

Modeling Human Activity With Seasonality Bursty Dynamics

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I. INTRODUCTION

Abstract—The public's purchase incentive increases dramatically during the holiday season and subsequently returns to normal levels. This seasonality is common in various scenarios and highlights the following questions: how does the public's purchase incentive fluctuate over the course of a year? Which factors are conducive to this seasonal behavior and how can they be modeled? In this paper, we propose a model that explicitly integrates temporal point process theory with the construction of a networked community, to describe the dynamics of collective action propagation with seasonal fluctuation. Furthermore, a database is constructed of sales records for 21 video game consoles and 13 237 video games in France, Germany, Japan, the U.K., the USA, and worldwide from 1989 to 2018. Experimental results suggest that peak desire always appears in the holiday season about one week before Christmas and is about four times higher than consumption desire in a normal period in all areas.

Index Terms—Complex network, temporal human behavior, temporal point processes, video game industry.

THE DYNAMICS of human activity, driven by countless hybrid factors, is a joint interest of psychology, economics, and sociology and is one of the most complex issues in science. This topic has been extensively investigated for more than a century. Additionally, collective human activities, such as purchasing a product, watching a movie, or resharing a book, commonly make certain man-made entities popular in a social network, a phenomenon known as “item popularity.” Characterizing and understanding collective human activities are of theoretical importance for explaining many socioeconomic phenomena, and such knowledge may also have significant business applications. However, the process by which the public accepts a new thing is often not a smooth one. The popularity of a man-made entity always cools off and remains stable for a long period of time; then, that popularity suddenly explodes in a short time period. Hence, *temporal burst* is a universal phenomenon found in a variety real-life scenarios [1], including market transactions, web browsing, movies, and especially other business actions.¹ A plurality of literature assumes that temporal bursts are caused by endogenous mechanisms, such as memory effects [2], varying interest [3], [4], and task priority, while a few works argue that these bursts originate from exogenous factors. The heterogeneity and seasonality of human activities have recently been recognized as one candidate to explain temporal bursts of human activities. Personal interest in or desire for man-made knowledge and entities is heavily driven by exogenous influences; for example, a greater price cut will lead to a higher desire to consume something, and vice versa. In particular, the public's desire to consume things is influenced by hybrid factors that combine mutual acquaintances and broadcasting, resulting in pseudoperiodic patterns. For instance, every year from late November (following Halloween) to early January, many developed countries enter the holiday season, also called the Christmas season, which is an annually recurring period, and a festival season that is highly valued by the public. The Christmas or holiday shopping season, which lasts until mid-January, is always a peak for the retail sector.

The commonly recognized behavior that leads to temporal bursts prompts us to investigate the underlying mechanisms

Manuscript received April 5, 2019; revised May 31, 2019 and June 19, 2019; accepted June 20, 2019. Date of publication July 4, 2019; date of current version January 14, 2020. This work was supported in part by the National Science Foundation of China under Grant 61703355, in part by the Guangdong Youth University Innovative Talents Project under Grant 2016KQNCX223, in part by the Natural Science Foundation of Guangdong Province under Grant 2018A030313351, in part by Guangzhou Industrial Technology Major Research Project in 2018 under Grant 201802010035, and in part by the Industrial Internet Innovation and Development Project in 2018 under Grant MIZ1824020. Paper no. TII-19-1263. (Corresponding authors: Choujun Zhan; Ying Gao; Xiping Hu; Bin Hu.)

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This paper has supplementary downloadable material available at <http://ieeexplore.ieee.org>, provided by the authors.

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TII.2019.2926885

¹We find that temporal burst phenomena generally exist in the growth of movie gross revenues, the total views of TED and YouTube video, the number of “like” clicks, the sales of video games, and the growth of crowdfunding projects. These results are presented in our forthcoming work.

responsible for its emergence. The increasing evidence of temporal burst behaviors raises fundamental questions: what is the origin of temporal bursts and how can they be modeled? Analysis of human activity at the population level shows that temporal bursts may result from a hybrid mechanism that entails endogenous and exogenous influences. Two main laws can be considered: 1) individual activity is heavily influenced by the activities of one's neighbors within a social network, which introduces correlations in activity; and 2) human activity is also driven by external factors from outside a social network, such as seasonal and yearly cycles and holiday effects, which lead to variations in customers' affection. Patterns of collective human activities are of significant importance in such diverse domains as social media, business, and economics. However, due to the diversity and complexity of human activities, the quantitative understanding of human activities has long been a challenge and remains a central problem of modern science. In most previous works, due to the lack of detailed data recording human activities, researchers commonly account for uncertain stochastic models or extended models based on stochastic processes, e.g., modeling collective human activities as temporal point processes [5] or investigating statistical patterns of human activities [6], [7]. Other researchers assume that individuals form social networks, that each individual is influenced by mutual acquaintances inside the network and external information sources outside the network, and that independent events occur at a constant rate, which leads to a class of epidemiological/cascade models [1], [8], [9].

Thanks to the development of new technology, we can easily collect detailed digital records to quantitatively investigate various aspects of collective human activities over sufficiently long time periods [10], [11]. In this paper, we use the video game market as our illustrative example. The video game industry has become a booming market, and the total market capitalization of the video game market had reached 20 billion U.S. dollars in 2018. In particular, temporal bursts are common in the sales of a video game or console. We study a database of sales records for video games and consoles released in the USA, the U.K., France, and Japan from 1980 to 2018, a period of 37 years. Each record comprises historical sales data of a particular video game console or video game in a particular area. The dataset contains 73 time series of video console sales and 29 679 time series of video game sales with a weekly time resolution. The availability of sales records of almost every video game console and video game, thus quantifying deliberate human activity in business, makes the video game market an attractive proxy for studying collective human activities with temporal bursts.

Seasonality is a phenomenon that is widely observed in a variety of social systems. The change of behavior induced by seasonality is conducive to temporal burst behavior. In the following sections, we show that seasonal and holiday behavior can be sufficient to cause temporal bursts of collective human activity. We demonstrate that a class of collective human activities characterized by temporal bursts is the result of promotions from outside a social network and from inside influences from mutual acquaintances in the network; the outside influence presents cyclical and seasonal fluctuations. In this paper, we

developed an interest-based model that incorporates cascading features of human activity and hypothesized seasonal or periodic influences. Using a primary process, which can be modeled as a nonhomogeneous Poisson process, we account for temporal patterns of periodic activity found in many human activities. Then, we combine a cascading nonhomogeneous Poisson process and complex network theory, which integrates external influences on activity with individuals' tendencies to continue participating in an activity; this approach allows us to propose a mechanistic model. Additionally, a system identification technique to estimate the model's parameters is also developed. Then, we apply this model to real-life activity by studying the historical data recording sales of consoles and video games in France, Germany, Japan, the U.K., the USA, and the whole world from 1989 to 2018. Experimental results indicate that the predicted sales of consoles generated by the proposed model are consistent with the historical data. All of these predictions are confirmed by the real-life data, suggesting that the change in individual purchase incentives of the public (consumer desire) is directly caused by the external influence, which is one of the most important factors in consumer behavior and a fundamental aspect of human activity. Also, dynamic changes in the purchase incentives of the public can be estimated. Our findings provide valuable insights into the origins of collective human activity with temporal bursts.

The rest of this paper is organized as follows. In Section II, preliminaries of the mechanistic model, console sales data, and details of holiday effects are given. The development of the model is addressed in Section III. A summary of the experimental results is presented in Section IV. Finally, Section V concludes this paper.

II. RELATED WORK

It is essential to understand the propagation of human activities through social systems organized in different ways. Despite the idiosyncratic complexity of individual and collective human activities, efforts at analyzing and predicting phenomena of collective human activity through social networks have a long and illustrious history in the social sciences [12]. These efforts have led to a number of techniques and methods describing individual and collective human activities, as reported in [13] and [14]. However, the propagation of human activity is always a nonhomogeneous temporal process consisting of rapid propagation bursts in short intervals alternating with long periods of slow propagation that repopularize man-made knowledge and entities, as seen in the repopularization of a song or movie, the revival of a rumor, or the reemergence of a sport. Here, we call all of these *temporal bursts*, referring to a wide range of phenomena of human activity [1], [15], [16]. It is of practical and critical importance to study how collective human activity with temporal bursts influences economic and social outcomes. However, in recent studies, few scholars have focused on developing mechanistic models describing dynamic patterns of collective human activity with bursts; instead, they have focused on statistical properties, such as characterizing the interevent time distribution. Many literature works study collective human

activity based on complex network theory, as many real-life relationships in the world can be represented as complex networks with nodes representing individuals or organizations and with links standing for interactions among the nodes, meaning that influence can flow from one node to another [17]. In addition, collective action propagation can be modeled as a transition network, in which each node may assume several states, such as users and prospective users or active and inactive, and nodes can transition from one state to another [8], [9]. The research on transition networks provides a convenient way to analyze collective human behavior, and several models are provided [18]. Actually, in most previous studies, dynamic patterns of human activity are generally formulated as Poisson processes, namely, random point processes with an exponential interevent time distribution [19], [20], leading to a statistical property in which the time gaps between individuals receiving the information and transitioning into another state should be almost uniform. These assumptions are mathematical abstractions suitable for various human activity processes that occur in a wide range of social systems [21]. In addition, there are various typical point process models, such as the Hawkes process [22], self-correcting process [23], and autoregressive conditional duration process [24]. Recently, the self-excitation point process [22] has become an emerging hot topic for those seeking to explain the temporal dynamics of context-aware recommendations [25], news-feed streams [26], online-user engagement [27], and information diffusion [28]. The main limitation of these previous studies is that they often make strong parametric assumptions about the underlying dynamics governing the generation of the measured point patterns, for instance, assuming the exponential factor is constant. In addition, plenty of human activities are heavily driven by personal decisions that are influenced heavily by external factors such as weekly and circadian cycles; these influences are observed in the actions of playing online games, watching online movies, and browsing the web. Hence, in this paper, we focus on proposing a mechanistic model that can learn an efficient and general representation of the latent dynamics from the historical data without assuming fixed parametric forms in advance. The advantage of this method is that the proposed model is more flexible, meaning that parameters about purchase incentives among the public can be automatically adapted to the historical data.

III. PROPOSED MODEL DERIVATION

In this section, we combine the complex network and point process theory to derive a model that describes the growth of collective activity propagation with temporal bursts. Then, we also provide an algorithm for estimating unknown parameters representing public purchase incentive and market size.

A. Development of the Mathematical Model

There exists a dataset $C = \{S^1, S^2, \dots, S^m\}$, where $S^i = ((t_1^i, x_1^i), (t_2^i, x_2^i), \dots)$ is a set of time series. A pair (t_j^i, x_j^i) represents the event of type x_j^i , which has occurred to the entity i at time t_j^i , and $t_j^i < t_{j+1}^i$. The meaning of the event and entity type depends on the specific application. In this paper, S^i

represents a sequence of sales pairs for a video game/console i , where x_j^i stands for cumulative sales of a video game or console in an area. The goal of our work is to build a dynamic model by combining the complex network and random point-process theory to predict pairs (t_j^i, x_j^i) . Additionally, we can use this model to estimate and quantify the strength of exogenous and endogenous influences as well as the purchase incentive of the public.

We consider a network $G = (V, E)$ of gamers and prospective gamers of a console or video game, where E and V stand for the sets of edges and nodes, respectively. Suppose there are N nodes, which represent individuals that can be in one of two possible states: G and P . An edge linking two nodes means that two individuals in a community are mutual acquaintances, e.g., roommates, colleagues, friends, or relatives, between whom information can propagate. A prospective gamer (P) can transition into a gamer according to two laws:

- 1) *Endogenous Influence*: A prospective gamer can be positively informed about a console or video game by other gamers whom this prospective gamer knows; then, under this endogenous influence, this prospective gamer transitions into a gamer;
- 2) *Exogenous Influence*: In reality, prospective gamers are often informed about a video game or console through broadcasting from the stakeholder, e.g., sales promotions or advertisements, and a prospective gamer can transition into a gamer.

The temporal point processes can be characterized via the conditional intensity function describing the next event time corresponding to all previous events. When a prospective gamer receives information from its network neighbor at time t , then the transition process is the Poisson process with a transition rate $\lambda_1(t)$. Otherwise, the transition process under the influence of the outside network is also the Poisson process with rate $\lambda_2(t)$. Let $[t, t + dt)$ represent an infinitesimal time window, and $\lambda_\mu(t)dt$ ($\mu = 1, 2$) is the probability for the occurrence of a new transition

$$\lambda_\mu(t)dt = \mathbb{P}\{\text{event in } [t, t + dt)\}. \quad (1)$$

Given the conditional density function $f_\mu(t)$, we can derive the conditional intensity function

$$\lambda_\mu dt = \frac{f_\mu(t)dt}{S(t)} = \frac{f_\mu(t)dt}{1 - F_\mu(t)} \quad (2)$$

where $F_\mu(t)$ stands for the cumulative probability that a new transition will happen before time t since the last event time t_e . We have the following exponential distribution:

$$\begin{aligned} f_\mu(t) &= \lambda_\mu \exp(-\lambda_\mu t) \\ F(t) &= 1 - \exp(-\lambda_\mu x) \end{aligned} \quad (3)$$

where $t \geq 0$ and $\lambda_\mu > 0$ are the parameters of the distribution. Combining (2) and (3), we can derive that $\lambda_\mu(t) = \lambda_\mu$, which is a constant. Various function forms of the conditional intensity function $\lambda(t)$ are proposed from different viewpoints to explain the phenomena of interest [29]. In the following, we review several representative examples of typical point processes, where conditional intensity functions have particular parametric forms.

- 1) *Poisson processes* [30]: The interevent times between one individual receiving information and taking action are independent and follows exponential distribution.
- 2) *Hawkes processes* [22]: A Hawkes process has a different form of conditional intensity, which is defined as $\lambda(t) = \gamma_0 + \alpha \sum_{t_j < t} \gamma(t, t_j)$. This kernel term is historically dependent on capturing the mutual excitation phenomenon among events, which is a stochastic process by itself.
- 3) *Self-correcting processes* [23]: A self-correcting process has a conditional intensity function $\lambda(t) = \exp(\beta t - \sum_{t_i < t} \alpha)$, where $\beta > 0$, $\alpha > 0$. It focuses on producing regular point patterns.
- 4) *Autoregressive conditional duration processes* [24]: As a recently developed model, this process provides an alternative method of conditional intensity parameterization and seeks to capture the dependency between interevent durations.

These methods or models are based on various parametric assumptions and predefine the form of the conditional intensity function, which limits the generation of the observed point patterns. In this paper, in contrast, we focus on proposing an extended model that can automatically adapt the parametric forms of the conditional intensity function from the growth history. The advantage of the proposed model is that the purchase incentive of the public is more flexible and can be automatically adapted to the real-life data.

B. Seasonal Variance Rate Model

Based on the previous assumptions, we propose a seasonal variance rate model: 1) the time is discretized into $\{T, 2T, \dots\}$ and labeled as $t = 0, 1, 2, \dots$. The probability of a transition occurring under an exogenous influence at time step t is denoted by $f(\tau) = \lambda_2(t)\exp(-\lambda_2(t)\tau)$ in time interval $[t_i, t_{i+1})$. The interevent time between two consecutive transitions is denoted by τ , while the rate of a transition at time step t is denoted by $\lambda_2(t)$; and 2) at time $t + 1$, the value of $\lambda_2(t)$ is updated as $\lambda_2(t + 1) = \phi(t)\lambda_2(t)$, where $\phi_l \leq \phi(t) \leq \phi_u$. In this definition, $\phi(t)$ is a parameter governing the changing rate of transition probability. Here, ϕ_l and ϕ_u are the lower and upper bounds of $\phi(t)$. In the following experiment, we set $\phi_l = 0.5$ and $\phi_u = 2$, which means in a time step (week), the rate λ_2 cannot reduced by more than half or more than doubled in a week. Hence, we have

$$\lambda_2(t) = \lambda_{2,0} \prod_{i=1}^t \phi(i). \quad (4)$$

Here, we assume that $\lambda_1(t)$ is constant, for the following reasons: 1) the promotion strategy provided by the stakeholders is the main reason that the interest of potential gamers is aroused. For instance, if there is no price drop on a video game or console, a potential gamer will not purchase it; and 2) we suppose that the endogenous influence mainly contributes to the inherent appeal of a video game or console, which cannot be changed dramatically in a short time or periodically. Based on the previous reasons, we set $\lambda_1(t) = \lambda_{1,0}$.

Here, we use “gamer” instead of “individual,” as the video game market will be utilized as an illustrative example. Assume that a social network or community $G(V, E)$ is homogeneous and uncorrelated (more detailed description of the dynamical procedure of community networks can be found in our previous work [8]). Obviously, the number of gamers is a positive integer $X = 1, 2, \dots, N$. Here, $P(X(t) = m)$ represents the probability of having m gamers in the network $G(V, E)$ at time t , while $P(X(t + \Delta t) = n | X(t) = m)$ stands for the transition probability that there are n gamers at $t + \Delta t$, conditional upon there being m gamers at the immediately preceding time t . For simplicity, we set $P_m(t) \triangleq P(X(t) = m)$ and $P_{n,m}(t, \Delta t) \triangleq P(X(t + \Delta t) = n | X(t) = m)$.

Assume that at most one prospective gamer undergoes a transition in an infinitesimal time interval Δt , namely, there is only one potential gamer transitioning into a gamer. Hence, $P_{n,n-1}(t, \Delta t) \neq 0$ ($n = 2, 3, \dots, N$); otherwise, $P_{n,m}(t + \Delta t) = 0$. Then, the occurrence of the event $X(t + \Delta t) = n$ can be treated as the occurrence of the joint event as follows:

$$P_n(t + \Delta t) = P_{n-1}(t) \times P_{n,n-1}(t, \Delta t) + P_n(t) \times (1 - P_{n+1,n}(t, \Delta t)). \quad (5)$$

At time t , $(N - n + 1)$ is the number of leftover prospective gamers and $(n - 1)$ is the number of gamers. If we assume that the gamers are homogeneously distributed in the network, then a prospective gamer will be roughly influenced by $\alpha(n - 1)$ actors, where $0 < \alpha \leq 1$ is a constant. The endogenous influence on each prospective actor is $\alpha(n - 1)\lambda_{1,0}$, while the exogenous influence on each prospective gamer is $\lambda_{2,0} \prod_{i=1}^t \phi(i)$. Then, each prospective gamer is under the combined influence of sources inside the network and outside the network, and the combined influence is the following:

$$\lambda = \underbrace{\alpha(n - 1)\lambda_{1,0}}_{\text{Endo - influence}} + \underbrace{\lambda_{2,0} \prod_{i=1}^t \phi(i)}_{\text{Exo - influence}}. \quad (6)$$

Hence, the transition probability $P_{n,n-1}$ can be formulated as follows:

$$P_{n,n-1} = (N - n + 1)\lambda\Delta t = (N - n + 1) \left((n - 1)\lambda_{1,0} + \lambda_{2,0} \prod_{i=1}^t \phi(i) \right) \Delta t. \quad (7)$$

Here, for conciseness, we replace $\alpha\lambda_{1,0}$ with $\lambda_{1,0}$, ($\lambda_{1,0} \triangleq \alpha\lambda_{1,0}$); then, combining (5) and (7), we have

$$P_n(t + \Delta t) = P_{n-1} \times (N - n + 1) \times \Delta t \left((n - 1)\lambda_{1,0} + \lambda_{2,0} \prod_{i=1}^t \phi(i) \right) + P_n(t) \times (1 - n(N - n)\lambda_{1,0}\Delta t - (N - n)\lambda_{2,0} \prod_{i=1}^t \phi(i)\Delta t). \quad (8)$$

Next, our goal is to derive a deterministic equation to describe the growth of the expected number of gamers at any time based on this stochastic process model (8). The expectation, denoted $E[X(t + \Delta t)]$, has the form

$$E[X(t + \Delta t)] = \sum_{n=1}^{\infty} n P_n(t + \Delta t). \quad (9)$$

Inserting (8) into (9), and taking the limit as $\Delta t \rightarrow 0$, we have

$$\begin{aligned} \frac{dE[X(t)]}{dt} = & N\lambda_{1,0} \times E[X(t)] \\ & - \lambda_{1,0} \times \left(1 + \frac{\text{var}(X(t))}{E[X(t)]^2}\right) \times E[X(t)]^2 \\ & + \lambda_{2,0} \sum_{i=1}^t \phi(i)(N - E[X(t)]). \end{aligned} \quad (10)$$

Here, $\text{var}(X(t)) = E[X^2(t)] - E[X(t)]^2$ stands for the variance of $X(t)$. We define $x_1(t) \triangleq E[X(t)]$, and (10) can be simplified as

$$\begin{aligned} \frac{dx}{dt} = & \left(\lambda_{1,0} N x - \alpha \prod_{i=1}^t \phi(i) \lambda_{2,0}(t) x^2 \right) \\ & + \left(\prod_{i=1}^t \phi(i) \lambda_{2,0} N - \prod_{i=1}^t \phi(i) \lambda_{2,0} x \right) \end{aligned} \quad (11)$$

where we assume $\alpha = 1 + \delta(x)$. Here, we assume that $\alpha \approx 1$. Then, in time interval $[kT \leq t \leq (k+1)T]$, we have

$$\frac{dx}{dt} = \left(\lambda_{1,0} x + \prod_{i=0}^k \phi_i \lambda_{2,0} \right) (N - x) \quad (12)$$

which has a closed-form solution

$$x(t) = \frac{N \exp^{(\alpha_k + t)(N\lambda_{1,0} + \prod_{i=0}^k \phi_i \lambda_{2,0})} - \prod_{i=0}^k \phi_i \lambda_{2,0}}{\exp^{(\alpha_k + t)(N\lambda_{1,0} + \prod_{i=0}^k \phi_i \lambda_{2,0})} + \lambda_{1,0}}. \quad (13)$$

Note that the proposed model is a mechanistic model, of which each parameter has a physical meaning. N stands for the network size or the market size, while λ_1 and λ_2 represent the attraction rate of a product.

From (4), (12), and (13), we can derive the algorithm to calculate the estimated sales of a product $\hat{x}_i$. The algorithm is shown in Algorithm 1. Note that Algorithm 1 has only a for loop; then, the complexity is roughly $O(n)$.

C. Parameter Estimation Algorithm

To evaluate the performance of the proposed model in describing a real-life dataset, we first need to optimize our estimated parameters of the proposed model from a historical sales dataset. Ideally, the data would let us specify the attraction rate $\lambda_{2,0}(t)$ at different times. Note that we do not know *a priori* of the change in $\lambda_{2,0}(t)$, namely, the function form of the pattern in the collective behavior propagation process. Here, we introduce an inverse method that enables us to nonparametrically infer the unknown parameters $\theta = \{N, \lambda_{1,0}, \lambda_{2,0}, \Phi, x_0\}$ from the

Algorithm 1: Algorithm for Calculating Time Series $\hat{y}_i$.

Input: The parameter and initial set of the model $\{x_0, \lambda_{1,0}, \lambda_{2,0}, N, \Phi\}$, where $\Phi = \{\phi_0, \phi_1, \phi_2, \dots, \phi_{K-1}\}$;

Output: A time series $\{\hat{y}_1, \hat{y}_2, \hat{y}_3, \dots, \hat{y}_K\}$;

Initialization:

1: Set $\lambda_2^{\{0\}} = \lambda_{2,0}$

LOOP Process

2: **for** $i = 1$ to $K - 1$ **do**

3: Calculate $\lambda_2^{\{i\}}$, α and $\hat{y}_i$

$$\lambda_2^{\{i\}} = \phi_{i-1} \lambda_2^{\{i-1\}}$$

$$\alpha = \frac{\log(\lambda_{1,0} x_{i-1} + \lambda_2^{\{i-1\}}) - \log(N - x_{i-1})}{N\lambda_{1,0} + \lambda_2^{\{i-1\}}}$$

$$- (i - 1)T$$

$$\hat{x}_i = \frac{N \exp^{(\alpha + iT)(N\lambda_{1,0} + \lambda_2^{\{i-1\}})} - \lambda_2^{\{i-1\}}}{\exp^{(\alpha + iT)(N\lambda_{1,0} + \lambda_2^{\{i-1\}})} + \lambda_{1,0}}$$

4: **end for**

5: **return** $\hat{y}_1, \hat{y}_2, \dots, \hat{y}_K$

historical data. Given the sales of a console or video game, we can estimate all of the proposed model's parameters and compare its predictions with the real-life sales data.

The parameter estimation problem can accurately be formulated as the following nonlinear programming problem:

$$\begin{aligned} P_0 : \min_{\{\lambda_{1,0}, \lambda_{2,0}, \Phi\}} & \sum_{i=0}^K w_i (\hat{x}_i - x_i)^2 + \lambda \sum_{i=0}^K (\phi_i - 1)^2 \\ \text{s.t.} & \begin{cases} (i) & \frac{dx}{dt} = \left(\lambda_{1,0} x + \lambda_{2,0} \prod_{i=0}^k \phi_i \right) (N - x), \\ & kT \leq t \leq (k+1)T \\ (ii) & 0 \leq \lambda_{1,0} \leq \lambda_{1,u} \\ (iii) & 0 \leq \lambda_{2,0} \leq \lambda_{2,u} \\ (iv) & 0 \leq N \leq N_u \\ (v) & \phi_l \leq \phi_i \leq \phi_u \end{cases} \end{aligned} \quad (14)$$

where (i)–(v) in (14) represent constraints. The first part is the error between the estimated sales provided by the model (4) and the actual sales and is calculated by Algorithm 1. The second part $\lambda \sum_{i=0}^K (\phi_i - 1)^2$ is the regularization term, which dictates that the Φ do not vary dramatically. If we knew the actual external influence from the promotion, or even the time of the promotion, it would be great help for computing the parameters $\Phi = \{\phi_0, \phi_1, \dots, \phi_{K-1}\}$ of the collective propagation process. The data, however, do not include this information, so we have to utilize heuristic methods to determine the optimal parameter set θ . We use a differential evolution method to minimize the cost function P_0 (14). This inverse method allows us to determine the optimal model that can generate the best-estimate sales, just based on the given data and our proposed model, without making any assumptions about the functional forms of the purchase incentive of the public. The optimization methods require

solving the proposed model (13) by utilizing Algorithm 1. At each iteration, we have to perform the numerical integration with a set of unknown parameter. During the process of parameter estimation, the integration is required to be executed thousands of times, which brings heavy computation burden. Then, one identification process may consume about an hour.

IV. EXPERIMENTAL RESULTS

Next, we compare the estimated sales generated by the proposed model based on a time-varying rate with the empirical sales data of consoles and video games in this paper.

A. Testing the Model

We utilize the video game industry as an illustrative example to show the availability of the model (12). The root-mean-square percentage error (RMSPE) is adopted as a criterion to evaluate the difference between the historical sales data and the sales predicted by the model. First, we apply the proposed model to study sales of consoles, including handheld consoles (Game Boy, Game Boy Advantage, Game Boy Pocket, Nintendo DS, Nintendo 3DS, PlayStation Portable, PlayStation Vita, WonderSwan, and WonderSwan Crystal) and home consoles (PlayStation 4, PlayStation 3, Wii, WiiU, Xbox 3y60, Nintendo Entertainment System, Super Nintendo Entertainment System, Xbox One, Nintendo 64, and Sega Genesis). Our dataset records the sales histories of these consoles in different regions. For instance, we have the sales history of Xbox One in six regions, e.g., France, Germany, Japan, the U.K., the USA, and the whole world. Hence, generally, one console or one game has six time series of sales history. Hence, this dataset includes 76 time series of console sales and 29 679 time series of video game sales history. However, most video games are not popular and generate fewer than 10 000 sales. Only sales data for the first few weeks are recorded. Here, we screen all the video games that have been sold for more than one year and find a total of about 280 cases. Each year is divided into 52 weeks, and for simplicity, the exogenous and endogenous influences inside a week remain unchanged. The growth model (12) with $\lambda_2(t)$ given by (4) is used to fit the video console sales data of consoles and video game sales in different regions. Here, for the sake of conciseness, we only show the results for sales of Nintendo DS in Japan and Wii throughout the world. The results of other game consoles are similar, and we will not present them here but rather in the supplementary material.

Fig. 1(a) shows the historical sales data $x(t)$ and model-generated sales $\hat{x}(t)$ of Nintendo DS and Wii. Historical sales data are plotted with dash curves, and the sales trajectory generated by the model is plotted with solid curves. Experimental results suggest that the trajectories generated by the model can accurately describe the dynamics of the sales histories of the two representative examples. We also apply this model to analyze video game sales. For video games, the 95% confidence level of RMSPE is $1.44 \pm 1.26\%$ for video games, while it is $1.34 \pm 1.02\%$ for consoles. The dash-dotted lines represent the estimated total market size, which is the total number of gamers and prospective gamers for a console or video game.

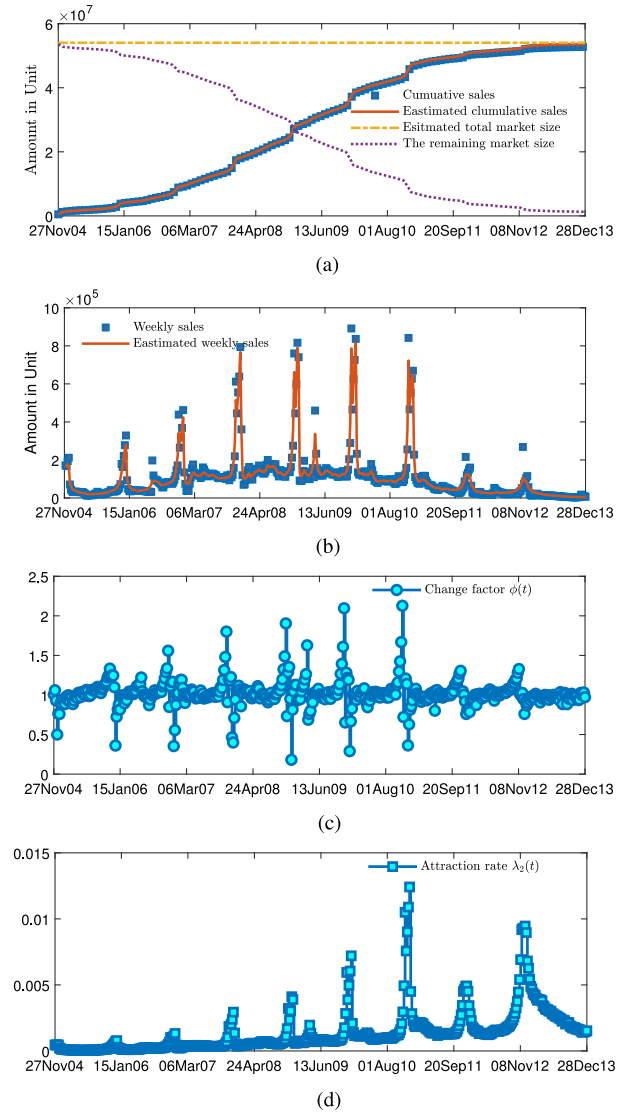


Fig. 1. How the global activity λ changes with time. Attraction rates of consoles in different areas. (a) Nintendo DS (USA): Cumulative sales $x(t)$. (b) Nintendo DS (USA): Cumulative sales $x(t)$. (c) Nintendo DS (USA): Change factor $\phi(t)$. (d) Nintendo DS (USA): Attraction rate $\lambda_2(t)$.

This estimate stands for the estimated overall spending power of all gamers. The dotted lines in Fig. 1(a) gives the estimation of *effective market size* $N - \hat{x}(t)$, which is the estimated market size minus the number of gamers who have bought a console or a game before time t . Thus, this effective market size stands for the potential demand remaining in the game market. For instance, the effective market size of Nintendo DS is about 30 million in the USA in June 2009, meaning that 30 million prospective gamers had not yet bought a Nintendo DS and would buy a DS in the future. Our results show that the effective market of DS and Wii was gradually decreasing.

Denote by $\lambda(t) = \lambda_{1,0} + \lambda_2(t)$ the combined purchase incentive of the public (i.e., the consuming desire at time t), the seasonality is evidenced by $\lambda(t) \approx \lambda(t + T)$, where T represents the period. In this paper, T is a year. We also give the combined incentive rate $\lambda(t)$ and the fitted results of

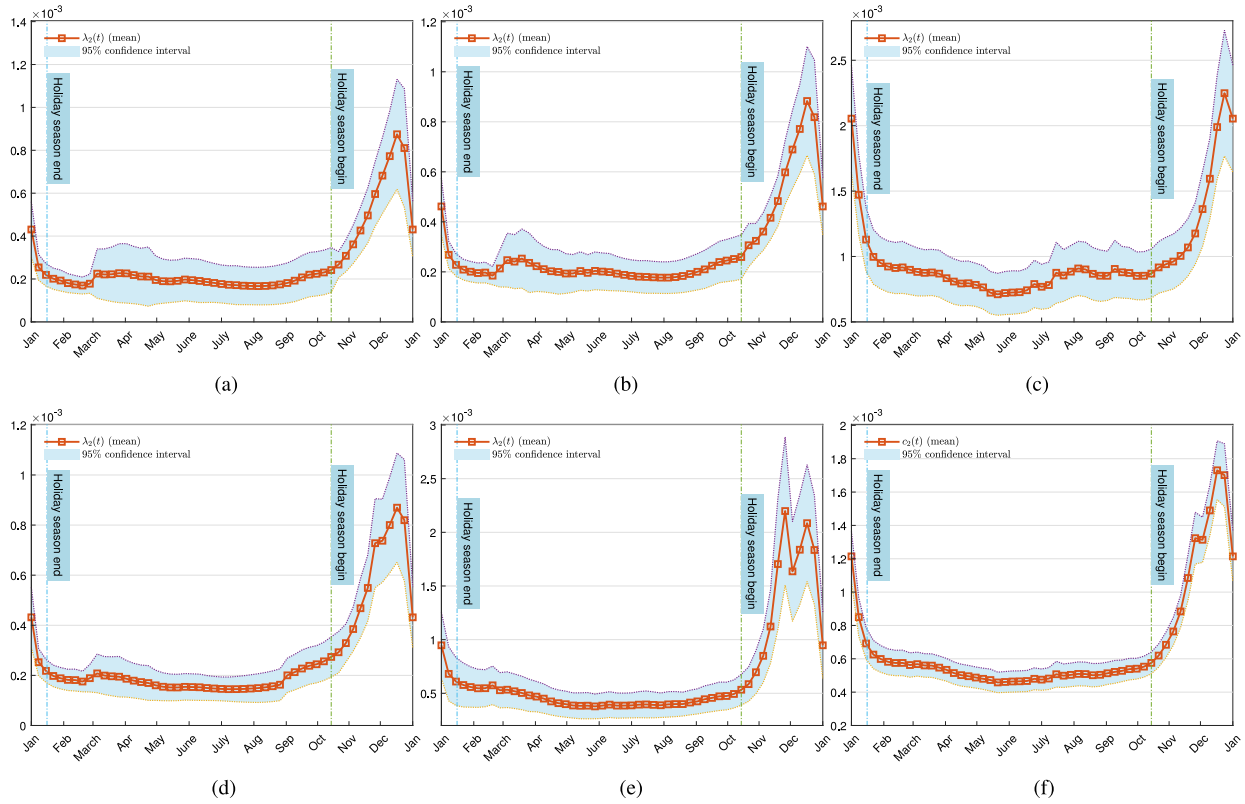


Fig. 2. Combined incentive rates of the console market in various areas. The solid square lines are the average combined incentive rates of different consoles in a particular region, while the light green region is the 95% confidence region of the combined incentive rates. The dash vertical lines indicate the beginning and end of the holiday season, in which the combined incentive rates increased dramatically. (a) France. (b) Germany. (c) Japan. (d) U.K. (e) USA. (f) All.

weekly sales. **Fig. 1(c)** shows the estimated change rates, while **Fig. 1(d)** shows the change in purchase incentives of these two consoles. It can easily be seen that the sales of consoles exhibit inactive periods throughout almost the entire year. Then, there is a burst of rapidly growing consumer desire. Additionally, the corresponding $\lambda_2(t)$ presents strong seasonal periodicities (quasi-periodic behavior). Comparing the modeling results to the experiments on two real-life datasets, we conclude that the temporal activity patterns contain endogenous bursts that can be estimated from the historical data. This model is powerful and general for unveiling the dynamic patterns of collective human activity with temporal bursts.

There are other interesting phenomena. Let us take the Nintendo DS as an example. **Fig. 1(d)** shows the combined purchase incentive; we can find that the peak combined incentive of Wii is about 0.0075 in 2009, which means that in one day, 75 out of 10 000 prospective gamers will purchase a DS, while the peak combined incentive is about 0.01 in 2012. However, in 2009, the peak weekly sales are about 1 million units, while the peak weekly sales are less than 20 000 units in 2012. How did this phenomenon happen? Note that $\Delta N = N - x$ is the number of remaining prospective gamers, and the market size is actually the number of remaining prospective gamers. However, the number of remaining prospective gamers for DS is about 30 million in 2009, whereas it falls below 0.5 million in 2012. This finding explains why the peak weekly sales of the Wii in

2012 are smaller than in 2010. The smaller number of remaining prospective gamers in 2012 produces a slow sales rate. For different products with similar $\lambda(t)$, the one with larger ΔN enjoys a larger sales rate.

B. Combined Incentive Rate $\lambda(t)$

From the proposed model, we can estimate the market size N and the transition rates $\lambda_{1,0}$ and $\lambda_2(t)$, corresponding to the endogenous and exogenous influences, respectively. Additionally, we can derive the sales speed and combined incentive rate. In this paper, we estimated the $\lambda(t)$ from the 76 cases about console sales and 281 cases about video sales. Then, we derive the combined incentive rates of each console's sales in various regions. For instance, in Japan, we have sales history on a total of 21 consoles, and we derive the combined incentive rate of each console. Still, we take the Nintendo DS as an illustrative example. Note that Nintendo DS was sold in Japan from 27/Nov/2004 to 28/Dec/2013, over a nine-year period. Hence, we can estimate the combined incentive rate of DS from 27/Nov/2004 to 28/Dec/2013 [$\lambda^{\text{DS}}(t)$ shown in **Fig. 1(d)**]. Then, we divide one year into 52 weeks and determine the week in the year to which time t belongs. If t belongs to the i th week in a year, then $\lambda^{\{\cdot\}}(t)$ will belong to the i th subset Λ_i . Then, we derive the mean and 95% confidence region of the combined intensive rate of the i th week, where $i = 1, 2, \dots, 52$.

Finally, we can draw a picture of the change in the combined incentive rate for consoles in Japan [see Fig. 2(c)]. Similarly, we can estimate the combined incentive rates for console sales in other areas (see Fig. 2). The results show that the combined incentive rate fluctuates every year following a pseudocycle form.

Fig. 2 shows the dynamic patterns of a combined incentive rate every week in different areas, including France [see Fig. 2(a)], Germany [see Fig. 2(b)], Japan [see Fig. 2(c)], the U.K. [see Fig. 2(d)], the USA [see Fig. 2(e)], and globally [see Fig. 2(f)]. Specifically, we anticipate that the combined incentive rate of an individual is low outside of the holiday season. Therefore, we expect that $\lambda_2(t)$ is small. During the holiday season, $\lambda_2(t)$ increases; then, $\lambda(t)$ is also increased. During the holiday season, a prospective gamer is more likely to transition into a gamer. The results clearly suggest that in developed countries and even around the world, the holiday season effect for the video game market begins in the middle of October, which is shown by the vertical dashed line in the Fig. 2. Additionally, the holiday season effect reaches its peak one week before Christmas, after which the combined incentive rate declines. Finally, in the middle of January, the incentive rate returns to the normal level. The results indicate that the peak combined incentive rate is always four times higher than the rate in a normal period. Japan and the USA have the highest combined incentive; in a normal period, Japan has a rate of about 8×10^{-4} and the USA has a rate of about 5×10^{-4} , while in the other three European countries, the combined incentive rates are about 2×10^{-4} . Similar results can also be found in video game sales cases. We can find that the peak combined incentive rates in the holiday season are about four times those of a normal period in all cases; these general results can be found in the sales of consoles and video games in all areas.

V. CONCLUSION

In this paper, we developed a mechanistic model that incorporates a seasonal effect and apply it to video game sales data. We adopted several simplifying assumptions regarding the leading forces that govern the dynamics of the growth of collective behavior propagation, and we rigorously derived a tractable model containing only four main ingredients.

- 1) Social ties between individuals form a social network, through which information can propagate.
- 2) Additionally, we consider an endogenous influence from the network neighbors, or “Word-of-Mouth” rules, a primary mechanism by which information and activity reach neighbors through social network ties and spread like a virus from individual to individual.
- 3) We consider these factors as exogenous influences, representing influences that come not from mutual acquaintances but from outside the network.
- 4) We consider a nonhomogeneous Poisson process, which results in seasonally based variance rate model.

The current model was driven by external changes in promotions. In this model, the external rates were time varying and determined by the promotion, while the consumer’s desire was

affected by the external influence. We used real sales data of the video game industry, including the sales history of 21 consoles and more than 10 000 video games from 1989 to 2018. An inverse method is developed to estimate $\lambda_{1,0}(t)$, $\lambda_{2,0}(t)$, and the effective (remaining) market size ΔN from the historical sales data. Then, the relative effectiveness of promotional efforts and customer service can be investigated. Here, we showed how the combined incentive $\lambda(t)$ and effective (remaining) market size $\Delta N = N - x$ influence the actor growth (sales) rate.

Our results clearly demonstrated that the change in external influence is one of the causes of bursts in collective behavior propagation. The question is: would rational decision making, together with external influence, be able to describe the whole picture of collective behavior propagation? In this paper, we showed that the market size and the external influence of different incentive factors contribute to the growth profile of the actor population of a product and service. Our findings revealed that both the holiday effect and sales promotion would influence sales profiles dramatically. We can derive the dynamic changing patterns of combined purchase incentives in different areas, including Japan, France, Germany, the U.K., the USA, and the whole world for console sales and video game sales. Based on this model, we can estimate several market information, including the public’s purchase incentive and the market size. Hence, we can achieve very useful information for making decisions in business. Our model was capable of pinpointing the various factors that contribute to shaping the sales profiles of products and services, and hence, it is able to provide guidelines for developing effective business strategies. In addition to providing a good description of collective human activities with temporal bursts, we claim that the proposed model is readily applicable to various temporal human activities. In this paper, our model was only applied to video console sales. However, it can be easily extended to incorporate the multitude of human activities in which temporal bursts exist.

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