Modeling Peer Influence in Time-Varying Networks

Matthias Wölbitsch, Simon Walk, and Denis Helic

Abstract Recently, networks of user interactions in online systems gained a lot of interest from our research community. Such networks are characterized by complex bursty patterns of human user behavior. A lot of models for such networks are based on the activity-driven time-varying network framework, which was introduced in an effort to model human interaction networks more accurately. Mostly, these models rely on intrinsic activity patterns of individuals and disregard external influences. However, such external influences are important factors in more complex interaction scenarios. In this paper, we propose an activity-driven network model by introducing a peer influence mechanism into the network dynamics. In particular, we allow for active individuals to motivate their peers to become active as well. We examine the ramifications of this mechanism on the topological and activity-related properties of synthetically generated networks and reveal its complex influence on the underlying dynamics. As expected, our results show that peer influence has positive effects on formation of network communities. At the same time the changes in activity patterns suggest a complex response of the system to the peer influence mechanism. This interesting preliminary result opens interesting avenues for further research in the future. Our main contributions are (i) the specification of peer influence for an activity-driven network generator and (ii) the analysis and discussion of the added peer influence mechanism on synthetic networks.

1 Introduction

On the Web, user behavior typically follows complex dynamics that are hard to capture. For example, activities, such as writing of e-mails or tweets, are often performed in bursts with long inactive intervals between the bursts [1]. Furthermore, on

Matthias Wölbitsch, Simon Walk and Denis Helic
ISDS, Graz University of Technology e-mail: m.woelbitsch@student.tugraz.at, e-mail: {simon.walk, dhelic}@tugraz.at

the Web, users are constantly exposed to peer influence. For example, a message on Twitter can trigger multiple responses, leading to additional activity in the Twitter network, which would otherwise not occur. Thus, user activity in such online networks is a combination of users intrinsic motivation to contribute and external peer influences.

Our research community has invested tremendous effort to model such activity dynamics [10, 15, 16, 20]. Among others, modeling approaches based on network and activity generators have gained a lot of attention in the past. One prominent example of such models is the activity-driven framework by Perra et al. [15]. This framework is based on time-varying networks [6] and allows to model activity of entire networks based on *activity potentials*—an intrinsic node property, which determines its activity profile. This model was used to study dynamic processes on networks such as the spreading of diseases [18].

In addition, models capturing and replicating activity patterns are applicable for various other tasks [17, 20]. For example, Walk et al. [20] investigate and explain why some online platforms are able to achieve a state of self-sustainability in terms of user activity, while others fade away due to the inactivity of their user base.

Problem. Currently, there exist several approaches based on activity-driven network generators, which aim to describe user activity patterns as realistic as possible [10, 12]. All of these models implement the intrinsic activity potential as a single source of activity in the network. In other words, these models neglect peer influence. However, to be able to model more complex scenarios, such as activity in social networks that is directly dependent on actions of other users, we need an additional and explicit mechanism.

Approach. In our approach, we propose an extension to activity-driven network generators that introduces external peer effects to the network dynamic simulations. More specifically, the activation of nodes in our approach is not solely determined by their intrinsic activity potential, but also by the activations of their neighbors in the network. As a result, active nodes can motivate their neighbors and increase the probability of neighbors becoming active as well.

Contributions. The main contribution of our work is the specification of peer influence as an extension to an activity-driven network generator. Additionally, we analyze and discuss simulation results on synthetic networks. The experiments highlight positive effects on the topological structures of the generated networks as well as effects on the activity patterns of nodes.

2 Related Work

One common way to represent activity patterns is by using a probability distribution for the intervals between two consecutive activities (i.e., the inter-event time distribution). The model should account for high probabilities of short inter-event times and a long tail that allows for the longer phases without activity. In general, a power-law distribution of the form $p(t) \sim t^{-\gamma}$ fulfills these requirements. For example, a well-known model that follows a power-law distribution is the queuing model [19].

Another straightforward method is a Poisson process to describe the inter-activity times [1]. In this process events occur independently at a given constant rate and thus this approach is not able to generate bursty patterns. Several approaches extend Poisson processes to avoid this issue. For example, Malmgren et al. [11] adopts a mixture of homogeneous (constant rate) and non-homogeneous (time-varying rate) Poisson processes to model the e-mail activity of users.

An approach that also captures other patterns of human behavior, such as periodic spikes, was proposed by Ferraz Costa et al. [3]. Their Rest-Sleep-and-Comment (RSC) model is based on a self-correlated stochastic process and was the foundation for a classifier, which is able to detect whether an activity sequence on Reddit was generated by a bot or by a person with high accuracy.

Another possibility to model user activity is by using Hidden Markov Models (HMM's) [16]. The Markov model consists of two hidden states, which describe the activity state of a user and yields inter-activity times with respect to the current state. The approach by Raghavan et al. [16] is based on coupled HMM's and takes the social network influence of other users into account as well. This is done by explicitly coupling the stochastic processes and letting the transition probabilities between states of individual users be dependent on the activity of their friends.

The activity dynamics model [20] and its extension [8] allows to study the development of activity in large collaboration networks over longer periods of time. It highlights the effects of the micro-behavior of users (i.e., their intrinsic activity as well as the influence on their neighbors) on the macro-behavior of the whole system.

Our work builds upon the activity-driven network framework by Perra et al. [15] and the community-aware variant of that framework by Laurent et al. [10]. We extend those frameworks by introducing peer influence effects, such that nodes are directly able to influence the activity patterns of other nodes in the network.

3 Methodology

3.1 Preliminaries

Activity-driven Time-varying Network Model. The model by Perra et al. [15] is based on the idea of *activity potentials*. Each node v_i in the network is assigned a probability to become active $a_i \in [\varepsilon, 1]$ in each time step, which is drawn from a suitable probability distribution $f(a)$. The time-varying network at time t is generated by first creating a new edgeless network G_t. Then, every node v_i becomes active with probability a_i. Finally, active nodes choose another node in the network uniformly at random and form a link with it. The individual networks G_t are called *instantaneous networks* as opposed to an *integrated network*, which is the union of all instantaneous networks up to some point in time T.

Activity-driven Community Extension. Laurent et al. [10] presented a model to produce adjustable community structures and weight-topological correlations in the integrated network. These two properties, which are often observed in real-world networks [4, 14], are generated by changing the way how an active node selects its communication partners.

MEMORY EFFECTS. By allowing nodes to remember all previous interactions with other nodes, which are more likely to be repeated, it enables the formation of strong ties (i.e., interactions that are repeated often) and weak ties (i.e., interactions that are repeated infrequently). The memory of a node is represented by an edge-weighted egocentric network that includes all other nodes, which were already part of one or more interactions in the past. The weight represents the number of previous interactions, and therefore the tie strength.

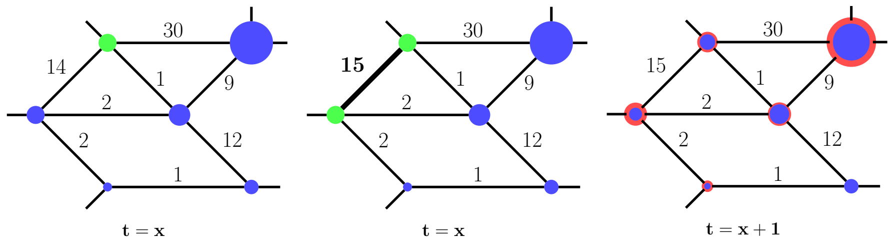
Depending on the number of neighbors, node v_i will either form a new tie or reinforce an existing one. If k_i is the size of egocentric network of v_i, the probability for v_i to form a new tie is given by $p(k_i) = {}^{c}/_{(k_i+c)}$, where the constant c determines the memory strength. When an active node v_i reinforces an existing tie, the probability for node v_j to be selected as communication partner is given by $p_{i,j} = {}^{w_{i,j}}/_{\sum_{k \in N(v_i)} w_{i,k}}$, where $w_{i,j}$ denotes the tie strength, and $N(v_i)$ is the set of neighbors of node v_i. This reinforcement process allows for the introduction of dependencies between successive interactions of node pairs.

CLOSURE PROCESSES. The selection of nodes for the formation of new ties is determined by two closure processes. The first one, *cyclic closure* [9], assures the formation of triangles that were linked to the emergence of communities in networks [2]. If a node wants to form a new tie, it tries to perform a cyclic closure with probability p_Δ, by interacting with a randomly selected neighbor of a neighbor. The second one, *focal closure* [9], emulates homophily of users (i.e., similar users connect to each other). This process is performed whenever a new tie should be created with a probability of $1 - p_\Delta$, or if there are no suitable candidates for a cyclical closure. This is, for example, the case if a node becomes active for the first time.

NODE DELETION MECHANISM. Additionally, nodes have an intrinsic probability p_d to be removed from the network in every time step. This ensures that the network can reach a stable state, in which the structural characteristics (e.g., the community structures) become invariant in time. Every time a node is removed from the network, a new one joins to keep the size of the network constant.

3.2 Peer Influence Extension

In the previous models, each node can become active either (i) by self-initiation, or (ii) by being contacted by another active node. Activations caused by other nodes are not necessarily independent of previous events due to memory effects. For example, when a node with low activity potential is part of a group of high-activity nodes with already established strong ties, the other nodes in the group will fairly



(a) (b) (c)

Fig. 1: **Illustrative example.** The size of the nodes represents their activity potentials and the weights the tie strengths between them. (a) depicts the activation of a node due to its intrinsic activity potential (green node). This node can now either form a new tie or, as shown in (b), reinforce an existing one, which activates another node as well. These two active nodes have an influence on the activation probability of their neighbors in the next iteration as shown in (c). The additional peer-influenced activation probability depends on the tie strength between the nodes and is depicted as an increase in the node size (red border).

often select the low-active node as communication partner when they become active. This mechanism alters the inter-event time distributions of nodes with small activity potentials. Nevertheless, this type of peer influence is hidden or implicit.

We propose a more explicit way to describe the influence between nodes. We represent peer influence $p_i(t)$ that a node v_i receives from its neighbors as probability for an activation and calculate it in each iteration step according to the number of active neighbors in the previous iteration (see Fig. 1). Also, we define $p_i(t)$ such that it depends on the strength of the ties to neighbors.

To that end, we first transform and normalize each weight in the egocentric networks of v_i using a softmax function: $w'_{i,j} = \exp(\beta w_{i,j}) / \sum_{k \in N(v_i)} \exp(\beta w_{i,k})$, where β is the inverse temperature parameter of the softmax function, which allows for the modeling of different influence scenarios.

Second, we calculate the weighted fraction of active neighbors $\alpha_i(t)$ of node v_i at time $t-1$: $\alpha_i(t) = \sum_{j \in N(v_i)} \mathbf{1}_{\{t_j = t-1\}} w'_{i,j} / \sum_{j \in N(v_i)} w'_{i,j}$, where $\mathbf{1}_{\{x\}}$ is the indicator function, which yields 1 whenever the predicate x is true.

Next, we map the weighted fraction of prior active neighbors to a peer influence probability in the range $[0, q]$, where parameter q is the maximum peer influence. We define this mapping using a monotonically increasing function. We chose an algebraic sigmoid function so that peer influence saturates after some fraction of active neighbors is reached, limiting the maximum peer influence that can be exercised on any node at every step in time. Moreover, the peer influence surges noticeable after some threshold of active neighbors is reached. Hence, the final equation for the peer influence for a node v_i is: $p_i(t) = (\alpha_i(t) q) / \sqrt{\alpha_i^2(t) + \theta^2}$, where $\theta > 0$ denotes a critical threshold, which determines the required fraction of active neighbors to set the peer influence probability close to its maximum.

In general, a node can now become active by itself based on its intrinsic activity potential, or based on the peer influence probability it receives from its neighbors (i.e., $P(v_i \text{ becomes active at time } t) = a_i + (1 - a_i)p_i(t)$).

4 Experimental Setup

We generate synthetic networks with $n = 5,000$ nodes over $T = 75,000$ iterations and run our experiments 40 times to account for statistical fluctuations. We report average results.

For our experiments we fix the activity potential distribution to $f(a) \sim a^{-2.7}$ with a lower bound of $\varepsilon = 10^{-3}$. This distribution reflects the heterogeneous activity patterns of people well, and is similar to distributions observed in real-world communication networks [7]. To ensure the formation of adequate community structures in the network we set $p_\Delta = 0.9$ for the triadic closure probability, and $p_d = 5 \cdot 10^{-5}$ for the node deletion probability. Furthermore, we adopt the memory strength constant $c = 1$ so that the probability for the formation of a new tie decays very fast with a larger egocentric network.

We fix the critical peer influence threshold to $\theta = 0.1$ to reflect the intuition that a small number of active neighbors is sufficient to affect the activity of a node to a large extent. Additionally, we adopt the current average tie strength as the temperature for the softmax weight rescaling. Hence, in each step β is set to the reciprocal value of average weight in the integrated network and is initialized with $\beta = 1$.

We measure the time-dependent topological properties of the integrated network only for nodes belonging to the temporal network. This implies that nodes deleted due to the node deletion mechanism do not influence the properties of the integrated network. Furthermore, we perform the experiments with different values for the maximum peer influence probability q to examine the effects of peer influence on the topological and activity-related properties of the generated networks.

Aside from analyzing the integrated network of all $75,000$ instantaneous networks and its properties we also study the evolution of these networks during the simulation. This allows us to collect further insights into how the model shapes communities as well as into the effects of peer influence on the resulting structures.

5 Results & Discussion

5.1 Average Local Clustering Coefficient

We first investigate how the average local clustering coefficient $C(t)$—a local property of a node that measures the cliquishness of its neighborhood [21]—evolves over

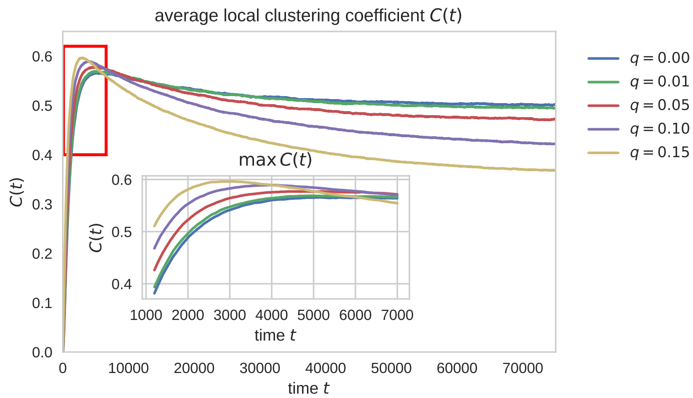


Fig. 2: **Average clustering coefficient evolution.** Higher values for q (solid lines) result in stronger peer influence effects. The average clustering coefficient (y-axes) increases rapidly in the first few hundred iterations (x-axes) until it reaches its maximum value. The maximum value of $C(t)$ and the time until it is reached depends on the degree of peer influence (see inset). After this rapid initial phase, $C(t)$ starts to relax until it reaches its stationary value. Note that q also affects the time until convergence.

time. We report the network average of $C(t)$, which indicates the extent and strength of communities, where higher $C(t)$ means more/stronger community structures.

Findings. The average clustering coefficient is very small in the first few hundred iterations of our simulations (see Fig. 2), due to the sparsity of the integrated network. However, shortly after this initial phase the clustering quickly increases until it reaches its maximum between roughly $3,000$ and $5,000$ iterations. Afterwards, $C(t)$ begins to decline until the network reaches its stationary state.

Furthermore, the clustering coefficient of networks with higher values for q (i.e., where nodes are able to motivate their neighbors to a larger extent) reach higher peaks of $C(t)$ faster (see inset of Fig. 2). For example, the network in which nodes

Table 1: **Clustering characteristics.** The maximum value for the average local clustering coefficient $C_{\max} = \max C(t)$ and the time to reach the maximum $t_{\max} = \arg\max C(t)$, for different values of q, the maximum peer influence probability. The proposed peer influence mechanism accelerates the formation and strength of the community structures in the network.

q	0.00	0.01	0.025	0.05	0.075	0.10	0.15
$t_{\max}$	5,140	4,919	4,839	5,192	4,173	4,044	3,038
$C_{\max}$	0.5659	0.5689	0.5721	0.5773	0.5822	0.5895	0.5963

are not able to influence their neighbors ($q = 0.00$) reaches it peak value for $C(t)$ after approximately $5,000$ iterations, while the network with $q = 0.15$ is more than $2,000$ iterations faster. However, the effect only occurs for networks with $q > 0.05$ and the maximum value of the local clustering coefficient is only slightly higher for higher levels of peer influence (cf. Table 1).

Fig. 2 also shows an effect on the converged community structures for different levels of peer influence. This is illustrated by smaller average stationary values for $C(t)$ for larger q at the end of the simulation (e.g., the last few thousand iterations).

Discussion. At the start of our simulations almost all nodes are disconnected and the number of triangles is small, compared to the size of the network. The subsequent and rapid increase of $C(t)$ is caused by the cyclic closure mechanism and the emergence of strong ties, which further amplify the biased local search of the cyclic closure mechanism. However, weak ties are eventually introduced to the network by the focal closure mechanism. These are rarely involved in the formation of new triangles, due to their bias towards strong ties, which contributes to the decrease of $C(t)$ until the network reaches its stationary state [10]. The proposed peer influence mechanism positively affects the development of topological structures in the network by increasing $C(t)$ in the beginning of our simulations. Further, peer influence injects additional activity into the network, which supports the formation of community structures and, as a direct consequence, influences $C(t)$.

The stationary value of $C(t)$ depends on the node deletion probability p_d, as low-activity nodes, which are not removed fast enough, introduce additional weak ties in the network [10]. Similar to the deletion probability, our peer influence mechanism influences the strength of the generated community structures. We can observe that the more likely an activation is due to peer influence, the smaller the stationary value for $C(t)$. As the peer influence mechanism increases the activity in the network, especially in already formed communities, active nodes motivate their neighbors to become more active as well. Further, note that the probability for the formation of a new tie is inverse proportional to the size of the egocentric network of a node. Therefore, an active node, which is already fully integrated in its community, will reinforce one of its existing ties, or at least close a triangle, with high probability. However, given enough iterations, such a node will eventually introduce new weak ties following the focal closure mechanism, so that the introduction of random links by active nodes increases, which leads to a smaller $C(t)$.

5.2 Inter-event Time Distribution

To examine the impact of the proposed mechanism on the burstiness of the generated activity patterns we study how the burstiness parameter [5] B changes with increasing levels of peer influence. B is defined as $B = {}^{(\sigma-\mu)}/_{(\sigma+\mu)}$, where μ and σ are the mean and the standard derivation of the inter-event time distribution of activities $\varphi(t)$, respectively. Hence, it is -1 for regularly occurring events, 0 for inter-event times that originated from a Poisson process, and 1 for an extremely bursty sequence of events. Note that we do not differentiate between different types of activations (i.e., due to peer-influence, intrinsic activity potential, or by being contacted by an active node).

Findings. For networks with $q = 0.00$ the burstiness parameter is $B \approx 0.19$. With larger q we can see larger increases for B (see Table 2). For example, the burstiness of inter-event time distribution of the network with $q = 0.15$ is $B \approx 0.24$.

This increase of B is also reflected in the development of μ—the mean value of the inter-event time distribution. It declines from about $\mu = 200$ in a network with no peer influence effects, to approximately $\mu = 37$ in a network with $q = 0.15$. Thus, the average time between two consecutive activations of nodes becomes shorter, favoring the emergence of bursty activation behaviors. Similar to the mean value, the standard deviation σ of the inter-event time distribution also decreases with increasing q. Fig. 3 depicts these findings. We observe an increase in probabilities for short inter-event times with increasing q. For example, the probability for two consecutive activations of nodes increases by about 20% over the range of possible values for q. On the other hand, the length of the tail of the distribution decreases, which is also reflected in the decrease of the standard deviation of $\varphi(t)$.

Discussion. In a network with no peer influence, two consecutive self-activations are independent of each other. Therefore, activations happen at a certain rate that is proportional to the activity potential of a node, which leads to exponentially distributed inter-event times [13] and results in a burstiness parameter that is close to $B = 0$. However, due to the memory effects in our proposed model, we receive different values for B (cf. Table 2) even when $q = 0.00$. Specifically, the memory effects foster reoccurring interactions within groups of nodes. Additionally, nodes with higher intrinsic activity potentials will select nodes from their local group with high probabilities. Hence, more active nodes activate less active nodes regularly, which can lead to bursty activity patterns of other nodes, and explains (at least partially) the burstiness value of $B = 0.19$ with $q = 0.00$. Our peer influence mechanism further amplifies this effect, as it increases activity within communities.

Even though we have managed to increase the burstiness in our network in general, not all observed effects in the inter-event time distribution are desired for real-

Table 2: **Inter-event time distribution characteristics.** Mean value μ, standard deviation σ, and the resulting burstiness parameter B of the inter-event time distribution for varying degrees of the maximum peer influence probability q. The peer influence mechanism increases the burstiness of activity in the network, also reflected in the decrease of μ. However, the decrease in σ indicates that the proposed peer influence mechanism obstructs further burstiness.

q	0.00	0.01	0.025	0.05	0.075	0.10	0.15
μ	198.71	184.59	164.26	132.80	102.43	76.28	37.23
σ	291.32	270.49	241.40	197.38	155.09	118.04	61.22
B	0.1890	0.1888	0.1902	0.1956	0.2045	0.2149	0.2437

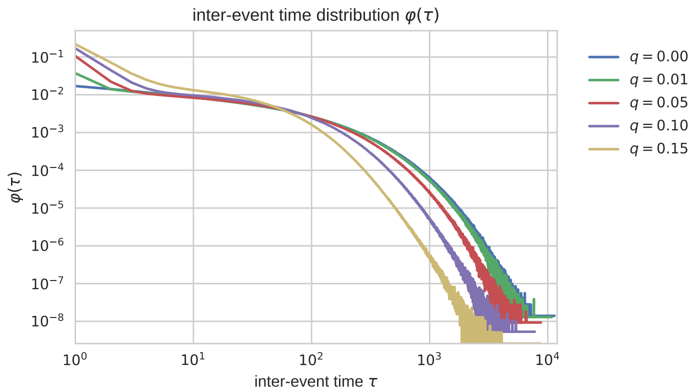


Fig. 3: **Inter-event time distribution.** Visualization of the probabilities (y-axis) of inter-event times t (x-axis) for varying levels of peer influence $q = 0, 0.01, 0.05, 0.1, 0.15$ in the network. The probabilities for smaller inter-event times are in general higher and the introduction of the proposed peer influence mechanism amplifies this characteristic. Furthermore, $\varphi(t)$ is a long-tailed distribution and its length is negatively affected by the peer influence effects. Therefore, bursts are more probable with increasing levels of peer influence, while longer phases of inactivity are not.

world activity simulations. The first property of typical human activity patterns—the possibility for multiple activities in a short period of time (i.e., bursts)—is captured more accurately with increasing levels of peer influence, due to the increased probability for small inter-event times. However, the second property of activity patterns—the opportunity for longer intervals of inactivity—is negatively affected by the decrease in the length of the tail of $\varphi(t)$. Hence, longer phases of inactivity become more unlikely with increasing levels of peer influence.

6 Conclusion & Future Work

The main intuition behind our approach is that actions of people on the Web are not solely based on their intrinsic motivation, but also on the influence of their online peers. For example, the activity of an individual user in a social network, such as Twitter, can be affected by the activities of other users in the form of retweets. This idea stands in contrast to the activity-driven network model, in which nodes can become active only based on their inherent activity potential. The introduction of the peer influence adaption resolves a number of important issues, such as the quantification of the influence of neighbors in the egocentric network of a node, or the determination of the relative influence of individual neighbors based on tie strengths. We see such aspects as the main contribution of our approach with respect to modeling activity in networks of user interactions.

After specifying the model[1] we analyzed and showcased its functionality and parametric evolution on synthetic networks. This includes an examination of the effects on the topological structures of networks, which showed that peer influence does accelerate the formation of community structures and their strength. Additional investigations revealed that (i) activation patterns of individual nodes are affected by peer influence, and (ii) the distribution of time intervals between two consecutive activations changes in a way that allows for increased burstiness, which is a defining property in human activity patterns.

However, while the probability for short breaks between activations increased with more prominent peer influence effects, the length of the tail of the inter-event time distribution decreased, restricting the possibilities for longer intervals between bursts, which might occur due to a badly fitted peer influence parameter q. On the one hand, with q set too low, activity is not noticeably affected. On the other hand, with q set too high, peer influence becomes too dominant and leads to bursts within communities that are frequently repeated. One potential solution would be to introduce memory effects for q, so that nodes cannot be easily influenced multiple times within a short period of time (i.e., a cool-down time for the effect).

Other ideas for future work include the introduction of negative peer effects in our model, which reduces the activity of nodes and could be used to study the presence of trolls in networks, or to apply the model to study dynamic processes on networks (e.g., disease spreading) with respect to peer influence effects.

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