Predicting Argumentative Influence Probabilities in Large-Scale Online Civic Engagement

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ABSTRACT

Large-scale online civic engagements (OCEs) with more than 100 participants have become possible due to recent developments in online social media technology. OCEs have the potential to achieve consensus building and collective decision-making with a large number of citizens, which is difficult to achieve in face-to-face contexts. However, most users in a large-scale OCE are rarely constantly active. Therefore, an important problem for the activation of a large-scale OCE is to facilitate the discussion by predicting which citizens will have significant influence in the discussion.

This paper examines the activation prediction problem in a large-scale OCE. We propose a novel influence model based on the impulse response of activity histories and argumentative pressures, as well as an effective testing algorithm. The experimental results demonstrate that the proposed models with impulse response and the lexical pressures show better accuracy compared with baselines. In addition, the testing time required by the proposed method can be reduced significantly by employing a node-cutting algorithm.

CCS CONCEPTS

• **Networks** → **Online social networks**; • **Mathematics of computing** → *Probabilistic inference problems*; • **Computing methodologies** → Natural language processing;

KEYWORDS

Influence prediction; Civic engagement; Online civic engagement; Online discussion; Social networks; Preference similarity

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1 INTRODUCTION

Online civic engagements (OCEs) are attracting significant attention because through OCEs, a large number of citizens can discuss various issues without time, place, or age restrictions. In an OCE, large-scale topic-centered transient discussions have become common in recent years. However, support tools are necessary to facilitate discussions in large-scale OCE forums effectively [31]. OCEs are also a powerful way to gather different perspectives about an issue in a short period [11], and they have the potential to achieve consensus building and collective decision-making [22]. In addition, some epoch-making large-scale synchronous discussions [11, 14, 19] and relevance studies have been reported.

Similar to face-to-face civic engagements, one key factor to a successful OCE is the participation of numerous citizens. However, most citizens in a large-scale OCE are rarely constantly active [30]. Therefore, one problem in a large-scale OCE is the prediction of which citizens will become active [25]. In contrast, there are few theoretical approaches to civic engagement [37] even though citizen activation prediction is an interesting field of study. Therefore, we propose an influence prediction method to solve the activation prediction problem for a large-scale OCE. Predicting the activation probability of each citizen is expected to be applied to automatic OCE facilitation, maximizing the effectiveness of discussions and consensus building.

There are two key assumptions relative to the influence model and activation prediction method in a large-scale OCE. First, we assume that a large-scale OCE is an interest-based weak-tie (partially strong tie) network. Herein, the original discussion platform provides a single discussion stream and no apparent strong-tie properties such as Facebook while it includes some sort of strong-tie properties (i.e., threads). In general, only a few citizens participate in in each discussion thread, which is similar to a strong-tie. This characteristic helps us model influence diffusion because weak-tie networks can promote collective action more effectively [36]. Second, we follow the groundbreaking work into activation prediction by Goyal et al. [17, 18] because research into learning influence probabilities for a large-scale OCE is highly limited, and one possible way to approach such research is by applying the techniques of well-established theories. Goyal et al. assumed a general threshold model and proposed a method to learn influence probabilities and predict activation using the general threshold model from datasets of online social networks and media; however, OCEs were not their primary focus. Their propagation framework introduced *Active* and *Inactive* states for a node. Here, *Active* means that the user has already performed some action and *Inactive* means that the user has not performed the same action and is expected to be active in the future. While Goyal's model [17] primarily focused on static and time-dependent models to primarily capture influence, influence probability techniques can consider other elements such as user preferences. Therefore, we introduce the social

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science concept that strong-tie properties provide the social pressure required for behavior adoption [36] to the Goyal's model.

Our primary contribution is a method to model an influence framework for the OCE platform. In addition, we demonstrate how influence probabilities can be learned or predicted. Initially, we define an inter-participant argumentative "strength" employing a preference event as a certain strong-tie hypothesis and active probability (impulse response). Then, methods to estimate the influence probability among participants are proposed. Note that the impulse response, common preferences, and lexical preference are considered when predicting influence probability. Moreover, the proposed method is evaluated relative to activation prediction accuracies using original datasets of a large-scale OCE. This OCE was held from the end of 2016 to the beginning of 2017 using the original *COLLAGREE* [23, 30] discussion tool, and it included more than 800 citizens discussing the topic "The charm of Nagoya City."

The remainder of this paper is organized as follows. First, we describe related research in Section 2. We then formalize the large-scale OCE problem in Section 3. In Section 4, we propose methods to predict the influence probabilities of inter-participants, and in Section 5, we propose a testing algorithm to remove unnecessary nodes. The proposed methods are evaluated and compared to baselines in Section 6. Finally, we present conclusions in Section 7.

2 RELATED WORK

Due to recent developments in online social networks (OSNs), analysis of OSN user relationships and the propagation models of information and claims have received increasing attention [1–3, 8, 20]. It is important to detect nodes with high centrality [6, 16] and the center of information diffusion in social networks. However, centrality cannot effectively reveal the connections among users because it cannot consider diffusibility in a social network. Therefore, various studies into information diffusion models have been conducted. For example, the pioneering contributions to diffusion model research are independent cascade (IC)[4] and linear threshold (LT)[18].

Our primary goal is to control a network by spreading influence at the lowest cost or conversely by suppressing a specific influence such as flaming. Chen et al. [9] conducted groundbreaking research into controlling influences. Note that modeling influence probability between nodes is required to maximize influence. Although the IC and LT models are quite simple and powerful, they do not consider influence probability estimation based on data. Therefore, even though such models may be theoretically sound, they are impractical for our purposes. Recently, several studies have tackled such a problem [17, 33, 35].

In addition, agent-based modeling approaches have been proposed in combination with social network analyses [5, 13, 28]. For example, one study focused on long-term influence maintenance in agent-based models, which was applied to control arguments [26].

We also focus on data utilization, including natural languages. In terms of natural language processing, Rowe et al. examined the prediction of influence probabilities [32]. Their method applied lexical features to the analysis of the influence of terrorists. In their study, they considered the specific words of a terrorist group, and an adaptation probability of the words was applied to influence prediction.

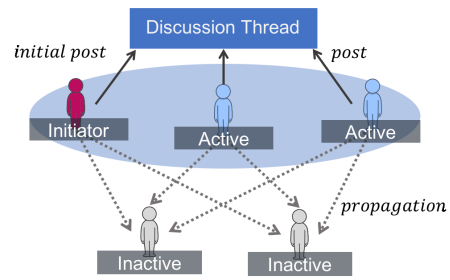


Figure 1: Influence model for OCE thread. The *Initiator* is the creator of the thread. A user who has posted to the thread is *Active*. *Inactive* nodes are affected by the neighboring *Initiator* and *Active* nodes.

3 PROBLEM FORMALIZATION

Herein, we describe our influence model and its problem formalization for OCE platforms, which serves as our influence probability prediction algorithm.

3.1 Elements and influence model for the OCE platform

In this paper, as an analogy for general forums, a post and a thread, i.e., a collection of posts, are considered as forum elements. We first apply the influence model proposed by Goyal et al. [17] to the forum elements. In their study, Goyal et al. defined *Active* as meaning a user has already entered a specific group. Accordingly, we define *Active* to mean that a user has already posted a comment to a specific thread. This assumption is justified because reaching critical mass is more likely when networks of like-minded individuals (e.g., users in a same thread) are activated [36]. In our problem setting, activation prediction is the prediction of "whether a user will join an arbitrary thread."

Figure 1 illustrates an influence model of an OCE platform comprising a thread and its users. Herein, the user who generated a discussion thread is defined as the *Initiator*, users who post to the thread are *Active*, and users who have never posted to the thread are *Inactive*. As can be seen, *Inactive* nodes are affected by neighboring *Initiator* and *Active* nodes. The social pressure received by *Inactive* nodes increases as more people post to the thread.

3.2 Activation probability formalization

We introduce the general threshold model to predict whether a user will join a thread. Given an undirected OCE graph $G = (V, E)$, where V denotes the user node set and E is the edge set of each

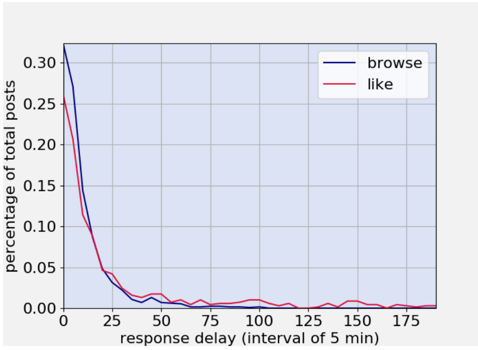


Figure 2: Ratio of delay time to post on a thread after activities on another thread

node, the graph that represents the social ties of each user at timestamp $\forall t \in \mathbb{N}$ is expressed as follows:

$$G^{(t)} = \left(V^{(t)}, E^{(t)}\right),$$
$$V^{(t)} = \{v \in V \mid t \geq jo(v)\},$$
$$E^{(t)} = \left\{(v_i, v_j) \in E \mid t \geq jo(v_i) \wedge t \geq jo(v_j)\right\},$$

where $jo(v)$ represents the timestamp of when the user registered on the OCE platform. Herein, for simplicity, we assume that social ties are never broken. Then, we introduce an activation probability of *Inactive* node v. This activation probability represents the probability of an *Inactive* user posting a comment to a given thread. Using a set $S_v \subset V^{(t)}$ of the contiguous *Initiator* and *Active* neighbors of v, the activation probability $P_a(v)$ is defined as follows:

$$P_a(v) = 1 - \prod_{u \in S_v} (1 - p_{u \to v}),$$

where $p_{u \to v}$ is the influence probability from u to v. Since $P_a(v)$ is a complementary event of the joint probability that all neighbors will fail to activate v, it is a probability to activate v with factor of her neighbor nodes.

The main technical contribution of this paper is the prediction of influence probabilities $p_{u \to v}$. There are several approaches to learning an influence probability; however, most existing methods cannot utilize the properties of a large-scale OCE. For example, Figure 2 shows the aggregate delay time in 5 min from the latest activity (e.g., voting *like* or browsing of each user that performed at least one activity to the time at which a post was made to an unrelated thread). Herein, the fact that many citizens are inactive 20 minutes after the latest activity is confirmed. This property differs from the existing offline civic engagements. Therefore, we introduce active probability, which represents whether each user is active at the time of thread creation (*initiation*), where we define $act_v^{(t)}$ as an event in which user v is active at time t.

Next, we refer to a social strong tie [36], where we define $pref_{u \to v}$ as an event in which u prefers v. For simplicity, we assume that $pref_{u \to v}$ and $act_v^{(t)}$ are independent. Under these conditions, the influence probability from u to v can be calculated as

$$p_{u \to v} = p\left(act_v^{(t)}\right) * p\left(pref_{u \to v}\right).$$

4 PREDICTING ARGUMENTATIVE INFLUENCE PROBABILITIES

4.1 Learning active probability

Figure 2 shows that the delay time to post on a thread after the latest activity decays exponentially. Therefore, users' activities can be considered as a discrete-time signal process. Concretely, the activities are considered to be the input to a linear time-invariant system and the response function is an exponential decay function whose parameter is learned.

Before we describe our problem formalization, we define the activity, i.e., voting *like* or browsing, set of v as $A_v = \bigcup_{i=1}^{N_v} \{a_i^{(v)}\}$. Note that N_v is the number of actions of v in the dataset. We define $A_{v,t}$, which is a set of activities of v from $t - T_{limit}$ to t, as follows:

$$A_{v,t} := \{a \in A_v \mid T(a) < t \wedge T_{limit} \geq t - T(a).\} \quad (1)$$

We denote the timestamp of activity element a as $T(a)$. T_{limit} is a hyperparameter that prevents the activity history of v from being traced infinitely, which makes the model fast and simple. Then, we present an exponential decay that is a modification of the discrete model [17] as follows:

$$p\left(act_v^{(t)}\right) = \begin{cases} \exp\left(-(t - a_{v,t})/\tau_v\right) & A_{v,t} \neq \emptyset \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where $a_{v,t} := \max\{T(a) \mid a \in A_{v,t}\}$, i.e., the latest activity timestamp of v before t. Note that the active probability cannot be predicted if v never performs an activity, providing it as 0. Herein, τ_v is a trainable parameter that is learned for each node because the activities of users vary. However, the learning results of τ_v are overfitted when discussions do not proceed to a satisfactory extent due to a lack of activity history samples for each node. Therefore, we solve this problem by learning the average response time of all users who have posts and activity histories. Thus, τ_v is approximated as follows:

$$\tau_v \approx \frac{\sum_{d \in D} \sum_{v \in V^{(T(d))}} t_{v,d}}{\sum_{d \in D} \sum_{v \in V^{(T(d))}} I(P_{v,d} \neq \emptyset \wedge A_{v,T(d)} \neq \emptyset)} \quad (3)$$

where I is an indicator function, $D = \bigcup_{i=1}^{N_D} \{d_i\}$ is a thread set, and N_D is the number of threads in the dataset. We denote the timestamp of the *initiation* of thread d as $T(d)$. In addition, $P_{v,d} = \bigcup_{i=1}^{N_{v,d}} \{p_i^{(v,d)}\}$ is the post set for user v in thread d, and $T(p)$ is the timestamp of post p where $N_{v,d}$ is the number of posts of v in d. The numerator of equation (3) represents how many response delays are observed, and the denominator is the cumulative sum of the response delays. Therefore, τ_v represents the average response time of all users who have posts and activity histories. We assume that activation prediction should be applied at thread *initiation* time. Given $t_{v,d}$, the response time of v in d is expressed as follows:

$$t_{v,d} = \begin{cases} p_{v,d} - a_{v,T(d)} & P_{v,d} \neq \emptyset \wedge A_{v,T(d)} \neq \emptyset \\ 0 & \text{otherwise} \end{cases}$$

where $p_{v,d} := \min\{T(p) \mid p \in P_{v,d}\}$ indicates the timestamp of the first post of user v in thread d (if it exists), and $a_{v,T(d)}$ denotes the

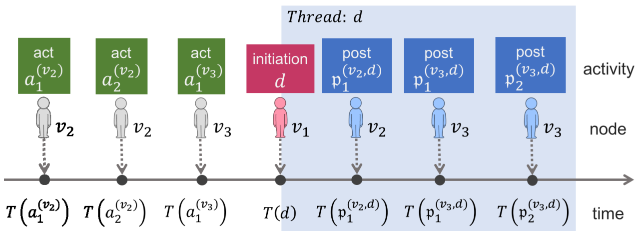


Figure 3: Example of calculation process for average delay τ_v. The activity colors indicate the type of activity: green represents activities (e.g., voting *like* or browsing), red represents thread creation, and blue represents posts to the thread. Here, $a_1^{(v_2)}$ and $a_2^{(v_2)}$, and $a_1^{(v_3)}$ indicate the activities of v_2 and v_3, respectively.

timestamp of the latest activity of v before the *initiation* timestamp of d (if it exists).

Figure 3 shows an example of this calculation process. Here, we assume that the training dataset comprises only thread d. There are three activities ($a_1^{(v_2)}$ and $a_2^{(v_2)}$, $a_1^{(v_3)}$ by v_2, and v_3) that were recorded before d was created by node v_1. In Figure 3, the axis represents time. To simplify the example, we set $T_{limit} = \infty$. In this case, we have $\tau_v \approx \{T(p_1^{(v_2,d)}) - T(a_2^{(v_2)}) + T(p_1^{(v_3,d)}) - T(a_1^{(v_3)})\}/2$ by simply taking an average.

4.2 Learning preference probability

Bond et al. showed that homophily and strong ties are more conducive to mobilization for large-scale networks [7]. In other words, we can expect that behavior adoption is caused by the similarity among user preferences. Therefore, we introduce preference probability $p\,(pref_{u\to v})$. Herein, we consider the following three factors: natural language, preferences (e.g., *likes*) from the discussion data.

Maximum likelihood eEstimation. Goyal et al. proposed a technique to learn influence probability using maximum likelihood estimation (MLE)[17, 18], which serves as our baseline.

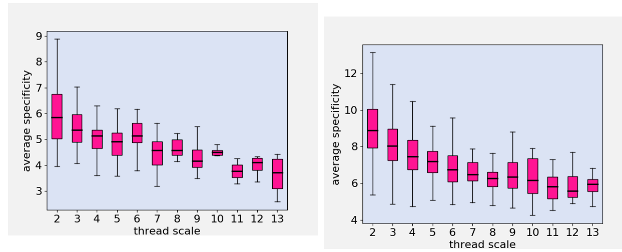
Common preference similarly. Herein, we consider agent-based common preference similarity (CPS) [24, 27] to capture preference ties. CPS measures the common parts of users' preferred choices. Herein, we consider posts as the choice and *likes* as a preference for the post. For simplicity, we express the set of posts that represents all posts in a thread set as follows.

$$P = \bigcup_{d \in D} \bigcup_{v \in V} P_{v,d}$$

Here, if $P \neq \emptyset$, the CPS between users u and v ($\{u, v\} \subset V$) is defined as follows:

$$cps_{u,v} = \left|\left\{p \in P \mid r_{u,p} = 1 \land r_{v,p} = 1\right\}\right| / |P| \tag{4}$$

where $r_{u,p} \in \{0, 1\}$ is a variable that represents whether user u prefers post p. Note that $r_{u,p} = 1$ when u *likes* p; otherwise, $r_{u,p} = 0$.



(a) COLLAGREE dataset (1,327 posts) **(b) Reddit dataset (363,390 posts)**

Figure 4: Relationship between thread scale and average word specificity

Word Specificity. Morio and Fujita focused on influence diffusions by co-occurring words to capture the relationship between users in a large-scale OCE [29]. In other words, high similarity between two consecutive sentences means that the influence was propagated more. However, co-occurrences cannot capture user interest or preference effectively. Therefore, we consider word specificity [38] based on pointwise mutual information (PMI) [10]. The word specificity of a word w in all posts of $d \in D$ is defined as follows:

$$S_d(w) = \log \frac{\mathbf{P}_d(w)}{\mathbf{P}_D(w)} \tag{5}$$

where $\mathbf{P}_d(w)$ is the frequency of w in d and $\mathbf{P}_D(w)$ is the frequency of w in a train thread set.

Figure 4 illustrates the relationship we observed between "community" ("thread" in our case), scale (i.e., the number of posts in the thread), and average word specificity in large-scale Reddit [21] and *COLLAGREE* discussion datasets. In these datasets, thread specificity tends to increase as the scale decreases. This indicates that equation (5) can be employed effectively. Herein, the word specificity of w in thread $d \in D$ is expressed as follows:

$$wss_{v\to u} = \frac{\sum_{d \in D} \sum_{w \in W_{v\to u,d}} S_d(w)}{\sum_{d \in D} \sum_{w \in W_{v,d}} S_d(w)} \tag{6}$$

where $W_{v\to u,d}$ is a word set propagated from u to v in d, and $W_{v,d}$ is a word set of v's posts in d.

5 TESTING ALGORITHM

In this section, we describe our testing algorithm. Note that the training algorithms are omitted because they are self-explanatory for each equation (3), (4) and (6). Our testing algorithm is based on the evaluation algorithm proposed by Goyal et al. [17]. This testing process predicts who will perform an action among neighboring *Active* nodes at each time step. In the proposed model, this means who will join a thread due to the social pressures of *Active* nodes. We also propose an effective testing algorithm to eliminate unnecessary nodes by calculating the impulse response demands within the range of T_{limit}.

Algorithm 1 shows our testing algorithm with cutting for an activation prediction. At line 6, the loop for each p of the posts in d in chronological order is conducted. Here, v is the poster node of p (line 7). The Boolean $perform_v$ becomes 1 if v is already stored in

Algorithm 1 Test - cutting

1: **Input:** Test thread set D^{test}, τ_v, $cps_{u,v}$, $wss_{v \to u}$ where $(v, u) \in E$
2: **Output:** $result\_list$: tuple list of Boolean labels and probabilities
3: $result\_list \leftarrow \phi$
4: **for each** $d \in D^{test}$ **do**
5: $\quad table = \phi$ ▷ $table$ has node, activate probability and correct label
6: $\quad$ **for each** p in posts of d in chronological order **do**
7: $\quad\quad v \leftarrow$ the poster node of p
8: $\quad\quad$ **if** $v \in table$ **then**
9: $\quad\quad\quad perform_v \leftarrow 1$
10: $\quad\quad$ **else**
11: $\quad\quad\quad$ add $(v, p_v = 0, perform_v = 2)$ to $table$
12: $\quad\quad$ **for each** $u : (v, u) \in E^{(T(p))}$ **do**
13: $\quad\quad\quad$ **if** $A_{u,T(d)} = \varnothing$ **then** ▷ Skipping inactive nodes that do not act within T_{limit} before d has been created
14: $\quad\quad\quad\quad$ **if** $u \notin table$ **then**
15: $\quad\quad\quad\quad\quad$ add $(u, p_u = 0, perform_u = 0)$ to $table$
16: $\quad\quad\quad\quad\quad$ **continue**
17: $\quad\quad\quad p_{v \to u} \leftarrow p\left(act_u^{(T(d))}\right) * p\left(pref_{v \to u}\right)$
18: $\quad\quad\quad$ **if** $u \in table$ **then**
19: $\quad\quad\quad\quad$ update $table$ with $p_u \leftarrow \{p_u + (1 - p_u) * p_{v \to u}\}$
20: $\quad\quad\quad$ **else**
21: $\quad\quad\quad\quad$ add $(u, p_u = p_{v \to u}, perform_u = 0)$ to $table$
22: $\quad$ **for each** $(u, p_u, perform_u) \in table$ **do**
23: $\quad\quad$ **if** $perform_u = 1 \vee perform_u = 0$ **then**
24: $\quad\quad\quad$ add $(perform_u, p_u)$ to $result\_list$

the $table$; v is *Active* (lines 8-9). Otherwise, $(v, perform_v = 2, p_v = 0)$ is added to the $table$ because v is an *Initiator* (line 11). Then, the loop with each u, i.e., v's neighbor, is run. The proposed method can remove users that are beyond the range of T_{limit} before $T(d)$ (line 13). The $table$ is converted to a list of tuples with $perform_u$ and p_u. Note that the probability of act_u at time $T(d)$ must be estimated (line 17) to observe their activation probability at thread initiation. The list of tuples comprises pairs of the correct label and the probabilistic score. Here, u is posted to the thread and becomes *Active* when a correct label is $perform_u = 1$. The score represents the probability to be *Active* (lines 22–24).

6 EXPERIMENTS

6.1 Experimental settings

To demonstrate the effectiveness of the proposed method, we compare it to baselines. To the best of our knowledge, no well-established large-scale OCE dataset exists. Thus, we obtained testing and training data from *COLLAGREE* from Dec. 2016 to Jan. 2017. *COLLAGREE* is a large-scale OCE platform [23, 30] co-hosted by the government of Nagoya City, Japan and the Nagoya Institute of Technology.[1] The data include 826 citizens, 1,327 posts, 120,186 words, 399 threads, 4,326 *likes*, and 21,993 browses. In addition, the average number of posts per thread is 3.33 (standard deviation 3.29). Note that we cannot provide a detailed analysis of the *COLLAGREE* datasets due to space limitations.

We introduce a strong baseline **MLE** [17] and a random baseline (where users are selected randomly for activation prediction) for comparison. We compare the following proposed methods to the baselines.

- **ACT**. A learning model that uses impulse response, where the exponential decay is $p\left(act_v^{(t)}\right)$ and $p\left(pref_{u \to v}\right) = 1$
- **CPS**. A learning model that uses the CPS of equation (4) as $p\left(pref_{u \to v}\right)$ and $p\left(act_v^{(t)}\right) = 1$
- **WSS**. A learning model that uses the word specificity score of equation (6) as $p\left(pref_{u \to v}\right)$ and $p\left(act_v^{(t)}\right) = 1$

We also compare the following three proposed models.

- **MLE*ACT**. A learning model that applies impulse response with an exponential decay function to **MLE**
- **CPS*ACT**. A learning model that applies impulse response with an exponential decay function to **CPS**
- **WSS*ACT**. A learning model that applies impulse response with an exponential decay function to **WSS**

In our experiments, users with no posts were removed. As a result, the dataset contained 204 users. This dataset was then divided into training and test sets ($|D^{train}| : |D^{test}| = 8 : 2$). The precision-recall (PR) curves of positive cases were plotted after executing multiple training and test iterations for each model. Herein, a positive case means a plot indicating $perform_u = 1$ in $result\_list$, as indicated in Algorithm 1.

As mentioned previously, in a large-scale OCE, most citizens post infrequently. In other words, prediction accuracy between citizens who post frequently and those who post infrequently differ significantly. Therefore, we evaluated the PR curves of users with a number of posts that was greater than or equal to a given threshold. Note that this threshold (i.e., the minimum number of posts) is referred to as **discussion density**. The range of discussion density is from 1 to 20, which is sufficient.

6.2 Influence probability prediction accuracy

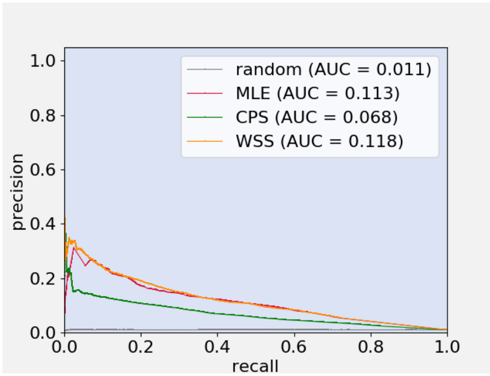
Herein, we discuss the accuracy of the classifier used in the proposed activation prediction method (Algorithm 1). Note that the PR curve and the area under the curve (AUC) were used for quantitative evaluation[2].

The PR curves of the random baseline and models with preference probability only are shown in Figure 5a. Figure 5b shows the PR curves of the proposed models. As can be seen, accuracy is low. This is common, however, in social influence prediction because behaviors are complex and difficult to spread [36]. Thus, the AUC scores of the proposed methods (**WSS**, **MLE*ACT**, and **WSS*ACT**) should be compared to the AUC scores of the baselines (**MLE** and random) because the proposed models can predict highly influential citizens more accurately compared to the baselines.

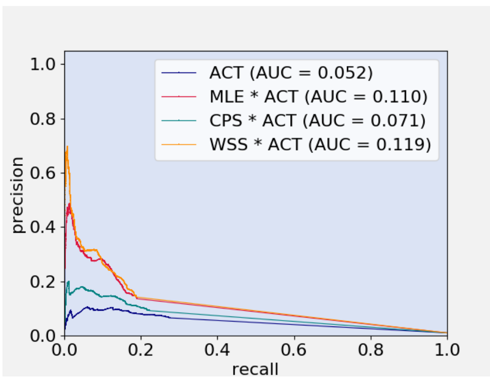
As shown in Figure 5b, only **ACT** demonstrates poor performance in terms of AUC. However, the methods that combine **MLE**, **WSS**, and **CPS** with **ACT** (**MLE*ACT**, **WSS*ACT**, and **CPS*ACT**, respectively) demonstrate better performance than the other proposed methods. This means that our proposed influence model for a large-scale OCE is effective because the proposed models (which

[1] This discussion dataset, including access records, posts, and *likes*, is not an open dataset.

[2] Although the receiver operating characteristic curve [15] is more popular than the PR curve when applied to binary classifications, we use the PR curve in this experiment because it provides more information for imbalanced datasets and it focuses on high-order ranked data [12, 34].



(a) Baseline and preference probability



(b) Preference and exponential decay

Figure 5: PR curves of models (discussion density is 1)

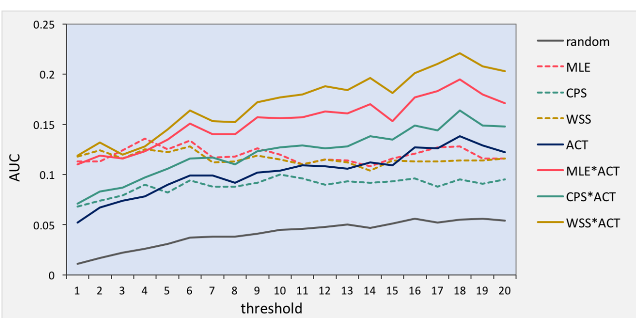
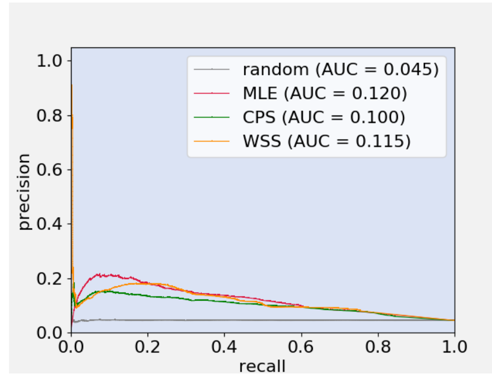


Figure 6: Relationship between discussion density and prediction accuracy

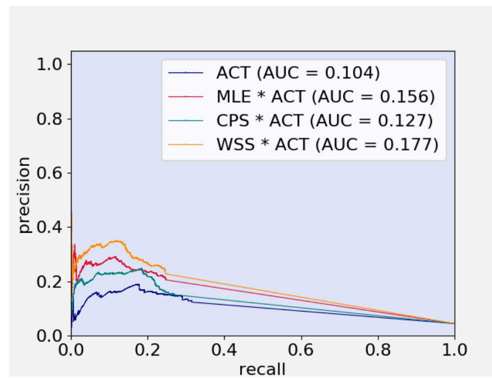
consider common preferences and textual information) are more effective when the impulse response is incorporated.

6.3 Prediction accuracies of influence probabilities when discussion density is changed

To demonstrate that estimation accuracies differ significantly according to discussion density, we compared the AUC of users for whom the number of posts is greater than the discussion density. Figure 6 shows the relationship between discussion density and AUC. The estimation accuracy improves as the discussion density



(a) Baseline and preference probability



(b) Preference and exponential decay

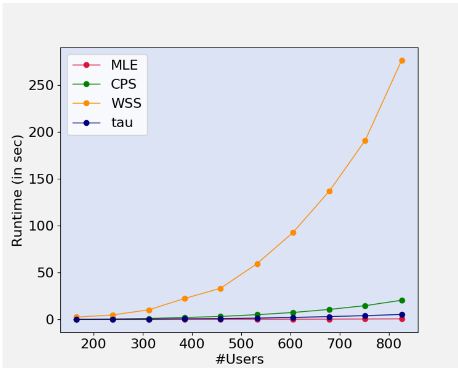
Figure 7: PR curves of models (discussion density is 10)

increases because the classification becomes easier as the number of users decreases. In addition, an increasing activity history per user simplifies the prediction process. Figures 7a and 7b show the PR curves obtained with a discussion density of 10. As can be seen, the proposed **WSS*ACT** and **MLE*ACT** methods outperform the baselines significantly when the discussion density is high, which indicates that the proposed methods are more effective for an extremely active OCE.

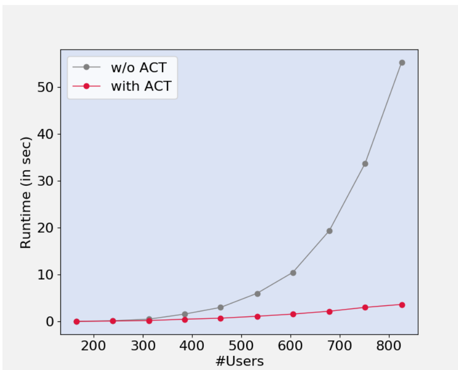
6.4 Training and testing execution time

We also investigated the runtimes of the proposed models. Typically, execution time (training or testing) increases significantly as the number of nodes increases. Therefore, we compared the execution times of **MLE**, **CPS**, **WSS**, and **tau** (τ_v). Training time is shown in Figure 8a, and the testing times of the cutting algorithm (**with ACT**) and without cutting (**w/o ACT**) are shown in Figure 8b.

As can be seen in Figure 8a, the execution time of the baseline **MLE** method was less than that of the other methods. In contrast, the runtime of the **WSS** method increased rapidly because it must calculate the word weights (i.e., PMI) for each thread. In fact, the **WSS** method required more than 4 min to calculate all nodes. However, relative to runtime, the inference process is prioritized in applications as opposed to the time required for training.



(a) Training execution time



(b) Testing execution time

Figure 8: Execution times of baselines and proposed methods

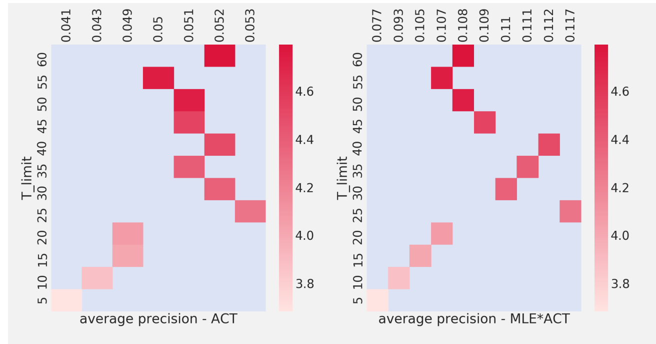
Figure 8b shows that the runtime of the proposed method **with ACT** was significantly less than that of the baseline method proposed by Goyal et al. [17]. This indicates that the proposed node-cutting algorithm performed well. Instant prediction of argumentative influence probabilities is essential; thus, the cutting algorithm enables large-scale OCE operations relative to user activation, including various model parameter adjustments.

6.5 Tradeoff between accuracy and execution time

Herein, we show tradeoff results to analyze the performance gains obtained by the hyperparameter T_{limit}. Recall that the T_{limit} adjusts the range of the histories used for activation prediction. Thus, execution time increases as T_{limit} increases when the number of nodes is sufficiently large. This tendency is shown in Figure 9a and 9b for the **ACT** and **MLE*ACT** models, respectively[3]. The horizontal axis is the AUC, the vertical axis is T_{limit} in minutes, and the color density represents execution time of testing in seconds. Note that darker colors indicate slow execution times.

As shown in Figure 9, there is a tradeoff among T_{limit}, execution time, and accuracy. Execution time and accuracy improves as T_{limit} increases up to $T_{limit} = 25$. Furthermore, accuracy does not

[3]Herein, discussion density is 1 with 204 nodes.



(a) ACT **(b) MLE*ACT**

Figure 9: Tradeoff between AUC and execution time for each model (color density represents execution time in seconds)

increase even if T_{limit} is greater than 25, at which time the active probability intuitively comes close to 0, as shown in Figure 2.

However, we assume that when the forum has a long decay time, improving accuracy requires significant execution time. However, we could not locate large-scale OCE discussion data with a long decay time. In both cases, setting T_{limit} properly can reduce testing time and improve accuracy.

7 CONCLUSION

In this paper, we have demonstrated how an influence model can be applied to activation prediction for large-scale OCE. Specifically, we have shown how to model an OCE's properties and argumentative strength in the network. For example, the active probability of citizens declines exponentially, which results in the introduction of an impulse response with an exponential decay function. In addition, the proposed model considers strong-tie pressures such as preference probability based on CPS and word specificities. The experimental results demonstrate that the activation prediction accuracy of the proposed models outperforms the baselines: random baseline and Goyal et al. [17] method. Moreover, the proposed method was remarkably effective for extremely active online discussions. In addition, by employing the node-cutting algorithm, the proposed models reduced testing time significantly compared with a baseline.

Possible future work includes improving influence probability accuracy by considering the semantic contexts of posts. It may be possible to obtain accurate influence probabilities by employing natural language processing to analyze the semantics of posts. We will also consider applying the proposed models to an influence maximization problem and the construction of automatic facilitation systems.

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REFERENCES

[1] Aris Anagnostopoulos, Ravi Kumar, and Mohammad Mahdian. 2008. Influence and Correlation in Social Networks. In *Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'08)*. ACM, New York, NY, USA, 7–15. https://doi.org/10.1145/1401890.1401897

[2] Eytan Bakshy, Jake M. Hofman, Winter A. Mason, and Duncan J. Watts. 2011. Everyone's an Influencer: Quantifying Influence on Twitter. In *Proceedings of the Fourth ACM International Conference on Web Search and Data Mining (WSDM'11)*. ACM, New York, NY, USA, 65–74. https://doi.org/10.1145/1935826.1935845

[3] Eytan Bakshy, Itamar Rosenn, Cameron Marlow, and Lada Adamic. 2012. The Role of Social Networks in Information Diffusion. In *Proceedings of the 21st International Conference on World Wide Web (WWW'12)*. ACM, New York, NY, USA, 519–528. https://doi.org/10.1145/2187836.2187907

[4] Sushil Bikhchandani, David Hirshleifer, and Ivo Welch. 1992. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy* 100, 5 (1992), 992–1026. https://doi.org/10.1086/261849

[5] Eric Bonabeau. 2002. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences* 99, suppl 3 (2002), 7280–7287. https://doi.org/10.1073/pnas.082080899

[6] Phillip Bonacich. 1987. Power and Centrality: A Family of Measures. *Amer. J. Sociology* 92, 5 (1987), 1170–1182. https://doi.org/10.1086/228631

[7] Robert M. Bond, Christopher J. Fariss, Jason J. Jones, Adam D.I. Kramer, Cameron Marlow, Jaime E. Settle, and James H. Fowler. 2012. A 61-million-person experiment in social influence and political mobilization. *Nature* 489, 7415 (09/2012 2012), 295–298. https://doi.org/doi:10.1038/nature11421

[8] Meeyoung Cha, Alan Mislove, and Krishna P. Gummadi. 2009. A Measurement-driven Analysis of Information Propagation in the Flickr Social Network. In *Proceedings of the 18th International Conference on World Wide Web (WWW'09)*. ACM, New York, NY, USA, 721–730. https://doi.org/10.1145/1526709.1526806

[9] Wei Chen, Yajun Wang, and Siyu Yang. 2009. Efficient Influence Maximization in Social Networks. In *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'09)*. ACM, New York, NY, USA, 199–208. https://doi.org/10.1145/1557019.1557047

[10] Kenneth Ward Church and Patrick Hanks. 1990. Word Association Norms, Mutual Information, and Lexicography. *Comput. Linguist.* 16, 1 (March 1990), 22–29.

[11] Kushal Dave, Martin Wattenberg, and Michael Muller. 2004. Flash Forums and forumReader: Navigating a New Kind of Large-scale Online Discussion. In *Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work (CSCW '04)*. ACM, New York, NY, USA, 232–241. https://doi.org/10.1145/1031607.1031644

[12] Jesse Davis and Mark Goadrich. 2006. The Relationship Between Precision-Recall and ROC Curves. In *Proceedings of the 23rd International Conference on Machine Learning (ICML'06)*. ACM, New York, NY, USA, 233–240. https://doi.org/10.1145/1143844.1143874

[13] Abdulrahman M. El-Sayed, Peter Scarborough, Lars Seemann, and Sandro Galea. 2012. Social network analysis and agent-based modeling in social epidemiology. *Epidemiologic Perspectives and Innovations* 9, 9 (2012), 1–9.

[14] Thomas Erickson, N. Sadat Shami, Wendy A. Kellogg, and David W. Levine. 2011. Synchronous Interaction Among Hundreds: An Evaluation of a Conference in an Avatar-based Virtual Environment. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 503–512. https://doi.org/10.1145/1978942.1979013

[15] Tom Fawcett. 2006. An Introduction to ROC Analysis. *Pattern Recogn. Lett.* 27, 8 (June 2006), 861–874. https://doi.org/10.1016/j.patrec.2005.10.010

[16] Linton C. Freeman. 1978. Centrality in social networks conceptual clarification. *Social Networks* 1, 3 (1978), 215–239. https://doi.org/10.1016/0378-8733(78)90021-7

[17] Amit Goyal, Francesco Bonchi, and Laks V.S. Lakshmanan. 2010. Learning Influence Probabilities in Social Networks. In *Proceedings of the Third ACM International Conference on Web Search and Data Mining (WSDM'10)*. ACM, New York, NY, USA, 241–250. https://doi.org/10.1145/1718487.1718518

[18] Amit Goyal, Wei Lu, and Laks V. S. Lakshmanan. 2011. SIMPATH: An Efficient Algorithm for Influence Maximization Under the Linear Threshold Model. In *Proceedings of the 2011 IEEE 11th International Conference on Data Mining (ICDM'11)*. IEEE Computer Society, Washington, DC, USA, 211–220. https://doi.org/10.1109/ICDM.2011.132

[19] Wojciech Gryc, Mary Helander, Rick Lawrence, Yan Liu, Claudia Perlich, Chandan Reddy, and Saharon Rosset. 2009. *Looking for Great Ideas: Analyzing the Innovation Jam*. Springer Berlin Heidelberg, Berlin, Heidelberg, 21–39. https://doi.org/10.1007/978-3-642-00528-2_2

[20] Adrien Guille, Hakim Hacid, Cecile Favre, and Djamel A. Zighed. 2013. Information Diffusion in Online Social Networks: A Survey. *SIGMOD Rec.* 42, 2 (July 2013), 17–28. https://doi.org/10.1145/2503792.2503797

[21] Reddit Inc. 2017. reddit. (Oct. 2017). Retrieved October 20, 2017 from https://www.reddit.com/

[22] Takayuki Ito, Yuma Imi, Takanori Ito, and Eizo Hideshima. 2014. COLLAGREE: A Faciliator-mediated Large-scale Consensus Support System. In *Proceedings of the 2nd International Conference of Collective Intelligence*.

[23] Takayuki Ito, Takanori Ito, and Eizo Hideshima. 2017. COLLAGREE. (2017). http://collagree.com/?locale=en

[24] Chang Jiang, Weihua Li, Quan Bai, and Minjie Zhang. 2017. *Preference Aware Influence Maximization*. Springer Singapore, Singapore, 53–164. https://doi.org/10.1007/978-981-10-2564-8_11

[25] Philipp Jugert, Katharina Eckstein, Peter Noack, Alexandra Kuhn, and Alison Benbow. 2013. Offline and Online Civic Engagement Among Adolescents and Young Adults from Three Ethnic Groups. *Journal of Youth and Adolescence* 42, 1 (01 Jan 2013), 123–135. https://doi.org/10.1007/s10964-012-9805-4

[26] Weihua Li, Quan Bai, Tung Doan Nguyen, and Minjie Zhang. 2017. Agent-based Influence Maintenance in Social Networks. In *Proceedings of the 16th Conference on Autonomous Agents and MultiAgent Systems (AAMAS'17)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 1592–1594.

[27] Weihua Li, Quan Bai, and Minjie Zhang. 2016. Agent-Based Influence Propagation in Social Networks. In *2016 IEEE International Conference on Agents (ICA)*. IEEE CPS, China, 51–56. https://doi.org/10.1109/ICA.2016.021

[28] Charles M. Macal and Michael J. North. 2010. Tutorial on agent-based modelling and simulation. *Journal of Simulation* 4, 3 (1 Sep 2010), 151–162. https://doi.org/10.1057/jos.2010.3

[29] Gaku Morio and Katsuhide Fujita. 2017. Competence Estimation: Classifying Expertise of Web Discussion Participants. In *2017 6th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI)*. 801–807. https://doi.org/10.1109/IIAI-AAI.2017.123

[30] Tomohiro Nishida, Takayuki Ito, Takanori Ito, Eizo Hideshima, Shunpei Fukamachi, Akihisa Sengoku, and Yumika Sugiyama. 2017. Core time mechanism for managing large-scale internet-based discussions on COLLAGREE. In *2017 IEEE International Conference on Agents (ICA)*. IEEE CPS, China, 46–49. https://doi.org/10.1109/AGENTS.2017.8015299

[31] Kate Raynes-Goldie and Luke Walker. 2008. Our space: Online civic engagement tools for youth. *Civic life online: Learning how digital media can engage youth* (2008), 161–188.

[32] Matthew Rowe and Hassan Saif. 2016. Mining pro-ISIS radicalisation signals from social media users. In *Proceedings of the Tenth International Conference on Web and Social Media*. AAAI Press, California, 329–338.

[33] Kazumi Saito, Ryohei Nakano, and Masahiro Kimura. 2008. Prediction of Information Diffusion Probabilities for Independent Cascade Model. In *Proceedings of the 12th International Conference on Knowledge-Based Intelligent Information and Engineering Systems, Part III (KES'08)*. Springer-Verlag, Berlin, Heidelberg, 67–75. https://doi.org/10.1007/978-3-540-85567-5_9

[34] Takaya Saito and Marc Rehmsmeier. 2015-03-04 00:00:00.0. The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. *Plos One* 10, 5 (2015-03-04 00:00:00.0), e0118432. https://doi.org/10.1371/journal.pone.0118432

[35] Jie Tang, Jimeng Sun, Chi Wang, and Zi Yang. 2009. Social Influence Analysis in Large-scale Networks. In *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'09)*. ACM, New York, NY, USA, 807–816. https://doi.org/10.1145/1557019.1557108

[36] SebastiÃąn Valenzuela, Arturo Arriagada, and AndrÃľs Scherman. 2014. Facebook, Twitter, and Youth Engagement: A Quasi-experimental Study of Social Media Use and Protest Behavior Using Propensity Score Matching. *International Journal of Communication* 8, 0 (2014). http://ijoc.org/index.php/ijoc/article/view/2022

[37] Britt Wilkenfeld, James Lauckhardt, and Judith Torney-Purta. 2010. The Relation between Developmental Theory and Measures of Civic Engagement in Research on Adolescents. (08 2010), 193 - 219 pages.

[38] Justine Zhang, William L. Hamilton, Cristian Danescu-Niculescu-Mizil, Dan Jurafsky, and Jure Leskovec. 2017. Community Identity and User Engagement in a Multi-Community Landscape. In *Proceedings of the Eleventh International Conference on Web and Social Media, ICWSM 2017, Montréal, Québec, Canada, May 15-18, 2017*. AAAI, Canada, 377–386.