styles. Hence, we conclude that our model adds this composition of populations as an important variable to existing methods for studying information diffusion in social simulations.

However, it is important to select and calibrate the agent types carefully for such a simulation to yield meaningful results for understanding user behavior. To that end, it is necessary to analyze available real world data and identify typical activity patterns [6]. Then, potential underlying motivations can be derived from those observations in order to define the required actor types and their combinations [9] [21]. With this work, we have shown how such actor types can be modeled for exploring user behavior in agent-based social simulations.

VI. Conclusions and Future Work

In this paper, we have developed an agent-based model of user behavior in social media. This model facilitates dynamic analyses of complex communication processes which are difficult to assess by means of conventional approaches. In such a context, agent-based social simulations allow for experimentally exploring emergent behaviors [6].

Our model focuses primarily on the decision-making of social actors communicating about a specific topic. This is in contrast to existing work on information diffusion, which analyzes the impacts of social network structures on the spread of messages. Instead, we have modeled motivational causes for user behaviors by utilizing complex agents based on sociological theory. To that end, we have presented a general concept for representing and combining four different actor types in agent-based social simulations. In addition, we have applied this concept to model and analyze Twitter communication about a German television program. Our evaluation shows that particular combinations of different motivations either within individual agents or across an entire population drastically impact communication dynamics. Therefore, we conclude that it is crucial to consider these motivations carefully in order to realistically model and explain user behavior in social media.

While our model provides a promising first step to agent-based simulations of social media usage, there are several extensions we consider for future work. Firstly, we are working on calibrating the model to accurately imitate the user interactions observed in our real world example. This will provide insight into the achievable realism when combining the four basic actor types into complex agents and populations. As a first result, we have already demonstrated that our model is indeed capable of reproducing the communication activities of real world users [39].

Secondly, it would be interesting to integrate the agent decision method with existing information diffusion approaches [29]. This will complement those methods with motivational aspects of *why* information is spread within a social network. In that context, the population composition will provide an additional variable which impacts communication dynamics. The various actor types can then produce behavioral heterogeneity on a more detailed and explanatory deeper level than the addition of abstract random noise to an equational modeling approach [35].

Finally, it will also be necessary to model the activity options for the agents in more detail. This covers particularly the message contents. 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 [40] for encoding discourses in agent-based social simulations.

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