On Studying Information Dissemination in Social-Physical Interdependent Networks

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***Abstract*—Most existing studies for information dissemination in the online social network are based on variations of the classical epidemic model. In such a model, nodes recursively infect, or share information to, their neighboring nodes with a certain probability. The higher degree a node has, the more likely it gets infected by its neighbors. Although widely accepted, we found there are certain discrepancies between existing epidemic models and social interactions in reality. Firstly, the real-world social network is actually a dual-layered network, where a person shares information online to her online friends, and also offline to her real-life friends. More importantly, since a computer do not automatically share information, a computer exposed to information will not *effectively receive* it (*i.e.*, getting infected and starting to infect others) unless its user receives it. Secondly, contrary to the epidemic model, the more friends a person has, the less likely she is going to *effectively receive* a certain piece of message (just imagine how easily a message can be flushed and ignored by a human user because of overwhelming newer information). In other words, in social networks, *the infection rate of a node may not be positively correlated with its degree*. Based on these observations, we develop the *social-physical interdependent (SPI) model* to capture and analyze the unique characters of social networks. Our study provides new observations, and sheds light on a new direction for the study of information dissemination in social networks.**

I. Introduction

Online Social Networks (OSNs), such as Facebook and Twitter, have undergone phenomenal growth in the recent decade. According to Statistia [1], Facebook has reached 2.2 billion active users worldwide in 2018. Due to the far-reaching and borderless characteristics, the OSNs have overtaken conventional media such as televisions and newspapers, becoming the predominant carrier of information dissemination.

Along with the popularity of OSNs was the surge of studies on characterizing how information propagates in such networks. In this regard, existing research on studying information dissemination in OSNs is mainly based on the classical epidemic model [2], which was originally developed to characterize how a virus spreads among a group of people and has them infected. In the classic epidemic model, each person is modeled as a node, and an edge exists between them if they have a physical contact (an edge between the two nodes) that allow the virus to spread. To begin with, it is assumed that a set of nodes are infected with the virus, after then the virus begins to spread and infect more nodes based on existing edges. The objective of these studies is usually to characterize the speed and scale of such an infection.

Intuitively, this epidemic model is suitable to model information dissemination in OSNs. In particular, a piece of information is analogous to the virus, and the spreading of the virus is similar to how the information is being "shared" between users among the OSN. For years, the approach to model OSNs with different variations of the classic epidemic models is well adopted in the research community, and many works have been carried out based on such an assumption.

Nevertheless, we argue that this well-accepted epidemic model is inadequate to provide a good approximation of the behavior of social interactions in the real world, and we summarize the discrepancies in the following.

Firstly, a real social network is a dual-layered network with heterogeneous characteristics and priorities:

1) Although the *online* social network is convenient and far-reaching, it is impractical to assume that a human user shares information merely with her online friends.

In fact, a person would share social content with both her online friends, and (offline) friends in her real life. Meanwhile, the two networks induced by online and offline social interactions exhibit different properties. Compared to the offline network, a person usually has more online contacts (which indicates a higher degree in OSNs), as well as more frequent activities. For instance, a Facebook user can easily have hundreds of online friends, check new feeds much more frequently than she encounter and talk with a real-life friend.

2) It is also worth noticing that this dual-layered network differs from traditional *interdependent networks* [3] in that nodes in the two network have different priorities. Assume the online network is composed of smart devices (such as smart phones or computers) and the offline network is composed of human users who own corresponding devices. A piece of information that reaches a smart phone will not be automatically forwarded unless the human decides to. In other words, nodes in the offline network dominate those in the online network, whereas in traditional interdependent network it is assumed that nodes

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in both networks proactively share the information and affect each other equally.

Secondly, in existing epidemic models, the probability a node gets infected is positively related to its degree. Intuitively, the more contacts a person has, the more likely he/she gets exposed to, and infected by the virus. However, in a social network, especially the OSN, it is not necessarily the case. The reason behind this is that human being only has limited time and effort to receive and process information. Therefore, the more information a person is exposed to, the less likely she will *effectively receive* a specific information. To understand this, simply imagine how easily a message can be flushed and overwhelmed by all the newer feeds on the Facebook News Feed page. Thus, from the perspective of any given information, the correlation between a node's infection rate and its degree is not necessarily positive. This character is extremely different from the assumption in epidemic models.

Based on these observations, we propose a dual-layered social network model based on heterogeneous interdependent network. Our model is composed by two networks, *i.e.*, the OSN where nodes represent smart devices and edges represent online friendship, and the offline social network in which nodes represent owner of the smart devices, and edges represent their real-life relationships, such as close friends, colleagues or relatives. We formally formulate our model and apply system-level simulation and real-world data to validate our model by comparing it with classic epidemic models. We demonstrate that our model is able to profile the trend of online information dissemination with higher accuracy.

The remaining of this paper is organized as follows. In Sec. II, we briefly review existing studies on the study of information dissemination in OSN, and then introduce the *Social-Physical Interdependent* (SPI) model in III. With the proposed model, we conduct a case study with real-world data traces in Sec. IV to validate the proposed model. Finally, this paper is concluded in Sec. V.

II. Background

Spreading of information/news in networks, especially OSNs, have been extensively studied from various aspects, *e.g.*, estimating the structure of an OSN with sampling measures [4], identifying the most influential nodes to accelerate the circulation of information [5], and the recurrence cycle of popular social contents [6]. Due to the similarity between the information propagation and virus spreading, that is, both the information and the virus are passed from one person/node to another through individual contacts, and change the state of an individual (node) as they propagate along [7], [8], the propagation process of information in social networks are usually modeled as an *epidemic* process. In such processes, an individual that has been shared with the information will become infected immediately (in SI [9], SIS [10], SIR models) or after a period of time (in SEIR [11] model)[2]. Once infected, an individual is activated to spread the virus to anyone she has contact with, for indefinitely long time (in SI models), or a random period of time (in SIS, SIR, and SEIR models).

Despite the differences in individual states, the aforementioned models share a common ground, that is, the probability of an information to be picked up by an individual, is proportionate to the number of its infected neighbors. In reality, however, another influence brought about by the OSN has been neglected in existing models, that is, the the so-called *information overload* effect [12], [13]. As a result, the more news/information a person is prompted through OSNs, the less likely he/she will read a particular one among them. In other words, the probability of a news/post being read is *reverse proportionate* to the total number of news/post updates, considering the limited amount of time and energy a person can spend on OSNs. Observing this phenomenon, this paper proposes a novel propagation model that can better explain the social information dissemination processes in reality.

From the networking perspective, existing literature can be divided into two categories: *population* dynamics and *network* dynamics [14], with respective to how people interact to spread a certain piece of information. The former views people of interest as a homogeneous ensemble of individuals, in which any person contacts another with a fixed probability during a time interval, creating an evenly-mixed population unconstrained by any network topology, *e.g.*, [15]. On the contrary, the later category study information spreading in a *network* that are composed of heterogeneous (in the sense of whom they can contact) individuals, whose contact patterns can be captured by *edges* of a network/graph, hence the name network dynamics. To this end, various properties of information spreading have been discussed: the spreading time of information [16], [17], influence of network topologies [16], [18], measures to accelerate the propagation [10], and so on. Though existing network dynamics prove to be suitable in describing information propagation in one *single* network, *i.e.*, either online (in OSNs), or offline (face-to-face) alone, they fail to capture one key characteristic of realistic social interactions, that is, propagation is carried out in *both* networks. As a result, a new model is needed to jointly consider both online and offline contacts, and the complex dependence between the two, which motivates us to propose the novel SPI model detailed in the following section.

III. System Models

To reveal the impact of human and computer interaction in real-world social information propagation processes, we develop the *social-physical interdependent* (SPI) model that takes both online and face-to-face (i.e., offline) propagation measures into consideration, and captures the *information overload* effect [12], [13] in human browsing habits.

A. Network Model

We consider information propagation in an interdependent network $\mathcal{G} = (G_h, G_c)$. In this model, subgraph $G_h(V, E_h)$, referred to as the offline social network (subscript h denotes

[2]In epidemics-related research, states S, I, E, R stand for susceptible, infected, exposed, and recovered, respectively.

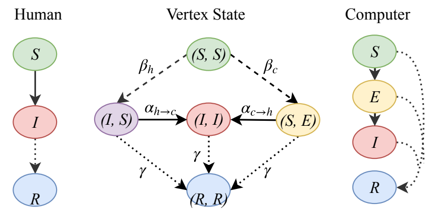


Fig. 1: State Transition Diagram

human), captures daily social interactions among a group V of people, while subgraph $G_c(V, E_c)$, referred to as the online network (subscript c denotes *computer*), represents the online social information exchanges among the same group V. Network G_h and G_c describe the two information acquisition measures, both of which are assumed to be connected and undirected. They share the same set V of individuals, but with different edge sets. Each vertex $v \in V$, is composed of a human node v^h and a computer node v^c, where the former partially controls the latter in the propagation process.

B. Propagation and State Transition

Consider a discrete time system, where time t advances in discrete time steps $\{1, 2, \cdots\}$. With respect to a piece of information, *e.g.*, a news, the *state* $X_t(v)$ of a vertex v at time step t is an ordered pair $(x_t^h(v), x_t^c(v))$, determined by the states of the two nodes v_h and v_c, in graph G_h and G_c respectively. From the perspective of a person, or human node v^h, he/she either has not heard of the information before (*susceptible*), or is already aware of the information. In the latter case, the state of a human node v^h can be further divided into *infected*, which means that v^h is willing to spread the information, and *recovered*, which means v^h is indifferent to the information and will not participate in the propagation any more. On the other hand, for a computer node v^c that is associated with human node v^h, there is one more state, *exposed*, which corresponds to the case that the information has reached vertex v from the OSN G_c, but has not been read by the human v^h yet. This setting is reasonable, because it is highly unlikely that a person will check or respond to every piece of information pushed by OSN's at every moment. Considering that a computer node will not respond to a piece of information by itself, the state of a computer node, $x_t^c(v)$, is correlated to the state of its corresponding human node $x_t^h(v)$. Therefore, each vertex $v \in V$ can be in one of the following five states at every time instant t, as shown in Fig. 1.

1) Susceptible (S, S)*:* State (S, S) indicates that the information has not reached vertex v from either the offline social network G_h or the OSN G_c. In this state, vertex v will not participate in the propagation process.

2) Known (I, S)*:* If the information reaches a susceptible vertex v from the offline network G_h (through a propagation process with infection rate β_h) at time t, that vertex v will transit into the *known* state, (I, S), in the next time step $t+1$, indicating that this person v^h is aware of (i.e., being infected by) the information and will spread it in its offline network G_h. Transition from (S, S) to (I, S) is due to information propagation in the offline network G_h.

3) Exposed (S, E)*:* If the information reaches the susceptible $(X_t(V) = (S, S))$ vertex v first from the online network G_c (through a propagation process with rate β_c) at t, then $X_{t+1}(v) = (S, E)$, referred to as the *exposed* state, indicating that the information in locally available at computer node v^c, but has not been read by human v^h yet. Transition from (S, S) to (S, E) is due to information propagation in OSN G_c. In this state, the computer node v^c will not spread the information in G_c because it is controlled by the human node v^h.

4) Infected (I, I)*:* From the *known* state (I, S) (respectively the *exposed* state (S, E)), the information can *crossover* from G_h to G_c (resp. from G_c to G_h) with probability $\alpha_{h\to c}$ (resp. $\alpha_{c\to h}$), when a person reads the information and decides to participate in the propagation process so that vertex v becomes infected, *i.e.*, $X_{t+1} = (I, I)$. In this state, both node v^c and node v^h join the propagation process, in network G_c and G_h respectively. Note that probability $\alpha_{h\to c}$ and $\alpha_{c\to h}$ are innate properties of vertex v. Specially, the online to social crossover probability $\alpha_{c\to h} \propto \frac{1}{d_c(v)}$, where $d_c(v)$ is the degree of v^c in G_c. The intuition behind this assumption is that when a person receives too many feeds from the online network (due to the large number of online neighbors in G_c), the probability that she picks up a specific news will be low.

5) Recovered (R, R)*:* As time goes, the information becomes stale, such that it will be deleted or forgotten after a lifetime τ. In this case, the state of a vertex v will become (R, R) (referred to as *recovered*), indicating that this person v^h is indifferent to the information, and will retreat from the propagation process in both online and offline networks.

The proposed *SPI* model differs from existing epidemic information propagation models in the following three aspects: firstly, both online and offline social interactions are captured, such that the underlying network of information propagation processes is formulated as an interdependent network, where actions and states of both human and computer are clearly defined; secondly, *information overload* effect is taken into consideration, and its impact is incorporated into the model as the *crossover* infection probability α; lastly but not least, each social content (information) is assumed to have a *lifetime*, which follows from the news cycle observation [17].

IV. Case Study: Traces, Simulation and Discussion

With the proposed *SPI* model and the online-offline state transition assumption, we carry out a case study in which we develop a simulation platform based on a practical social network, compare simulation results with traces obtained from a real-world information propagation processes, and validate the suitableness of the proposed model on capturing such processes in practice.

A. Datasets and Traces

Since our model is to track the evolution of information dissemination in social networks, the simulation was run based on a practical topological social network, and the simulation result is then compared with a real data set that reflects the evolution trend of a selected online topic.

Because of user privacy concerns, despite the popularity of information dissemination studies in social networks, it is rarely available a comprehensive data set that contains both the network topology and the information dissemination character. For instance, graph for Facebook user connectivity is generally available in the research community [19], however, it is hard to find a data set that depicts how a piece of information is shared among users in the same network. Consequently, we combine several datasets to generate a synthetic data trace (i.e., the ground-truth) to facilitate our simulation and validation.

Specifically, we run our simulation based on the topological graph of one social network, and then compare the simulation result with a real-world information dissemination case that is *not* obtained from the same social network. Because of this discrepancy, we do not seek for an exact match; rather, we compare the *trend* between the simulation result and the real-world example. It is worth noticing that, albeit the discrepancy, our simulation result fits the real-world example very well, which confirms the validity of our newly developed model.

The following is a brief description of datasets (See corresponding references for details) utilized in our simulation.

1) The topological graph: The social network topology is obtained from [20], which depicts a fairly large social network with 75,879 nodes and 508,837 edges. More detailed parameters of this network are provided in Table I.

2) The"Special Olympic" dataset: Real-world example of information dissemination is made available by the Memetracker [21]. The Memetracker is an online tracker that tracks quotes and phrases that appear most frequently over time across its entire online news spectrum. To be more specific, we choose the "Special Olympic" dataset that was used in [22], and briefly explain in the following.

On March 20th 2009, President Obama joked about his bowling skills, saying "It was like a Special Olympics, or something" on *The Tonight Show* with Jay Leno [2]. Considered offending to certain populations, this news got popular in the next following days. The evolution of the number of mentions of this topic in the online environment is captured by the Memetracker.

3) Human activity pattern: To accurately study information dissemination in social networks, it is essential to consider human activities on a daily basis due to the news cycle [17] in comparable time span. For example, people are more active and likely to share information during the daytime. Thus, we integrate the factor of human behavior into our simulation, whose pattern is obtained from [23], and plotted as the solid green line in all the figures in Sec. IV-C. Generally, following this model, human activity reaches the peak at around 15:00pm, and the valley at 5:00am.

B. Simulation Setup

The simulation platform is written in Java. Particularly, we developed two topological networks to represent the device-to-device OSN G_c, and the person-to-person offline social network G_h. Both networks share the same set of nodes V with a one-to-one mapping, *e.g.*, $v_h \rightarrow v_c$ (while one person can own more than one smart devices, we abstract all devices as one node, without loss of generality). Edges of the online network G_c follow the OSN described in Sec. IV-A. For the offline network G_h, edges are randomly generated to create a sparsely-connected network with an average degree of six.

TABLE I: Statistic property of simulated social network.

Social Network Dataset Statistics	
Number of Nodes	75,879
Number of Edges	508,837
Average Clustering Coefficient	0.1378
Diameter (longest shortest path)	14
90% Effective Diameter	5

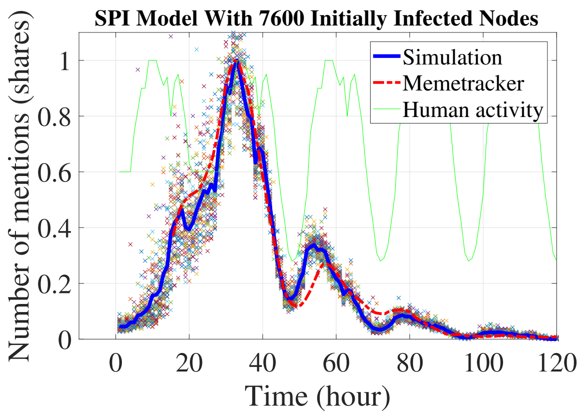
A person and a smart device behave differently during the procedure of information dissemination. In particular, when a person v_h receives a piece of information, she has a certain probability to share the information both online (*i.e.*, β_c) and offline (*i.e.*, β_h). On the other hand, when a smart device v_c receives the information, it does not share it to other nodes immediately. Instead, it will first try to "inform" its owner v_h. And the probability that the owner v_h is successfully informed (*i.e.*, $\alpha_{c \rightarrow h}$) is set to be negatively related with the degree of the device node $d_c(v)$. If successfully informed, the person v_h will then decide whether to share this information; otherwise, the device returns to the "susceptible" state. It is also assumed that if a person has been exposed to this information and decided not to share, both the human node v_h and the device node v_c will never share this information in the future, *i.e.*, they become immune to this information, and transit to the "recovered" (R, R) state. Finally, each piece of information is assumed to have a lifetime (*i.e.*, τ), since most information will not last long in social networks.

At the beginning of the simulation, we assume a small set of person and/or computers are in "infected" state. To evaluate the evolution of the propagation process, we record the *number of information shares in the online network G_c only*, because as mentioned above, the Memetracker only tracks the number of mentions of a topic in online social networks.

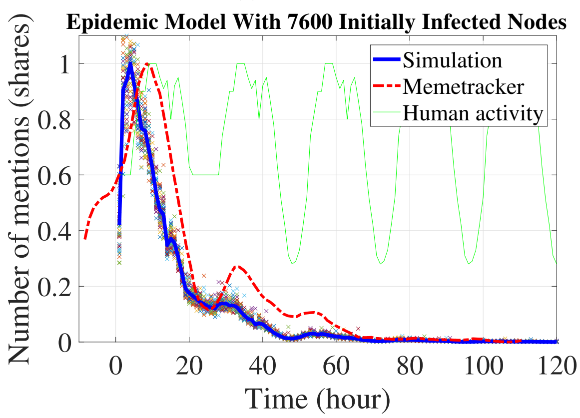
C. Simulation Result and Discussion

As explained above, since the Special Olympic dataset is not obtained from the simulated social network, it is very unlikely that our simulation result can quantitatively match this example. Consequently, we represent and compare normalized results in the following figures. Specifically, the *number of shares* for both our simulation results and the Special Olympic dataset are normalized to be ranging between 0 and 1. Also, since we do not know how long after the event when the Memetracker started the tracking, the x-axis should be considered as *relative* time instead of absolute time.

During our simulation, we adjust the parameters mentioned in the previous subsection, and run multiple simulations, in order to find a best fit between the simulation result and the Special Olympic dataset. The same approach is taken for both the *SPI* model and the epidemic model. Due to the page limit, we only present the best results that we were able to obtain.



(a) *SPI* Model.



(b) Epidemic Model.

Fig. 2: Simulation result with 7600 computer nodes (10% of total population) initially infected.

We adopt the following simulation parameter setting: β_h and β_c are both set to 0.65, $\alpha_{c\to h}$ is set to be $\frac{1}{d_c(v)}$ while $\alpha_{h\to c}$ is set to be 1, and τ is set to be 48 hours.

D. Simulation Results for the SPI Model

We first present the simulation result of the *SPI* model.

In this simulation, it is assumed that 7,600 (10%) computer nodes are initially exposed to this information. Simulation result is plotted in Fig. 2a. The tiny crosses in various color shows samples in multiple simulation runs, whose average is calculated and plotted in blue. The Special Olympic dataset is plotted in the same figure with a dashed red line. Human activity pattern is plotted in the background with solid green line. It is assumed that for the first 24 hours after the information is released, people keep higher-than-average interests on this topic, so we set the activity pattern to be lower-saturated at 60% during this time, which is also reflected in Fig. 2a.

Since it is unknown when the Memetracker started to track the event after it happened, we shift the simulation result and the Special Olympic dataset horizontally in x-axis, to fit the peaks and valleys of these plots according to the depicted human activity pattern. For example, the main peak of both the simulated data and the Special Olympic data are fitted to be 15:00pm (Note that the x-axis is relative time).

From Fig. 2a, we first observe a ”slow-start” phase during the first 24 hours, where people gradually get to know this topic, and begin to share it to their online and offline friends. After a few hours cooling down (where time $x \in (18, 25)$), the plot experience the second hike and reaches its overall maximum after about 32 hours from the beginning. Note this peak is accompanied with the highest human activity level. After then, although the human activity remains high for another few hours, the topic begins to show its age, and the number of mentions drops dramatically to a local minimum at $x = 48$. Then it gets a second peak for a short period ($x \in (50, 60)$, with peak at $x = 53$), and drops again. We can also observe the third and fourth waves, which diminish quickly. After about 96 hours, or 4 days, this information has been largely phased out.

Comparing our simulation result to the Special Olympic data, we can observe that our new model matches the real-world data very well. In particular, our model catches the “slow-start” phase during the first 24 hours, and also catches the second and third waves.

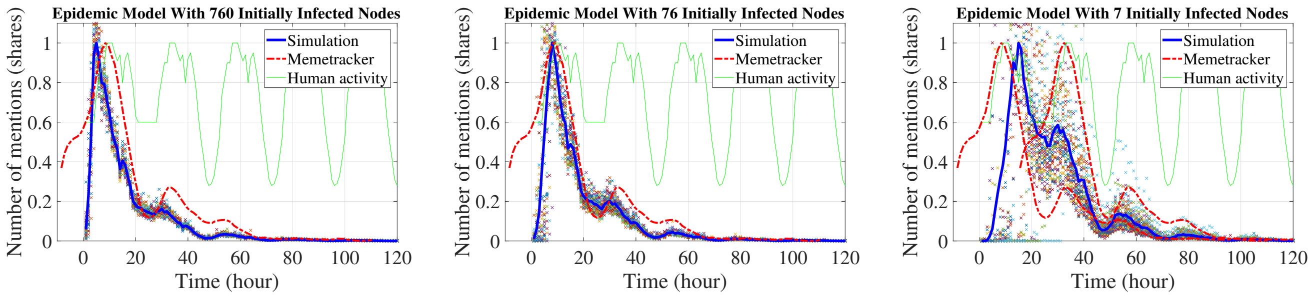
We also found there are some noticeable discrepancies between the two data. For instance, the second wave of the simulation result comes a few hours earlier ($x = 53$) compared to the Special Olympic data ($x = 58$), and the second valley (at $x = 72$) of the simulated result is deeper. Considering the three data sets that we tested, i.e., the topological social network, the Special Olympic data, and the human activity pattern are not related, we denote such discrepancies are still in a tolerable range.

By and large, the *SPI* model clearly follows the evolution of the real-world data by correctly reflecting the ”slow-start” phase, and the second and third waves.

E. Simulation Result for the Epidemic Model

For the same setup stated above, we run the simulation using the traditional epidemic model, i.e., the infection rate of a node is positively correlated to its degree. In order to better compare and demonstrate, we plot four figures in Fig. 2 and Fig. 3, with the number of initially infected nodes ranges from 7600 (10%) to 7 (0.01%). The reason we enumerate these three scenarios is because, during our simulation, we found the existing epidemic model does not posses a ”slow-start” phase, especially when the initial infection rate is high. For example, as shown in Fig. 2b, when 10% of the nodes are initially exposed to this information, we observe the plot reaches its peak within a very short time period (less than 5 hours). This is because since all nodes are interconnected in the network, and the infection rate of a node is positively related to its degree, the spread rate of the information is exponential. The large number of initially infected nodes provides a large base to the exponential increase. As shown in Fig. 2b, most of the nodes are infected during the first wave, and as a result, there is not obvious second and third wave of infection any longer.

As we decrease the number of initially infected nodes from Fig. 2b to Fig. 3c, the rising slope of the first peak becomes slightly flat, but is still too steep compared to the Special



(a) 0.01% Infected Nodes. (b) 0.1% Infected Nodes. (c) 1% Infected Nodes.

Fig. 3: Classical Epidemic Model with Various Initial Infected Nodes.

Olympic data. Among the four scenarios, Fig. 3b seems to be the best fit to the Special Olympic data. Notwithstanding, the first wave is still too sharp to fit the example, and the second and third waves are barely visible. Note that in Fig. 3c, we shift the Special Olympic data by 24 hours across the x-axis and try to fit the peak of the simulated and real data.

V. Conclusions

Observing the discrepancy between existing epidemic information propagation models and real-world social interactions, we propose a novel *social-physical interdependent (SPI)* model to better capture the information propagation dynamics in social networks. Specifically, we model the social network as a dual-layered heterogeneous interdependent network, and formulate the information overload effect into a crossover infection action. We formally presented our model, and use simulation as a case study to validate the proposed SPI model. By comparing the simulation result of both our mode and the classic epidemic mode against a real-world data trace of information propagation, we demonstrate the validity of our model. Our work sheds light on a new direction to study the information dissemination in social networks.

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