Diffusion in Social Networks: A Multiagent Perspective

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***Abstract*—In recent years, significant attention has been paid to diffusion in social networks (SNs), which is, factually, the collective behavior of a set of autonomous social actors for interacting on something in SNs (such as opinions, viruses, or innovations). While this subject has been intensively reported, there have been relatively few systematic reviews concerning the typical diffusion elements and models that are relevant to this subject. Because multiagent computing has already been widely envisioned to be a powerful paradigm for modeling the collective interactions of autonomous multientity systems. In this survey, we review diffusion in SNs through a multiagent perspective. First, we review the following essential elements in diffusion: 1) diffusion actors (who will diffuse), which can be understood to be the interacting agents; 2) diffusion media (where to be diffused), which can be understood to be the interaction environments in multiagent systems (MASs); and 3) diffusion contents (what to be diffused), which can be understood to be the interaction objects in MASs. Next, based on varying situations of diffusion elements, we review the representative diffusion models (how to diffuse), which can be understood as the decision-making mechanisms and interaction protocols in MASs. For each class of diffusion elements and models, we summarize the existing studies and discuss the challenges for solving the complex diffusion problems by applying multiagent methodologies. Finally, we discuss the advantages and disadvantages of our multiagent perspective by comparing other typical perspectives (the empirical research perspective and the theoretical perspective in empirical research), and we conclude with suggestions for further research.**

***Index Terms*—Diffusion, interaction, multiagent systems, social networks, spread, survey.**

I. Introduction

DIFFUSION in social networks (SNs) has received considerable attention recently in many fields [1]–[4], [109]. Usually, a diffusion process in a SN includes the following essential elements: 1) diffusion actors that represent who will diffuse something in a SN, such as individuals, groups, or organizations in the society; 2) diffusion medium that represents the SN environment where the diffusion takes place, such as the connection characteristics (e.g., weak ties and strong ties) or the network structures (e.g., clustered-lattice networks and random networks); and 3) diffusion content that represents what to be diffused in the SNs, such as innovation, rumor, behavior, or virus. In existing studies, many diffusion models have been presented for varying situations of those elements, which mainly define the decision making mechanisms of actors and the interaction protocols in the diffusion processes. For example, the threshold model [5] and the epidemic model [6] are two common models for the decision making of actors in diffusion; and pull and push mechanisms are two common interaction protocols in diffusion [1]. However, although a large number of related studies on diffusion in SNs have been done, there are few systematic reviews on the typical diffusion elements and models presented in existing studies.

In fact, diffusion in SNs can be described as the collective behavior of a set of autonomous social actors for interacting on something in the SNs [7]. Furthermore, modeling diffusion as emerging phenomena from the interaction of individuals has recently attracted a substantial amount of activities of researchers [8], [9]. Moreover, multiagent computing has already been widely envisioned to be a powerful paradigm for modeling the collective interactions of autonomous multientity systems [10], and SNs can be modeled as multiagent systems (MASs) [7], [11]. Therefore, in this paper, we review the state-of-the-art on diffusion in SNs through a multiagent perspective; the diffusion elements and models can be modeled based on a multiagent interaction framework: diffusion actors (who will diffuse), which can be understood as the interacting agents, diffusion media (where to be diffused), which can be understood as the interaction environments in MASs, and diffusion contents (what to be diffused), which can be understood as the interaction objects in MASs; after analyzing varying typical situations of diffusion elements, we review the typical diffusion models (how to diffuse) that can be understood as the decision-making mechanisms and interaction protocols in MASs.

Moreover, for each typical class of diffusion elements and models, we discuss the challenges in existing studies and present the future research directions based on multiagent methods. Finally, we compare our multiagent perspective with two other prevalent perspectives, the empirical research perspective and the theoretical perspective in empirical research. We argue that our multiagent perspective can be integrated

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TABLE I
COMPARISON BETWEEN DIFFUSION IN SNs AND INTERACTIONS IN MASs

Interactions in MASs	Diffusion in SNs		Comparison
A	*A*	Diffusion Elements	The diffusion actors can be modeled as agents that should consider more social characteristics.
I	*N*		The interaction relations in MASs can display in varied forms and be relatively static; the interaction relations in SNs are more dynamic and on a larger scale.
O	*C*		The diffusion contents in SNs can be in varied forms, but the interacting objects in MASs can be more abstract. Moreover, the strategies of actors when they are confronted to the diffusion of certain contents are much simpler than the strategies of agents when they negotiate about certain interacting objects.
P	*P*	Diffusion Model	The protocols of diffusion in SNs are more dynamic, in varied forms, and practical; the interaction protocols in MASs are more rigorous and can be validated effectively being built on solid theory foundations.
D	*D*		The decision in MASs can be more complex and have many strict assumptions; the decisions in SNs can be large scale, dynamic, and uncontrollable.

with these two perspectives to improve the practical feasibility and suitability of our perspective to investigate complex diffusion problems in SNs.

To the best of our knowledge, only Kiesling *et al.* [57] made a similar survey that reviewed the agent-based simulation of innovation diffusion. However, they only considered the innovation diffusion but not the general diffusion in SNs. In summary, the main contribution of this paper is that it systematically reviews the state-of-the-art of general diffusion in SNs from a multiagent perspective. The remainder of this paper is organized as follows. In Section II, we analyze the relationship between diffusion in SNs and interaction in MASs; in Section III, we review the typical elements of the diffusion in SNs via a multiagent perspective; in Section IV, we review the typical diffusion models via a multiagent perspective; in Section V, we compare our perspective with other typical perspectives; and finally, we discuss and conclude our paper in Section VI.

II. RELATIONSHIP BETWEEN DIFFUSION IN SNs AND INTERACTIONS IN MASs

A. Framework of Diffusion in SNs

The diffusion in a SN is the process by which a few members of the SN initially adopt a strategy which over time is adopted by more individuals until all (or most) members adopt it [2].

Definition 1 (Diffusion in SNs): Diffusion in a SN can be described by a tuple $<A, N, C, P, D>$, where

- A is the set of actors who diffuse something in SNs;
- N is the SN, and $A \times A \rightarrow \{0,1\}$ indicates a social connection between any two actors;
- C is the diffusion content representing what to be diffused in the SN, such as innovation, rumor, behavior, or virus. Generally, actors may choose certain strategies while they are confronted with the diffusion of certain content. For example, for the diffusion of rumor, *strategies* = {*believe, not believe*}, denotes that the actors can adopt to believe or not believe the rumor;
- P denotes the diffusion protocols, such as interaction forms, and temporal or spatial dependence in diffusion;
- D denotes the decision-making mechanism of actors while they encounter the diffusion.

In fact, the A, N, and C, respectively describe the essential elements of diffusion in SNs: diffusion actors, diffusion medium, and diffusion content; P and D describe the diffusion models.

B. Framework of Interaction in MASs

Based on [12], we next define here a formal framework of interaction in MASs, as follows.

Definition 2 (Interaction in MASs): The interactions in a MAS can be described by a tuple $< A, I, O, P, D >$, where

- A is the set of agents that are involved in an interaction;
- I denotes the set of interaction relations among agents, which can often be described as a network structure. With the interaction relations, some interacting constraints may be endowed on agents, such as strategy constraints, resource constraints, and temporal constraints;
- O denotes the interaction objects, which is the range of issues over which an agreement must be reached. The object could contain a single issue or multiple issues;
- P denotes the interaction protocols and regulations, which are the set of rules governing the interaction;
- D denotes the decision-making mechanism of agents in the interaction under the constraints of I.

C. Comparison Between Two Frameworks

From Definitions 1 and 2, the frameworks of diffusion and multiagent interaction can be closely correlated, and there is an almost exactly corresponding relation between them. Therefore, the elements and models of multiagent interaction can be used as a motivation and heuristics for reviewing the diffusion in SNs. Moreover, the research on diffusion in SNs can be conducted based on existing multiagent interaction models rather than on developing the diffusion model from scratch which could be costly.

Certainly, there are still some differences between the diffusion in SNs and the interaction in MASs. Next, we briefly compare them based on Definitions 1 and 2, shown in Table I.

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In general, the following problems should be noticed if we want to really apply MAS methods in the research on diffusion in SNs.

1) The diffusion in SNs can be more large-scale, dynamic, and active, but the interaction in MASs can be relatively restricted and artificial. The interaction mechanisms in MASs often have high efficiency with a small number of trading partners; however, the diffusion in the SNs can involve a very large number of actors. Research on the interaction in MASs often focuses on the development of negotiation theory and models, but the research on diffusion in SNs often focuses on the empirical analysis on the observed data. Therefore, how to improve the practicality of MAS methods to satisfy the large scale and dynamics of real diffusion in SNs is a crucial problem.
2) The final objectives of interaction in MASs are manifold, such as guaranteed success, maximizing social welfare, pareto efficiency, individual rationality, and stability [12]. In comparison, the final objectives of diffusion in SNs are relatively simple, such as maximizing influence or minimizing it. To consider the large scale and dynamics of SNs, the simplicity and efficiency of a diffusion model is very important because a complex diffusion mechanism could be costly. Therefore, a rough but simpler diffusion model can be more effective and more useful than a strict but complex model. Therefore, we should take measures to revise the MAS models to satisfy the requirements of diffusion in SNs.

III. Elements

A. Diffusion Actors

1) Review of Typical Types of Diffusion Actors From Multiagent Perspective: In MASs, the agents can be categorized from different views according to the agents' roles and relationships in the interaction process [14], [73]; generally, the following classification criteria are often observed: 1) cooperative or noncooperative: cooperative agents work together toward achieving some common goals [30], but noncooperative agents pursue their own goals irrespective of the others [15]; 2) truthful or untruthful: truthful agents provide true information and behave by obeying the protocols in the interaction [16], but untruthful agents are deviant from the desired protocols and might even tamper with the information in the interaction [17]; and 3) homogeneous or heterogeneous: homogeneous agents are uniform in characteristics and always fall into the same type [18], but heterogeneous agents are diverse in characteristics and could vary in different types [19].

In fact, the diffusion actors in SNs can be easily modeled as interacting agents in MASs. Therefore, the concepts of agents and actors are interchangeable in this paper. Based on those typical classifications of agents, the diffusion actors in SNs can also be classified into the following three types of categories: cooperative or noncooperative actors, truthful or untruthful actors, and homogeneous or heterogeneous actors. The corresponding relation between the interacting agents and the diffusion actors is shown in Fig. 1.

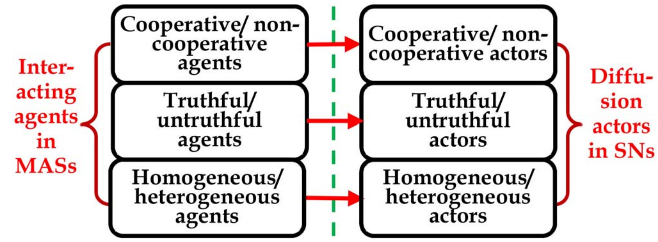

Fig. 1. Summary of the typical types of diffusion actors from a multiagent perspective.

a) Cooperative versus noncooperative diffusion actors: *i) Cooperative actors:* Cooperative diffusion actors can have some common goals and can cooperate with each other. Thus, they will adopt cooperative attitudes when they encounter the diffusion influences of other actors. Currently, there are many interaction techniques in cooperative MASs that can be used to investigate the interactions among cooperative diffusion actors in SNs. For example, the alignment rule is a widely adopted approach in which an individual agent adjusts its behavior by considering the behavioral strategies of its neighbors [20], and imitation is a special form in which an agent imitates the average strategy of other agents [21].

In fact, the techniques that are used in diffusion among cooperative actors are similar to the alignment rule in MASs, i.e., actors use specific mechanisms to adjust their behaviors by considering the strategies of other interacting actors in SNs. Moreover, the cooperative actors in SNs often learn which strategy to adopt by imitating the strategy of the best-performing player that they observe [22]; thus, an imitating mechanism is often used.

Currently, it is to be observed that cooperative actors in SNs often form some communities. Therefore, diffusion related to communities has attracted much attention. For example, Salathe and Jones [23] used empirical and simulated networks to investigate the diffusion of diseases in networks that have a community structure; they found that an infected individual is more likely to infect members of the same community than members outside of the community.

ii) Noncooperative actors: Noncooperative coordination has attracted much attention in the area of MASs, in which the agents are self-motivated and attempt to maximize their own benefits [25], [26]; similarly, there are selfish actors that participate in diffusion in SNs [27]. Usually, the methods that are used for collective decision making of noncooperative actors in diffusion are very similar to the methods that are used for noncooperative multiagent interactions, such as game theory [15], which can guarantee that noncooperative actors reach a collective strategy or decision.

Game theory can be used in diffusion scenarios in which an individual's behavior is the result of a strategic choice among competing alternatives [13], [28], such as the diffusion of technologies, advertisements, or innovations. Montanari and Saberi [28] studied the noncooperative diffusion of innovations in SNs that were based on the dynamics of coordination games: each actor must make a choice between two alternatives ($x_i \in \{+1, -1\}$); the payoff of each of the two choices for the actor increases with the number of neighbors who are adopting the same choice. Rodríguez-Achach *et al*. [29] studied a noncooperative diffusion model of innovations in a network of actors that are characterized by their technological level; there, the actors can follow Nash or Pareto strategies when they decide whether to upgrade their level or not.

b) Truthful versus untruthful diffusion actors: In an open SN, an actor can choose to be truthful or untruthful in diffusion. Untruthful social actors are different from the noncooperative social actors because untruthful actors could have a subjective (deliberate) initiative to make some deviation or malicious behaviors in the diffusion [16], [31]. However, noncooperative actors can be truthful or untruthful.

In fact, untruthfulness is also often observed in MAS domains, where some agents can fail to carry out their obligations and lie to one another during the interaction, either by hiding some information or by creating fictitious information [32]. To address the untruthfulness of MASs, a trust and reputation mechanism is often used, which can estimate the trustworthiness of the agents. According to the same rule, the trust and reputation-based mechanism is also used for diffusion scenarios that have truthful and untruthful actors in SNs [7].

Trust can be defined as an actor's expectation of another actor's behavior based on their past interactions. An actor will be inclined to adopt another actor's behavior strategy if it trusts that actor. For example, in the diffusion of recommendations, an actor will decide whether to rely on another's recommendation according to its trust in the actor [33]. Hang *et al*. [34] presented an evidence-based approach to trust propagation in undependable SNs, which provides efficient operations, concatenation, aggregation, and selection, that can propagate trust accurately.

The reputation of an actor refers to other actors' opinions on that actor, which is available to other actors even when they have not interacted with that actor. If an actor's reputation is high, then its behavior strategies will be more easily accepted by other actors in the diffusion. For example, Paolucci and Conte [35] focused on social reputation as a fundamental mechanism in the diffusion of socially desirable behavior and presented a cognitive analysis of reputation.

c) Homogeneous versus heterogeneous diffusion actors: Synchronization is a typical phenomenon in MASs, which denotes that all agents can reach an agreement on their behavior strategies [21], [36], [37]. There are two synchronization mechanisms [21]: one mechanism is flat synchronization, in which all of the agents are homogeneous and have the same synchronization capacity; another mechanism is nonflat synchronization, in which agents are heterogeneous and different agents have different synchronization capacities. Diffusion in SNs can, in fact, be viewed as a special form of synchronization because one of the main aims of diffusion is maximizing the influence over the whole SN; therefore, drawing inspiration from those situations in MASs, the diffusion actors in SNs can also be categorized into homogeneous and heterogeneous actors.

The homogeneous actors have the same characteristics in diffusion, such as the threshold value, response time, and link degree. Diffusion among homogeneous actors can take place with the same constant speed. Each actor has the tendency to imitate the states in its neighborhood and will update its state according to the average state of its neighbors. For example, a simple linear threshold model, the Watts' threshold model [38], can be used for the diffusion of homogeneous actors, where actors have the same threshold and will switch states if their perceived proportion of active neighbors exceeds a threshold. Such a model can be formally explained as follows: each actor is initially given an identical threshold τ in (0, 1], and an inactive actor with m active neighbors and k–m inactive neighbors will be activated only if the fraction m/k exceeds τ [39].

However, many SNs are heterogeneous and are composed of more than one type of actor [40]. It was observed that the heterogeneity of the actors could have noticeable effects on the diffusion in SNs. For example, Iribarren and Moro [8] studied how the large heterogeneity of actor activity rhythms controls the information diffusion dynamics, and they showed that the large heterogeneity that is found in the response time is responsible for the slow dynamics of the information at the collective level. Young [41] incorporated heterogeneity into diffusion, such as actors' benefits, costs, and times; the novelty of Young's study is that it explored the heterogeneity of actors from a more general view and solved the previous work in which the heterogeneity is used in a very restricted fashion.

Moreover, the number of links of various actors can be heterogeneous, e.g., some follow a power law distribution but others could follow a random distribution. For example, Liu *et al*. [43] investigated the infection dynamics range from heterogeneous (scale-free) to homogeneous (random) and found that heterogeneous networks are relatively more robust against diffusion of infections compared with homogeneous networks.

2) Challenges and Future Research Directions: Next, we summarize some challenges in existing studies on diffusion actors and present some insights on future research directions by applying related multiagent techniques, which are shown as follows.

a) *More Intelligent and Reasoning Actors:* In the existing studies, the behaviors of actors are relatively simple and passive in diffusion. However, the real social actors are very active and intelligent. To solve such a problem, we think that the reasoning of an agent is an important function and can be used in SNs to model and analyze the thinking of social actors in the diffusion. Furthermore, more learning and consciousness techniques of agents can be used for modeling the social actors' learning and evolving behaviors. Certainly, we should address the practical feasibility of the theoretical models of the reasoning and learning of agents in real SNs.

b) *Collective Behaviors of Diffusion Actors:* In existing studies, each actor often behaves and makes decision individually. Although there is a small amount of work on diffusion that is related to communities, the studies are essentially based on the mechanisms of individual actors. In the future, we can apply the coalition mechanism and collective decision-making mechanism

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of multiagents into the collective behavior of social actors in diffusion.

c) *Dynamically Transformable Diffusion Actors:* In current related studies, the roles of actors are always assumed to stay fixed during the diffusion. Obviously, such an assumption cannot fully reflect reality. In fact, social actors can dynamically change their roles in the diffusion, e.g., an untruthful actor can take a truthful action when it finds that such an action can bring more benefits. A competitive actor can also take cooperative actions in the diffusion. In fact, there are many advanced studies on the dynamic roles in MASs. In the future, those related models in MASs can be applied to model the actors having dynamic roles in the diffusion.

B. Diffusion Media

1) Review of Typical Types of Diffusion Media From Multiagent Perspective: The diffusion media are the SN environments in which the diffusion takes place. Because of the significant diversity and complexity of real diffusion environments, it is a challenge to make a systematic classification on the diffusion media in existing studies.

In the MAS domain, the interaction environments are always categorized according to the following aspects: 1) interaction structure topological characteristics, which represent the interaction relationships among the interacting agents; 2) interaction link types (single-linked interaction and multi-linked interaction), which represent that an agent must negotiate with a single agent or multiple agents about different issues; and 3) interaction link strengths, which represent the connection strengths between the interacting agents. For considering the correlation between the interaction environments in MASs and the diffusion media in SNs, as stated in Section II, we now also classify the diffusion media in existing studies from the multiagent perspective, which is shown in Fig. 2. In summary, the typical diffusion media in existing studies can be categorized as follows.

1) *Typical SN Structures:* Small world, random networks, scale-free networks, and clustered networks.
2) *Typical SN Link Types:* Simplex networks and multiplex networks.
3) *Typical SN Link Strengths:* Strong and weak ties.

a) Typical SN structures: The SN structure of who is connected to whom can critically affect the extent to which something diffuses across a population [44]. Overall, the following typical structures are often observed in the real diffusion of SNs [45]: small world networks, random networks, scale-free networks, and clustered networks. Next, we will review representative studies for such typical SN structures.

Small-world structure indicates that most actors are not neighbors but can be reached from every other actor by a small number of hops or steps. Obviously, such a small-world characteristic significantly influences the diffusion paths and velocities [42]. Zanette [46] studied the dynamics of an epidemic-like model for the diffusion of a rumor on a small-world network and showed that such a model exhibits a transition between the regimes of localization and propagation at a finite value of network randomness. Kuperman and Abramson [47] analyzed the model for the diffusion of an infection for different population structures and explored the small-world effect in such an epidemiological model, and they found a transition to self-sustained oscillations in the size of the infected subpopulation.

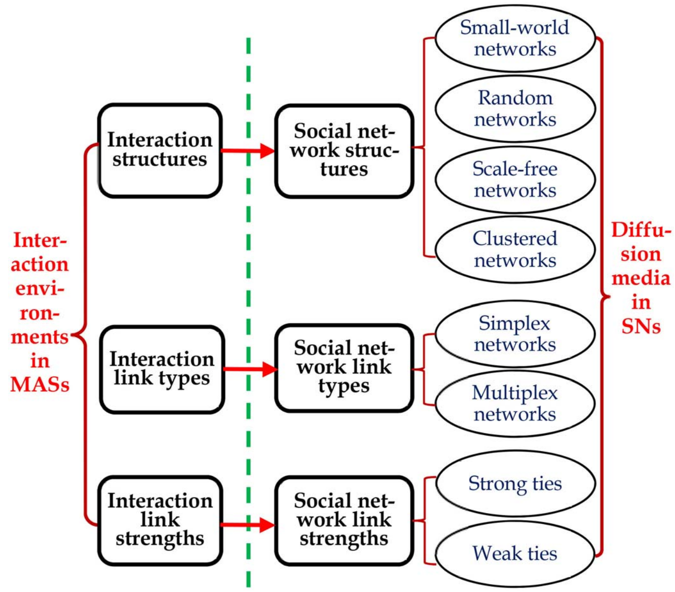

Fig. 2. Summary of the typical types of diffusion media from a multiagent perspective.

In random structures, the networks are generated by random processes and are determined by a probability distribution [50]. Watts [38] presented a possible explanation of the cascade phenomenon in terms of a random network of interacting actors; when cascade propagation is limited by the connectivity of the network, a power law distribution of cascade sizes is observed, which is analogous to the cluster size distribution in standard percolation theory and avalanches in self-organized criticality. López-Pintado [49] obtained the contagion threshold for random networks with different connectivity distributions and showed that, unlike standard epidemiology models, networks with intermediate variance in the connectivity distribution can be optimal for this diffusion process.

Scale-free networks are those in which a node of these networks has the degree k and usually follows a power law, $P(k) \propto k^{-\gamma}$, over a large range of k and an exponent γ that ranges between 2 and 3 [45], [53]. In fact, the diffusion in scale-free networks is very sensitive to the statistics of degree distribution that is characterized by the index γ [6]. Griffin and Brooks [52] examined the impact of the scaling factor on the diffusion of worms in a scale-free network and showed that the scale-free structure of networks makes network mono-cultures inconsequential with respect to the diffusion of epidemics. Moreover, Meloni *et al*. [54] presented a novel perspective on diffusion in finite-size scale-free networks in which the epidemic incidence is shaped by traffic-flow conditions, and they showed that the value of the epidemic threshold in scale-free networks depends directly on the flow conditions.

Moreover, it is found that most SNs are clustered, which means that there is a high density of loops of length three or short cycles. Clustering can decrease the size of the epidemics, but it also can decrease the epidemic threshold, making it easier for diseases to diffuse [55]. However, others have shown that clustering appears to raise the epidemic threshold [56]. This discrepancy occurs because there are many different approaches that are used to generate clustered networks [56]. Especially, a social behavior that requires social reinforcement will diffuse more effectively in clustered networks because clustered networks have more redundant ties and can provide social reinforcement for adoption [44].

Certainly, there are other properties of real SN structures [115]. To deal with the large scale and unforeseen levels of real SNs, Bergenti *et al*. [111] investigated the agent-based simulation of SNs, in which many properties of SNs are considered, such as average shortest path length, clustering coefficient, degree distribution, and assortativity coefficient. In the agent-based simulation, a controller agent selects the agent(s) that are going to add a link and then each of these agents chooses the other end of the link. Moreover, they argued that current methods for generating SNs fail to catch some aspects of real SNs [111]; especially, large online SNs often evolve and grow dynamically [112], [115], which may influence the diffusion significantly.

b) Typical SN link types: simplex networks versus multiplex networks: MASs have two types of interaction links: single-linked interactions, in which agents have only an interaction relation about one issue, and multilinked interactions, in which an agent must negotiate different issues with several agents [58]. Inspired by this interaction situation in MASs, the SNs can also be categorized into simplex networks and multiplex networks.

In simplex networks, all of the links are of the same type and the diffusion path is affected by only the distance between the diffusion actors. Therefore, while an actor decides its state, it considers only the proportion of neighbors who accept the influence of diffusion and ignores the link types between that actor and its neighbors.

In multiplex networks, the actors are connected by multiple types of links [24], [39], [59], [60], [61]. Diffusion in multiplex networks is more complex than in simplex networks. Many previous studies mainly consider the case in which diffusion occurs along the contacts of a simplex network. The diffusion in multiplex networks has been studied a substantial amount only in recent years [116].

A summary of typical SN link types is shown in Fig. 3. Because the related studies reviewed in other sections of this paper are mainly about the simplex networks, in this subsection we mainly review the existing studies in multiplex networks.

How to model the topological characteristics of multiplex networks is a crucial problem. For example, Gómez *et al*. [62] modeled the multiplex networks as structured multilevel graphs in which the interconnections between the layers determine how a given node in a layer and its counterpart in another layer are linked and influence each other. Jiang *et al*. [63] modeled a multiplex network as a set of associative network layers, where each network layer is composed of links of the same type and the involved actors. Moreover, Buldyrev *et al*. [64]

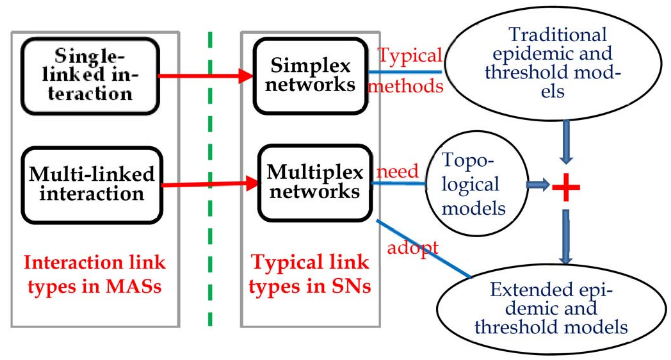

Fig. 3. Summary of the typical social network link types from a multiagent perspective.

presented a method for modeling multiplex networks that concerned the coupling and interdependence among different networks.

In related studies on the diffusion in multiplex networks, a common method is extending the existing models in simplex networks by considering the multiplicity of links. Two typical classes of approaches are: generalizing the epidemic model and the threshold model in simplex networks to the multiplex networks. Next, we introduce some representative studies.

The first typical class is generalizing a traditional epidemic model to multiplex networks. For example, Xuan *et al*. [65] generalized an epidemic diffusion model, called susceptible-infected-susceptible (SIS) dynamics, on duplex networks in which links were classified into two groups. Cozzo *et al*. [66] extended the SIS model and proposed a contact-based Markov chain approach to study epidemic-like social contagion in multiplex networks.

The second typical class is generalizing a traditional threshold model to multiplex networks. For example, Brummitt *et al*. [67] studied cascades in multiplex SNs by generalizing the threshold diffusion model, in which an actor is activated if a sufficiently large fraction of its neighbors in any type of link are active, i.e., the following condition is satisfied [39]:

$$\max_{i=1,\dots,r}\left(\frac{m_i}{k_i}\right) \geq \tau \tag{1}$$

where r denotes the number of link types, i denotes the type i links, m_i denotes the number of active neighbors, k_i denotes the total number of neighbors, and τ denotes a predefined threshold. Then, Yağan and Gligor [39] presented an improved model of the diffusion of influences in random multiplex networks. In their model, each link type is associated with a content-dependent parameter c_i in $[0,\infty]$, which measures the relative bias that type i links have in spreading such a context; a receiver actor will become active if the following condition can be satisfied [39]:

$$\frac{\left(\sum_{i=1}^{r} c_i m_i\right)}{\left(\sum_{i=1}^{r} c_i k_i\right)} \geq \tau. \tag{2}$$

c) Typical SN link strengths: strong ties versus weak ties: The strengths of the links in a SN also influence the diffusion results [7], [68], [71], which mainly include strong ties and weak ties. In general, many studies state that strong ties can promote the diffusion of behaviors in SNs because actors who interact more often have a greater opportunity to influence one another [69]. More precisely, strong ties can better promote the diffusion of behaviors that require multiple interaction reinforcements. However, Bakshy *et al*. [68] found that, although stronger ties are individually more influential, more abundant weak ties are responsible for the propagation of novel information. Therefore, we can suggest that weak ties could play a more dominant role in the diffusion of behaviors that require only a single interaction compared with behavior diffusion that requires multiple interactions [44].

There are also many other related studies about the effects of link strengths on diffusion. For example, Zhao *et al*. [70] found that positive weak ties are very important in connecting isolated local clusters for the further diffusion of information in online SNs. Friedkin [72] found that strong ties are more important than weak ties in promoting information diffusion about activities within an organizational subsystem, while the latter are more important than the former in promoting information flow about activities outside an organizational subsystem.

Moreover, in real SNs, most ties are not persistent, and the link strengths can be dynamic. Most of the previous studies that describe the network links by static strengths do not include information about the temporal aspects of how actors interact. To address such a problem, Miritello *et al*. [74] defined the dynamical strength of the social ties, which is a quantity that encompasses both the topological and temporal patterns of interactions among the actors.

2) Challenges and Future Research Direction: Next, we summarize some challenges in existing studies on diffusion media in SNs and present some insights into future research directions by applying related multiagent techniques, which is summarized in the following.

a) *Dynamic Diffusion Media:* SNs always evolve over time, and ties in such networks are often dynamic [75], [76]. However, in most existing studies on diffusion, the diffusion media are often assumed to be fixed during the diffusion. There are few studies on this issue, and they adopt some passive measures to quantify the dynamics. To address the problem, we can introduce the learning technology of MASs to investigate how the social actors can actively learn and predict the dynamic SN environments.

b) *Transfer Diffusion and Correlated Effects Across Network Layers in Multiplex SNs [7]:* The diffusion process can be transferred across network layers, and the diffusion in one network layer can have some influence on other network layers. To address this problem, we believe that in the future the transfer learning and cross-organizational coordination of MASs can be introduced. Certainly, the large scale, complexity, and dynamics of multiplex SNs will bring about new questions that must be explored.

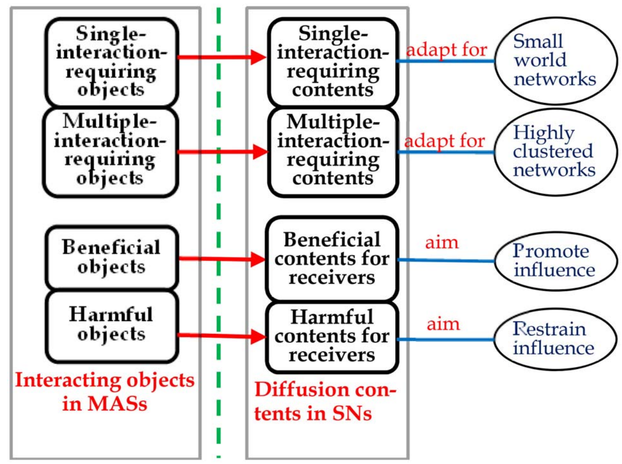

Fig. 4. Summary of the typical types of diffusion content from a multiagent perspective.

C. Diffusion Contents

1) Review of Typical Types of Diffusion Contents From Multiagent Perspective: The phrase diffusion content indicates something that will be spread in the SNs. There is a significant variety of diffusion contents in reality [77], like innovations, opinions, viruses, rumors, and diseases. Because there are too many types of diffusion contents, it is a challenge to summarize their categorization. Next, we also attempt to solve this problem by drawing inspiration from the MAS domain.

In MASs the interaction objects represent the range of issues over which agreement must be reached [14]. Usually, the following two situations are observed: 1) single interaction-requiring objects or multiple interaction-requiring objects, which mean that the coordination result can be obtained by a single interaction or by multiple interactions and 2) beneficial or harmful objects, which mean that the results of interaction will improve or decrease the overall welfare of the whole MAS. Therefore, based on these two typical situations with respect to the interaction objects of MASs, the diffusion contents in the SNs can be categorized accordingly into the following two types: 1) single interaction-requiring contents or multiple interaction-requiring contents; the former are often spread efficiently in small-world networks, and the latter are often spread efficiently in highly clustered networks and 2) beneficial or harmful contents for receiver actors; the former's influence should be promoted, and the latter's influence should be restrained. The corresponding relations between interaction objects and diffusion contents are shown in Fig. 4.

a) Single interaction-requiring contents versus multiple interaction-requiring contents: We can categorize the diffusion contents into single interaction-requiring contents and multiple interaction-requiring contents. The former can be accepted after only requiring a single interaction, such as the emotion and sentiments [78], or viruses or infectious diseases [79]; however, the latter can be accepted after requiring multiple interaction reinforcement, such as the technological innovations [28], living habits or opinions [44], or rumors [80].

Usually, in the diffusion of contents that require only a single interaction, the networks with small-world topologies can spread the contents farther and more quickly than highly clustered networks because the former network structure can provide more and faster single interactions. In contrast, in the diffusion of contents that need multiple interaction reinforcement, highly clustered networks can improve the spreading because such network structures can provide more redundant ties that can reinforce interactions [44], [81].

Therefore, if we want to extend the influence of single interaction-requiring contents, then we can add more long ties into the SNs; if we want to extend the influence of multiple interaction-requiring contents, then we can add more redundant ties into the SNs.

b) Beneficial contents versus harmful contents for receiver actors: Some diffusion contents can bring beneficial influences to the receiver actors, such as technological innovations, good living habits, and happiness; some diffusion contents can bring harmful influences to the receiver actors, such as bad living habits, infectious disease, viruses, and rumors. For the former, the aim of the research is to investigate the diffusion process and to maximize such diffusion's influence; for the latter, the aim of the research is to investigate the diffusion process and to restrain such diffusion's influence. Those two research objectives are detailed in Section 4.1.3.

Moreover, a few of researchers have studied the diffusion patterns of some typical contents. For example, Bollen *et al*. [78] studied the diffusion of some good psychological states in SNs and found that the general happiness of Twitter users, as measured from a six-month record of their individual tweets, is indeed assortative across the Twitter SN. Christakis and Fowler [84] investigated the extent to which smoking behavior transcends direct dyadic ties and found that decisions to quit smoking are not made solely by isolated persons; instead, they reflect choices that are made by groups of people who are connected.

In summary, the existing related studies mainly focused on discovering a diffusion pattern and how to promote or restrain such diffusion [86].

2) Challenges and Future Research Directions: Next, we summarize some challenges in existing studies on the diffusion contents and present some insights on future research directions by applying related multiagent techniques, which is shown in the following.

a) *Hybrid and associated contents in the diffusion:* In reality, there can be more than one type of diffusion contents in a SN. However, most existing related studies are only concerned about the situation in which there is only one type of content that is spreading at the same time. In fact, the problem of multiple issues in negotiation has been successfully solved in the MAS domain. Thus, the related methods of the MAS domain can be introduced to model the decision-making mechanism in which an actor confronts the diffusion of multiple types of contents. Moreover, the problem of associated effects among different types of contents should also be addressed.

b) *Evolutional diffusion contents:* In existing related studies, the characteristics of the contents are fixed during the diffusion process. However, some contents could change their characteristics during the diffusion. For example, the infectivity of a disease can become higher when it spreads across a certain population, and a novel living habit can become unattractive if it has been adopted by too many people. Therefore, the evolution of the diffusion contents should be considered in large-scale and long-playing diffusion.

c) *Constrained diffusion contents:* In real diffusion, the contents can be constrained by some situations, such as temporal or spatial constraints. For example, the spreading of a disease virus from one person to another person should be completed within a certain amount of time; otherwise, the disease virus can die. However, there are few systematic research studies on such constrained diffusion contents. To address this problem, we can introduce some constraint satisfaction problem solutions from MASs into the decision making and coordination of actors when they confront the constrained diffusion contents.

IV. Models

A. Review of Diffusion Models From Multiagent Perspective

Usually, an interaction model in MASs mainly considers the following aspects [12]: negotiation protocols and decision-making mechanisms, which are the set of rules that govern the interaction and decision making of agents; interaction forms, which shape the interaction relationships between agents; and optimization objectives, which control the final objectives of the interactions.

Similarly, diffusion models mainly restrict the protocols and regulations of decision-making mechanisms in diffusion, interaction forms, and diffusion objectives. Therefore, this paper reviews the existing studies on diffusion models based on the following aspects: typical decision mechanisms, typical interaction forms, and typical optimization objectives.

1) Typical Decision Mechanisms in Diffusion: In the interaction of MASs, the decision-making mechanism determines how the agents select their action strategies from several possible choices according to the interaction situations. Usually, there are two typical decision mechanisms [87]: a) the deterministic decision mechanism, which represents that the input–output relation in the decision-making process of an agent is deterministic and b) the nondeterministic decision mechanism, which represents that there are no deterministic relations between the input and output in the decision making of an agent and is often implemented by a probabilistic approach.

Similarly, the decision mechanisms in diffusion models can be categorized into: a) deterministic diffusion models, where an actor can adopt a state that is truly determined by the diffusion impacts from other actors, such as in a neighbor imitation model, threshold model, or deterministic game theory model and b) nondeterministic diffusion models, where an actor can adopt a state that is probabilistically related to the diffusion impacts from the other actors, such as in independent cascade models (SIS, SIR) or nondeterministic game theory models. This categorization is shown in Fig. 5.

a) Deterministic diffusion: In deterministic diffusion models, the receiver actor's state can be deterministically

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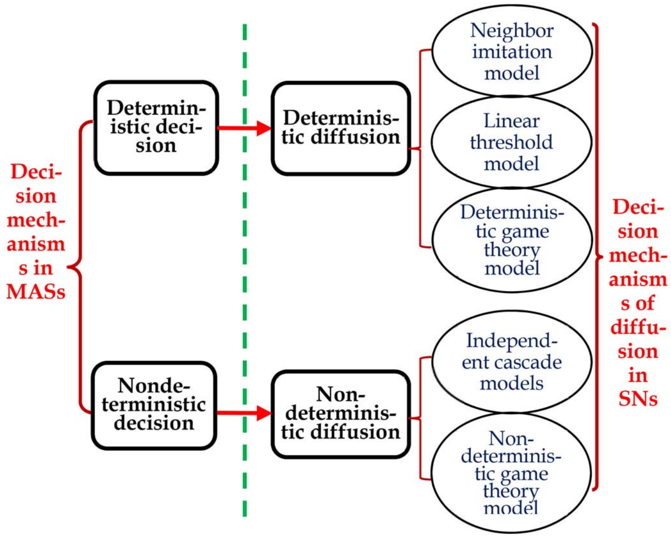

Fig. 5. Summary of the typical types of decision mechanisms in diffusion models from a multiagent perspective.

decided by the states of the sender actors. Usually, the following three deterministic diffusion models are often observed in existing studies: neighbor imitation model, linear threshold model, and deterministic game theory model.

The neighbor imitation model is a very simple deterministic diffusion model that represents that an actor acts solely on the basis of its own local perception of the SN and imitates the average strategy of its neighbors [21], [88]. Ohtsuki *et al*. [89] described a simple improved neighbor average model for the diffusion of cooperation in SNs that have various structures: an actor will become cooperative if the benefit of the malicious act, b, divided by the cost, c, exceeds the average number of neighbors, k, which means that $b/c>k$.

The linear threshold model is a widely used deterministic diffusion method, in which an actor is influenced by its active neighbors if the sum of their weights exceeds the threshold for the actor [90]. For example, Borodin *et al*. [91] presented a threshold model for a competitive influence in SNs; in that model, the actors that have low thresholds can easily adopt others' behavior strategies, and the actors that have high thresholds can adopt others' behavior strategies only after most of the others have adopted that behavior strategy. Jiang [3] presented an extended threshold diffusion model that not only was based on the proportion of actors that have already adopted a behavior strategy but was also based on the collective social positions of those adopter actors.

In the deterministic game theory-based diffusion model, none of the states of the actors are subject to chance (none are probabilistic), which is often used in scenarios in which an individual's behavior is the result of a deterministic strategic choice among competing alternatives. For example, Alon *et al*. [13] introduced a deterministic game-theoretic model for competitive diffusion, where the strategy for each actor in the diffusion can be decided by the deterministic game with other actors in the network.

b) Nondeterministic diffusion: In the nondeterministic diffusion models, the receiver actor's state is not deterministically decided but is only influenced with a probability by the states of the sender actors. Among the nondeterministic models, the following two typical classes are often observed: independent cascade (or epidemic) models and nondeterministic game theory models.

Independent cascade (or epidemic) models are widely used in related studies. The underlying assumption of these models is that the actors adopt a new behavior with a specific probability when they come into contact with others who have already adopted it. Therefore, the diffusion probabilities in this type of model should be considered and must be specified in advance [90]. Two basic epidemic models are the susceptible-infected-removed (SIR) model [85] and the SIS model [51]. In an SIR model, each actor can be in one of three different compartments with specific probabilities [85]: those who are susceptible to the diffusion content are in the susceptible compartment; those who are infected and can transmit the content to others are in the infected compartment; and those who have recovered and are immune are in the recovered compartment. The SIS model can be easily derived from the SIR model by simply considering that the actors recover with no immunity to the diffusion content, i.e., the infected actors are cured and become again susceptible with a specific probability [51]. Noticeably, Franchi [113] used an agent-based domain-specific language to implement the SIR model, which showed that the agent-based modeling approach can efficiently deal with the large simulations of diffusion in SNs.

Moreover, based on the above two basic epidemic models (the SIR and SIS models), many other improved models have been investigated [92]. For example, Shaw and Schwartz [93] created a model by adding a vaccinated class (V) to modify an SIS model. Cator and Van Mieghem [4] presented a modified SIS model (MSIS) that obeys the same evolution rules as the SIS model except that when there is only one infected node that is forbidden to heal in the network; thus, the MSIS model can prevent the epidemic from dying out. Wen *et al*. [94] proposed a novel SII model (susceptible-infectious-immunized) to solve two critical problems that were unsolved in the previous SIR and SIS models: temporal dynamics and spatial dependence.

Another typical class of models are the nondeterministic game theory models. The difference between game theory models and the independent cascade models is that the former are based on the notion of utility maximization rather than exposure; the basic hypothesis in nondeterministic game theory models is that, when adopting a new behavior, each individual makes a rational choice to maximize its payoff in a nondeterministic coordination game. For example, a representative study is that Montanari and Saberi [28] used a nondeterministic game theory model to study the spread of innovations in SNs.

2) Typical Interaction Forms in Diffusion: There are two typical factors for shaping the interaction forms in MASs: the interaction relationship and the interaction direction. Similarly, we categorize the typical interaction forms in the diffusion as follows: 1) typical interaction relationships, such as one-to-one or many-to-one and 2) typical interaction directions, such as push or pull. A summary is shown in Fig. 6.

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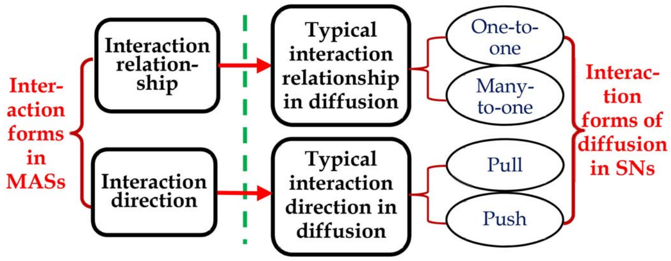

Fig. 6. Summary of the typical interaction forms in diffusion models from a multiagent perspective.

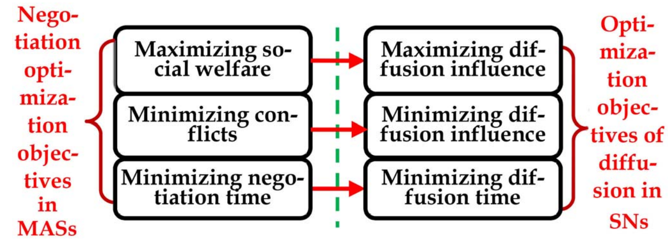

Fig. 7. Summary of the typical optimization objectives in diffusion from a multiagent perspective.

a) One-to-one and many-to-one forms: In the interaction of MASs, in terms of the number of participating agents, the one-to-one and many-to-one interaction forms are often observed [95]. Accordingly, the interaction forms in typical diffusion models can also be categorized into one-to-one and many-to-one according to the number of actors who participate in a diffusion step. Usually, neighbor imitation models and linear threshold models adopt a many-to-one interaction form; in game theory models and independent cascade (or epidemic) models, both many-to-one and one-to-one forms can be used.

In neighbor imitation models, each receiver actor will decide its states by averaging the states of all of its neighbors [21], [89]; in the threshold models, the receiver actor decides its state by considering the states of many interacting actors [67], [90]. Therefore, the interaction forms in these two models are definitely many-to-one.

In game theory models, existing related studies can adopt the many-to-one or one-to-one forms according to the diffusion elements. For example, in the game theory model presented in [13] to model the competitive diffusion in SNs, a many-to-one form is used where each actor can decide its strategy by considering many of its neighbors. In the game theory-based diffusion model of innovations presented in [29], a one-to-one form is used where an actor can take the technological level of one of its nearest neighbors or keep its own level.

In independent cascade (or epidemic) models, sometimes an actor can accept a behavioral strategy from others once it is influenced by another actor; however, sometimes an actor can accept others' behavioral strategies only after many of the others adopted such a strategy [7]. In the former situation, the one-to-one interaction form is often used; in the latter situation, the many-to-one interaction form is often used, where an actor can be infected by its infected neighbors at a probability that is proportional to the number of infected neighbors [97].

b) Push and pull forms: In MASs, the two typical interaction directions are reactive and proactive forms. The former indicates that the agents can perceive their environment and respond to changes that occur in their surrounding environment in a timely fashion, and the latter indicates that the agents can act by taking the initiative [98]. According to the same rule, the interaction directions in the diffusion can also be categorized into two classes: push-based diffusion, which indicates that an infectious actor always actively attempts to infect its neighboring actors, and pull-based diffusion, which indicates that a susceptible actor can become infected by connecting to an infected actor [1].

In the push-based diffusion, each infectious actor has a push-based infection capability that indicates its probability of successfully infecting a susceptible actor [1], [99]. For example, the epidemic spreading of a computer virus always adopts a push-based form [51], i.e., the virus in an infected computer can actively infect another susceptible computer. Another typical push-based diffusion is the spread of infectious diseases [92], where the diseases in infected people can actively infect other contacted people.

In the pull-based diffusion, each susceptible actor has a pull-based infection capability, in which it has a probability of becoming infectious because of its own proactive actions [1]. For example, a susceptible user can become infected by downloading some malicious contents from a compromised web site. Provos *et al.* [100] presented that the Internet users can be infected by actively connecting to the Internet and conducting their activities if some hosts are infected with malware.

Moreover, now there are some studies that combine the push and pull diffusion forms together. A representative study is that of Xu *et al.* [1], who conducted a rigorous benchmark study on a push-and pull-based epidemic model in arbitrary networks and presented sufficient conditions or epidemic thresholds under which the diffusion will become stable.

3) Typical Optimization Objectives in Diffusion: In MASs the negotiation objectives are important to decide the interaction protocols and decision-making mechanisms. In fact, there are many types of negotiation optimization objectives [12], [101], such as maximizing social welfare, minimizing conflicts, and minimizing the negotiation time. Inspired by the negotiation objectives in MASs, we summarize the optimization objectives in diffusion models into the following three typical classes: maximizing the influence, minimizing the influence, and minimizing the diffusion time (or maximizing the diffusion velocity). A summary is shown in Fig. 7.

Maximizing the diffusion influence is a major objective in many related studies. To maximize the influence, the core problem is selecting a small set of individual actors in a SN, to adopt the strategy in such a way that these actors can trigger a maximal cascade of further adoptions [82], [102]. In fact, the optimization problem of selecting the most influential actors is NP-hard; thus, many related studies attempt to present some heuristics to reduce the complexity. Kempe *et al.* [82] provided the first provable approximation guarantees for efficient algorithms and showed that a natural greedy strategy obtains a solution that is probably within 63% of the optimum for several classes of models. However, a conventional method under the greedy algorithm could bring about heavy computational costs. To solve this problem, Kimura *et al*. [103] proposed a method on the basis of bond percolation and graph theory, which can significantly reduce the computational costs.

Minimizing the diffusion influence is another common objective in related studies. The problem of minimizing influence is prevalent in the diffusion of harmful content for receiver actors, such as computer viruses, malicious rumors, or misinformation. Generally, there are three typical methods for minimizing influence: 1) removing a limited number of contaminated actors; 2) blocking a limited number of links to restrain the diffusion of bad content; and 3) launching a new diffusion campaign of opposite content to counteract the diffusion of a content. For example, Xia [104] proposed a belief diffusion algorithm to help criminal investigators find and remove the contaminated actors. Kimura *et al*. [105] proposed methods for efficiently finding good approximate solutions to the problem of blocking a limited number of links in a network to minimize the contamination. Budak *et al*. [106] studied the notion of competing campaigns in a SN to limit the diffusion of some contents.

Minimizing the diffusion time indicates that the diffusion can reach the whole network or reach equilibrium within a minimal time. While negotiation time in MASs is the steps of agents to reach an agreement on their strategies [14], the notion of diffusion time indicates the steps on the evolution of a diffusion process spreading throughout a network [114]. Antulov-Fantulin *et al*. [85] proposed the FastSIR algorithm, which can reduce the running time of the naive SIR algorithm by basing it on a probability distribution of the number of infected actors. Chen *et al*. [107] combined the objectives of influence maximization and time minimization and considered time-critical influence maximization in which one wants to maximize the influence spread within a given deadline.

B. Challenges and Future Research Directions

Next, we summarize some challenges in existing studies on diffusion models in SNs and present some insights on future research directions by applying related multiagent techniques, which is shown in the following list.

1) *Mixed Diffusion Models in a SN:* In existing studies, only one type of diffusion model is used for one case. However, due to the large scale and heterogeneity of real SNs, more than one type of diffusion model can be mixed to analyze the diffusion in a SN. Therefore, the hybrid effects of various diffusion models within a SN should be investigated in the future. We think that such a research direction can be based on the related research on hybrid negotiation in heterogeneous MASs.
2) *Group Interaction Mechanism in Diffusion:* As stated above, existing related studies mainly adopt the interaction forms of one-to-one or many-to-one, i.e., the diffusion model mainly concerns how individual actors decide their strategies. However, in many SNs, the actors can form some groups or communities. Therefore, in the future, the group interaction mechanism in diffusion will be explored based on the collective motion models of MASs.
3) *Concurrency of Multiple Diffusion Processes in SNs:* Existing studies mainly consider the situation in which only one diffusion process is taking place at a time or only two competing diffusion processes are taking place. However, in reality, there are multiple diffusion processes from collective actors to collective actors that can take place concurrently. Therefore, in the future, we must explore the concurrent mechanism and correlation effect of multiple diffusion processes in large SNs, which can be based on the previous work on the coordination of concurrent actions of large-scale MASs in the control area.

V. Comparisons With Other Perspectives

The previous perspectives of research on diffusion in SNs mainly include the empirical research perspective and the theoretical perspective in empirical research. Next, we compare our perspective with such previous perspectives.

A. Empirical Research Perspective

Most of the related studies adopt an empirical research perspective, which empirically analyzes and characterizes the elements and models of diffusion from the observed data [96]. The empirical perspective is a method of research based on the experimentation or observation data of the diffusion phenomena, which derives diffusion patterns and rules from actual experience rather than from theory.

In empirical research, massive quantities of data and efficient data analysis tools are required, which can offer a rich source of evidence and effective measures for studying the diffusion [7]. There are many types of data collection methods, such as interviews, observations, and questionnaires; especially in research on diffusion in online SNs, empirical data are collected from the Internet, and some web crawler tools are often used. On the other hand, the data analysis methods are crucial and constitute the majority of the related studies, such as statistical analysis or data mining.

The advantage of the empirical perspective is that it has good practical feasibility and can be easily used in real applications. Moreover, this perspective can understand and respond to the dynamics of real diffusion situations more appropriately. However, this perspective has the following drawbacks: 1) it mainly investigates diffusion in SNs from empirical data and ignores the proactive knowledge of experts; thus, an investigation can sometimes be costly or deviate from the research objective; 2) the research results are too dependent on empirical data which may be noisy or undependable in some environments; and 3) it often lacks rigorous induction, deduction, and proof for the inner mechanisms of diffusion, i.e., it lacks formal theory to explain the empirical observations [110].

To address the above drawbacks, many researchers introduced some theoretical measures into empirical research, such as graph theory, complexity analysis, dynamic stochastic processes, and probability analysis. Next, we introduce the theoretical perspective in empirical research.

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B. Theoretical Perspective in Empirical Research

The theoretical perspective is important because the theoretical assumptions can direct our research approach and provide effective frameworks for interpreting what we observe from the empirical data. Because a theoretical perspective can provide a way of explaining how and why diffusion takes place in SNs, researchers must have certain theory knowledge regarding the topic of diffusion under investigation. Generally, the following three theoretical tools are often used in empirical research: graph structure analysis, diffusion complexity analysis, and dynamic stochastic process and probability analysis.

The graph structure analysis perspective in empirical research mainly investigates how the structural characteristics of SNs can influence the diffusion [44], [48]. Typical related studies include the effects of varying the network topologies, connectivities, and node degrees on diffusion. Moreover, many other graph structure concepts can be used to analyze the effects of network structures on diffusion, such as dyads, triads, components, geodesics, centrality, density, and peripherality.

The complexity analysis perspective in empirical research mainly investigates the complexity of varying diffusion models [82], [103], [108]. Many problems in diffusion, such as influence maximization, diffusion with a minimum cost, and finding influential actors, are NP-hard. Thus, finding a method that has a lower complexity is crucial to realizing the optimization objectives in diffusion.

The dynamic stochastic process and probability analysis perspective in an empirical research mainly investigates the processes and evolution of diffusion [94]. For example, the propagation dynamics is often modeled by this perspective, which can be based on the independent cascade diffusion model. This perspective can effectively unfold and predict the diffusion process. Moreover, the state transition process of actors in diffusion can also be modeled well by this perspective.

In summary, the advantage of the theoretical perspective is that it has a solid theoretical foundation and there are many mature related theoretical tools that can be used. Additionally, the research results arising from using a theoretical perspective can be rigorous and provable. However, such a perspective ignores the effects of actors in the diffusion of SNs, which means that the activeness and autonomy of the actors might not be highlighted. Moreover, the theoretical perspective is mainly based on static data; thus, it might not perform well when the SNs are large and dynamic.

C. Our Multiagent Perspective

In fact, the multiagent method is effective for modeling and analyzing SNs [7], [11]. As a common phenomenon in SNs, diffusion can also be modeled by a multiagent method [57]. This paper mainly presents the multiagent perspective, which considers the application of multiagent interaction technologies to model and analyze diffusion in SNs.

1) Compared with the empirical research perspective, our multiagent perspective can provide a relatively economical means of investigating the diffusion phenomenon because it can simulate and predict the behaviors and evolution of diffusion in SNs. Furthermore, our perspective can better address the characteristics of self-organizing and distributed computing in the diffusion of SNs. Moreover, our perspective highlights the roles of actors that have critical effects on the diffusion. However, SNs are often very large and wide, where millions of actors act concurrently; thus, the complexity of the diffusion is much larger than that studied in MASs due to their realities and factors in real applications. Therefore, the practicability and suitability of our perspective in large and dynamic diffusion should be solved well.
2) Compared with the existing theoretical perspective, our perspective presents a more effective paradigm to model the diffusion of SNs from the characteristics of autonomy, interaction, and emergence, which can effectively explain the mechanism of self-adaptation and self-organization of diffusion in SNs. Certainly, the theoretical foundations and tools in the theoretical perspective can be introduced into our multiagent perspective to improve its correctness and exactness.

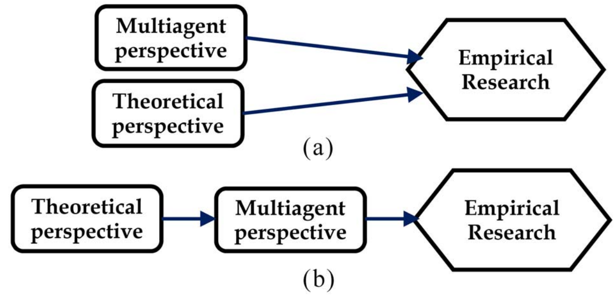

Fig. 8. Two methods of using the multiagent perspective. (a) Alterable method for modeling and analyzing the diffusion in empirical research. (b) Intermediary method between theoretical analyses and empirical research.

To improve the practical feasibility and theoretical correctness of our multiagent perspective, there are two methods for using our perspective: one method is to provide an alterable method for modeling and analyzing the diffusion in empirical research, where the multiagent perspective provides a simulation model and the theoretical perspective provides theory analysis tools for the empirical research, respectively, which is shown in Fig. 8(a); the other method is to provide an intermediary method between theoretical analysis and empirical research, where the traditional theoretical tools can be used to help construct a multiagent model, and the theory-validated multiagent model is used for empirical research, as shown in Fig. 8(b).

D. Typical Problems in Empirical Research That Can Adopt Multiagent Perspective

Generally, some typical limitations of current empirical research on diffusion may influence the study results, shown as the followings: 1) manual gathering of data regarding the diffusion in SN can be only applied into the relatively small SNs, which may affect the study for large-scale SNs where manual gathering of data may be costly and impractical;

2) the empirical research are often oriented toward certain concrete cases, so it is difficult to satisfy the requirements of current unprecedented development of SNs; 3) the empirical research needs complete and plentiful data, so it may be impractical for current dynamic and temporary SNs; 4) the empirical research fully relies on the gathered data which may be noisy or biased, so the study result may not reflect the real complex situations; and 5) the empirical research operates on the entire-level of the SN, thus it cannot capture complex emergent phenomena from individual-level that are highly relevant in diffusion research [57].

Therefore, based on [57] and [111], we think that it is possible with the adoption of the MAS perspective in the empirical research for the large scale and dynamic SNs where the gathering, analyses, and validation of entire-level data are difficult and the emergent phenomena from individual-level are very critical. Moreover, agent-based approach is very helpful to this respect because it provides solid approach for testing new ideas *in silico* before trying to put them into practice [111].

Now we can give some examples of concrete and typical problems in empirical research, which can be solved by using multiagent method, shown in the following.

1) *Problem of Quantitative and Microscopic Measure of Social Interactions in Diffusion:* In the diffusion of SNs, the social interactions among actors are very complex. In existing studies, these social interactions can only be understood from the macroscopic statistical viewpoint on empirical data. However, the inherent microcosmic mechanism of the social interaction cannot be measured effectively. Now, with the multiagent method, such a problem may be solved by modeling social actors as agents. For example, the negotiation-based interaction and the market-based interaction in agents can explicitly account for the benefits and the costs of coordination in small interactions of diffusion in a quantifiable way, which can implement the social interactions in a optimization way for achieving the best performance in diffusion; moreover, the swarm mechanism and social force mechanism of MASs can be used to analyze the large-scale social interactions, which can measure how the social interactions in diffusion are implemented to satisfy the requirements of most actors in diffusion.
2) *Problem of Learning and Adaptation in Diffusion:* In existing studies, social actors only proactively react to the influences of diffusion; but the learning and adaption of social actors in diffusion cannot be analyzed effectively. Such problem could be better studied if we use the multiagent method. In fact, learning and adaptation have been significantly studied and are typically addressed in MASs, such as learning from observations and reinforcement learning. The strong learning and adaptation abilities of agents can be equipped on the social actors in diffusion, which can make the social actors to learn the strategies of other actors in the diffusion and adapt themselves to achieve the best performance in diffusion.
3) *Problem of Social Dynamics and Emergence in Diffusion:* This problem can often be understood from the statistical analyses of empirical data in existing studies; but the inherent mechanisms and theoretical evidences are unknown. To solve this problem, the bottom–up building theory of complex MASs can be used to model the social systems in diffusion; the nonlinear model can be used to analyze the temporal variation of diffusion; the evolutionary dynamics theory of MASs can be used to analyze the emergence of diffusion. In summary, the multiagent-based modeling and simulation can operate on the individual level and can easily capture complex emergent phenomena in diffusion [57].

VI. Conclusion

Diffusion in SNs has been a heavily researched topic and has gained significant attention in recent years; a large number of related studies and results have been presented concerning this topic. However, there are few systematic reviews on existing studies, which could cause people to be puzzled by the enormous number of related studies.

To solve the above problem, in this paper, we make a systematic review of the essential elements and models of diffusion in SNs from a novel perspective, a multiagent perspective. From this perspective, we summarize the essential elements in diffusion to diffusion actors, diffusion media, and diffusion contents. Those three types of elements can, respectively, be modeled as interacting agents, interaction environments, and interaction objects in MASs. Then, the diffusion models in existing studies can be understood as the agents' decision-making models and protocols in interaction, which are reviewed from the viewpoint of corresponding multiagent interaction models. Through the review and analysis of existing studies, we find that diffusion in SNs can be understood well via the interaction in MASs and that there is a close corresponding relation between them. Therefore, we think that the related study results on multiagent interactions can be applied to advance the study of diffusion in SNs.

However, although this survey shows that a multiagent perspective can be envisioned to be a powerful paradigm for modeling and investigating diffusion in SNs, there are still many issues that must be addressed if we want to apply multiagent technologies truly and effectively. Especially, the complexity of diffusion is considerably larger than the complexity of multiagent interactions; diffusion processes are natural phenomena that can be difficult to predict, but MASs are artificial and can be predesigned. Therefore, we should improve the suitability and practical feasibility of multiagent methods to study diffusion in SNs.

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