Modeling the Information Spreading in Online Blog Communities Using Learning Automata

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Abstract- Today's online communities, as a multifaceted platform, have many applications in e-commerce, marketing and e-learning. Online blogging services are one of the most popular environment for user interactions. Users share their ideas, opinions, and information in this environment. The spread of information between users plays an essential role in the success of such online communities. However, these communities face challenges in post management and information spread. Modeling the life cycle of a post provides an opportunity to examine how information is disseminated among users. In these communities, each post after creation is reposted and transmitted by users. Depending on their content and online community structure, posts are spread in different ways in the network. Some posts are rapidly becoming epidemic and some are not welcomed by users. In this article, we are looking for a method that estimates the probability of an epidemic of a post. For this purpose, a learning method based on learning automata has been used. The evaluations show that this method is efficient in three evaluation datasets. Furthermore, we will introduce self-organized posts that facilitate the management of posts in online communities.

***Keywords-** Online Communities, Information Overload Problem, Epidemic probability, Learning Automata.*

1. INTRODUCTION

Nowadays, online communities provide a convenient place for communicating with users and receiving their opinions. There is very important information about the behavior, interests, preferences, and opinions of the users in the online communities [1]. This information has various applications in different fields. Extraction, storage, and analysis of this information require presenting objective methods in the domain of users' behavior. In this paper, a structured and practical method for modeling reposting behavior of the users in the online communities has been presented. In the online community of Twitter, more than 19% of the tweets are related to the organizations, products, and brands. The tweets interested by the users are less than 20% [2]. Predicting the behavior of the users regarding the advertising posts which probably stimulate their interest, can improve the sales and marketing of the different products and brands. Online Ads can use such effective messages to more efficiently target the users which visit frequently [3].

On the other hand, our digital life on the Internet consists of different social networks and structures. Welman (2001) mentioned that [4] "computer networks are inherently social networks that connect individuals, organizations, and their knowledge." Regarding this point of view, it can be inferred that the Internet is not only a tool for supporting the social communication of members, but also allows them to have completely virtual communication through membership in online groups and communities. These facilities have been provided through technologies for building online communities. The information flow between users is regarded as an important point in these online communities. For example, in the online community of Twitter, over 19% of tweets are related to organizations, products, and brand names, although less than 20% of these tweets are considered by users. Predicting the probability of epidemic of advertisements, which may stimulate the interest of users, can improve the sales and marketing of different products and brands. Online advertisements can use such efficient messages to effectively target the most visited users. In addition, estimating the probability of the epidemic of advertisements can provide more attractive content and consequently, increase user satisfaction and profits. Accordingly, media companies can produce effective content for the promotion and marketing of their products. The results of estimating the epidemic probability can be used in political, social, and other campaigns to attract users and successfully target them. Viral marketing is considered as one of the most common marketing strategies in e-commerce products, in which we can create high-impact posts and post them on the network by estimating the epidemic probability of a post. Millions of posts are created in these communities on a daily basis. In online communities, a topic becomes hot from time to time and everyone posts and reposts posts about it, which is called "Trend". Posts related to these topics are rapidly becoming epidemic with a large number of reposts. So far, no scientific method has been proposed to predict the occurrence of these trends. Various studies have attempted to detect these trends and estimate the volume of its extension, by evaluating the data on online communities.

In this paper, the concept of epidemic possibility is defined which is closely related to the ability to repost a post over a period of time. Further, the concept of post lifecycle is introduced in this study for the first time, in which a post, after the creation, is constantly transmitted between users during the various stages and eventually dies and does not repost. The present study aims to propose a self-train approach in order to calculate the dynamism of the epidemic probability of a post at any moment in the life cycle.

The rest of this article is organized as follows. Section 2 reviews the history of research in relation to predicting the epidemic probability of a post. Section 3 introduces the proposed method, in which self-organizing post is presented as one of the important solutions for solving post management problem in online communities. Section 4 presents the evaluation dataset and tests carried out on this dataset. Finally, section 5 summarizes and concludes the research.

2. LITERATURE REVIEW

In general, post content, post time, and the events outside the online communities are effective to publish the information, in addition to network structure. The present section reviews the research conducted on the epidemic of a post in the information dissemination. Further, this section examines the behavior of posting a post among users at the online community level, by analyzing online communities. Generally, studying the theory of information dissemination is of great importance in providing efficient methods. Based on the content, each post has different behavior in the information dissemination on the Internet.

Understanding the process of creating a post by users and their motivations to repost a post play an important role in modeling the user's repost behavior while confronting with a post. In fact, understanding what contents do users choose to repost can help explain the reason for reposting a particular post and its prediction. Reference [5] thoroughly investigated these motivations and identified the main reasons for repost decision by users. They introduced ten different motivations for reposting such as commenting on posts, posting posts to new recipients to notify special individuals or groups, and storing posts for future personal access. Although the focus of their study was not to model the epidemic of a post, the motivations mentioned for repost decision can be used to determine the effective variables for modeling the epidemic of a post.

Su et al. [6, 7] conducted studies to find the variables of the epidemic of a post. By using the principal component analysis (PCA) method, they extracted three implicit factors of the post characteristics and introduced a linear model to determine the possibility of an epidemic, while attempting to connect factors to obvious real features. Despite their unknown motivation for choosing a linear model to predict the repost decision, they did not discuss the effectiveness of the PCA method in finding important factors of repost capabilities. In this regard, they implemented experiments on only a limited dataset, which was provided by themselves, and concluded that content-based features such as hashtag and URL were very important in repost capabilities. However, this result was challenged by subsequent studies in [8], which indicated that the features related to a post content had failed to provide enough information to model the users' repost behavior, which was confirmed in [9].

Similar to study [8], an empirical study was carried out to estimate the epidemic of a post, in which an online learning algorithm was developed for prediction as fast as possible [10, 11]. Then, different datasets were generated based on time and day for the training phase of the proposed models and then, used to better utilize the time information of posts, in order to predict the epidemic of a post. As [6], this study did not explicitly mention the reason for using this model and the model had not been evaluated using a variety of datasets. Furthermore, the performance of the online learning method has not been compared with human predictions and claimed that this method works well as human predictions.

Zaman et al. [12] implemented research on modeling the user repost behavior based on the collaborative filtering method. Although other studies have used features directly extracted from posts or users, they applied indirect positive and negative feedbacks in their model. If active following users repost a post, it is considered as positive feedback; otherwise, it is referred to as negative feedback. However, teaching models based on at least one hour of data after posting a post is one of the disadvantages of the research. On the other hand, previous studies have shown that more than 90% of the reposted posts occur at the first hour after the creation. Therefore, teaching a model based on such a long time interval is not worthwhile in practice.

So far, a large body of research has measured the epidemic of a post simply by popularity and diffusion coefficient. The popularity of a post is measured by the number of post-reposting users in [13, 14] and by measuring the number of reposts, likes, etc. in [15, 16]. In [17], the diffusion coefficient is calculated by the average number of new users attempting to repost posts at each step. In microblogs like Twitter, the diffusion coefficient of a tweet is equivalent to the number of reposts of that tweet. In this regard, two issues have been highly considered in research. The first category evaluates the effective measures in the epidemic of a post while the second category attempts to estimate the rate of posting a post.

References [18] and [19] are among the studies related to the first category, which have shown that there is a significant correlation between the presence of hashtag in a post and its epidemic. Research [20] suggests that the stimulation of users' positive and negative emotions by post plays an important role in the epidemic of a post. The method presented in this study is more limited to news and has evaluated the impact of positive and negative news outside of online communities. However, the lack of evaluating the results with other posts is among the disadvantages of the approach presented in [20]. References [21] and [22] emphasized the role of the online communities' structure in the epidemic of a post and stated that epidemic posts in a structure with interconnected clusters have higher epidemic potential. Further, they claimed that the epidemic of a post is related to weak links in the online community structure. In another study [16], within the scope of research papers, it has shown that linguistic criteria such as the style of psychology and post readability play an important role in its effectiveness.

Regarding the second group of studies, [23], [24], and [25] proposed several models to predict the long-term impact of a post based on primitive patterns. Shama et al. [15] addressed a classification method based on observation and repost models and investigated the predictability of the epidemic of a video in the near future. [26] introduced another proposed classification method based on the regression of the content features of a post. In 2018, Cheng et al. [27] developed an image repost prediction method based on image content, posting users, and network structure.

Studies performed in [18] indicate significant differences in the ways of information dissemination in terms of subject. According to studies [18], the behavioral differences of posts with different topics can be examined based on two criteria of "stickiness" and "persistence" of posts. The stickiness of a post is the charisma level of a post for reposting when the user encounters it while persistence is the amount of increase or stability of a post to repost, despite frequent encounters by users. In addition to the precise explanation of these concepts, different studies have sought to answer the following questions accurately.

- Can we consider the stickiness of a post as a probability?
- Does the probability of stickiness lead to differences in the information dissemination?
- In the case of differences, is the repost behavior of a post different depending on the subject and the hashtag used?

Research [18] and [28] analyzed the source of these variations in the development of posts with various topics and investigated the changes in the two stickiness and persistence parameters in posts with different topics (and different hashtags). For example, posts containing political content represented higher persistence such that there was no significant difference in the repost rate of these posts with the repetition of users encounters to such posts. In contrast, common jokes in social networks have little persistence, despite their high stickiness. In addition, such posts are quickly reposted with very little encounters, although an increase in user's encounters drastically reduces their repost rates.

3. PROPOSED METHOD

Most research in this field investigate the data related to the online community and provide their own analysis offline. However, this article aims to dynamically (at any moment) calculate the epidemic probability of a post. It is worth noting that the proposed method should calculate this probability online. The life cycle of a post is a topic that should be considered in this regard. A post has a different epidemic probability within a specified time period from creation to attenuation. For this purpose, finding the epidemic probability at any given moment provides suitable conditions.

3.1. Problem Statement

Each online community can be represented as a graph (1), in which V represents the vertices of the graph for displaying users and E indicates the relationships between users. In online communities, posts are transmitted through communications between users $E' \subset E$ in the form of equation (2). A post is created at the time t_0 and attenuated at the time t_k. The attenuation time of a post refers to when the repost probability of that post is smaller than a certain limit (the post will not reposted practically). The epidemic probability of a post plays an important role in the dynamics and the publication of a post throughout its life cycle. This paper examines the life cycle of a post and estimates the epidemic probability of a post. In other words, the purpose of the considered problem is to find a method for estimating the epidemic rate of posts in online communities.

Equation (1): $G = (V, E)$

Graph vertices for displaying users: $V = \{u_1 ... u_n\}$

Graph edges for displaying communications between users: $E = \{(u,v) \mid v, u \in V\}$

Equation (2): $P = \{p_1 ... p_n\}$

The epidemic probability of a post has a direct relationship to the effectiveness of that post. The more the effectiveness of a post, the higher the epidemic of that post is. Considering the life cycle of a post in this problem, a post is created at a time and reposted at another time between the users and finally, transmitted to the online community structure.

3.2. Reinforcement Learning

The learning process of real social phenomena is regarded as one of the new research topics. These studies can be categorized into two general categories. The first category recognizes the learning principles of social phenomena and its stages while the second category seeks to provide a "methodology" for putting these principles in a machine. Learning is defined as changes made in the performance of a system, based on past experiences [29]. The ability to improve efficiency over time is an important feature of learning systems. In other words, the learning system aims to optimize a task, which is not well-known completely. Thus, an approach to this problem is to decrease the goals of a learning system to an optimization problem, which is defined on a set of parameters, aiming to find an optimal set of parameters [29, 30].

In the issue of estimating the epidemic probability of a post, there is no knowledge of the correct answers to the problem (which requires supervised learning). For this reason, the use of a learning method called reinforcement learning has been highly considered by researchers over the last few years. Reinforcement learning is not a subgroup of neural networks, nor an alternative to them, but it is an orthogonal approach to solving different and more difficult problems [31, 32]. This approach uses a combination of dynamic programming and supervised learning to achieve a robust machine learning system. In fact, a goal is identified for the learning agent to achieve it in reinforcement learning. Then, the agent learns how to achieve the specified target by trial and error in his environment [32]. In this case, the purpose is to find the epidemic probability of a post in order to identify epidemic (affecting) posts.

In reinforcement learning, the learning agent reaches an optimal control policy during learning through repeated interactions with the environment. The efficiency of these interactions with the environment is evaluated by the maximum (minimum) amount of the "reward" or "penalties" derived from the environment. Reinforcement learning methods first provide an almost optimal answer using almost simple, structured, and real learning. It should be noted that finding this optimal answer using traditional methods is very difficult. Secondly, since this learning method is implementing in real time, it can be performed simultaneously with the activity of the environment (such as online communities). In this case, all the unpredicted events are treated as a new experience that can be used to improve the quality of learning.

The lack of need for any kind of information from the environment (except the reinforcement signal) is the main advantage of reinforcement learning compared to other learning methods. "Stochastic Learning Automata" is one of the reinforcement learning methods, which seeks to find the answer without any information about optimal action, by considering the same probability for all actions at the beginning of the task. Initially, an automata action is selected randomly and applied to the environment. Then, the response of the environment is received and the probability of actions are updated according to the learning algorithm and ultimately, the above procedure is repeated [33, 34]. Stochastic learning automata refer to a stochastic automata, which works according to the above manner to increase its efficiency.

3.3. CALA & FALA Learning Automata

LA learning automata is a type of decision-making unit trying to choose optimal action from a set of possible actions through interaction with an unknown and stochastic environment. In each replication, each LA selects an action based on the probability distribution of its actions and sends it to a stochastic environment, which produces a random response to the LA by evaluating the selected action. This random response is called the reinforcement signal. Then, LA updates the probability distribution of its actions using reinforcement signals and a learning algorithm. This method has been widely used in optimization issues, due to its various applications.

In the learning automata, the environment can be displayed by a triple function $E=\{\alpha,\beta,c\}$, where $\alpha=\{\alpha_1,\alpha_2,...,\alpha_r\}$ represents a finite set of possible actions for each automata, $\beta=\{\beta_1,\beta_2,...,\beta_m\}$ indicates the values set of reinforcement signal, and $c=\{c_1,c_2,...,c_r\}$ shows the set of penalty probabilities. Each c_i corresponds to the action α_i. Depending on the penalty probabilities, the environment is divided into two constant and time-variable groups. The stochastic environment is considered stationary if these probabilities are constant and non-stationary if they changes with time. Figure. 1 illustrates the overall schema of stochastic learning automata.

Additionally, the stochastic environment is divided into three categories P, Q, and S based on the reinforcement signal value, which is considered as {0, 1} in the P-Model environment, and is in the range of [0, 1] in Q-Model environments. However, the values are continuous random in S-Model.

Learning automata can be grouped into two major classes of FALA and CALA based on possible actions. In FALA, the set of actions is a finite and the probability distribution of the actions of a FALA with r actions is like the r dimensional probability distribution. Unlike FALA, possible actions are real values in CALA and the probability distribution function is used for the probability

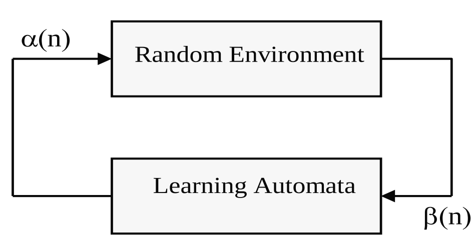


Fig. 1. The relationship between a learning automata and its random environment

of actions. A more precise definition of CALA will be presented in the following.

In CALA, the probability distribution function is determined as a normal distribution with mean and standard deviation. At any given time, the CALA selects an action among the possible actions based on the probability distribution function and updates the probability distribution of its action based on the reinforcement signal received from the environment through changing. Regarding the lack of knowledge about the environment's reinforcement signal, the CALA seeks to automatically optimize action by minimizing the value.

Formally, a FALA is defined as a quadruple $(A,B,T,p(k))$, where $A=\{\alpha_1,\alpha_2,...,\alpha_r\}$ demonstrates a finite set of actions, B depicts a set of inputs (or reinforcement signals) to the automata, T shows a learning algorithm for updating actions probability, and p(k) is the probability vector of actions at moment k, which is expressed as (3).

$$p(k)=[p_1(k),p_2(k),...,p_r(k)]^T \tag{3}$$

Figure 3 indicates the learning automata graph. The probability value of each action α_i at the moment k is always greater than or equal to zero ($p_i(k)\geq 0,\forall i,k$), and the sum of the probabilities of each action at the moment k is equal to one ($\sum_{i=1}^{r} p_i(k)=1 \forall k, k=0,1,2,...$). Thus, $p_i(k)$ is defined in the form of (4):

$$p_i(k)=\Pr[\alpha(k)=\alpha_i \mid p(k)], i=1,...,r. \tag{4}$$

The learning algorithm for updating $p(k)$ is presented in (5):

$$p(k+1)=T(p(k),\alpha(k),\beta(k)) \tag{5}$$

where T represents a function of the current probability of actions, p(k) indicates the action selected at the moment k, and β(k) denotes the environment reinforcement signal (environment response) to the selected action. Since $p(k+1)$ depends on values $\alpha(k)$ and $\beta(k)$, as random values, the value of $p(k+1)$ is a random quantity. As a result, $\{p(k),k=0,1,2,...\}$ is a stochastic process and its evolution is governed by this learning algorithm. As discussed earlier, in the P-model environment, i.e. the problem environment with two outputs of repost and no-repost, the learning algorithm is based on equations (6) and (7).

A. In case of a desirable response from the environment $\beta(n)=1$

$$\begin{aligned} p_i(n+1) &= p_i(n)+a[1-p_i(n)] \\ p_j(n+1) &= (1-a)p_j(n) \qquad \forall j,\quad j\neq i \end{aligned} \tag{6}$$

B. Undesirable response from the environment $\beta(n)=0$

$$\begin{aligned} p_i(n+1) &= (1-b)p_i(n) \\ p_j(n+1) &= \frac{b}{r-1}+(1-b)p_j(n) \qquad \forall j,\quad j\neq i \end{aligned} \tag{7}$$

where a and b are the reward and penalty parameters, respectively. If a and b are equal, the algorithm is called linear reward penalty (L_{RP}). If b is much smaller than a, then, the algorithm is called linear reward epsilon penalty ($L_{R\varepsilon P}$). Finally, if b is equal to zero, the algorithm is called linear reward inaction (L_{RI}).

3.4. The Proposed Method for Estimating the Epidemic Probability

The present study applied the method of learning using stochastic learning automata to estimate the epidemic probability of a post. The learning automata is one of the reinforcement learning methods, which was selected based on the problem specifications in Section 3.1. For this purpose, a learning automata is considered for each post at the time of creation. This automata has two actions of display and not display. On the other hand, the environment responds to the action selected by the learning automata through a dual-state reinforcement signal (environment response) of 1 (repost) and 0 (non-repost). When the automata action is “display” and receives the response 1 (repost) from the environment, the automata rewards for the display action. By using the learning algorithm, the automata increases the probability of display action and reduces the probability of not display action. If the automata chooses the display action but receives the response 0 (non-repost) from the environment, it considers a penalty for display action. As the previous state, the automata reduces the probability of display action and increases the probability of not-display action. The same procedure will be followed in other cases, in such a way that when the display action leads to the repost and the not-display action leads to non-repost, the post-learning automata considers a reward for the corresponding action; otherwise, the learning automata considers a penalty for the relevant action. It is worth noting that the chance of both actions is the same at first and equal to 0.5. These steps continue until the automata converges to one of the two actions. The convergence condition will be described in sub-section 3.2. The epidemic probability of a post at any given moment is equal to the probability vector C_1 for the display action. As shown in Figure. 2, the epidemic probability of a post is constantly updated by the post-learning automata. The post at the creation time has an epidemic probability of 0.5, which will be changed with each encounter with the user's decision to repost or not repost. Given the life cycle of a post, the epidemic probability tends to zero over time.

3.5. Self-Organizing Post

Self-organization, as one of the most important applications of the proposed method, is defined as follows [34]: "Self-organization" or "spontaneous order" (in social sciences) is a process in which a form of order arises from the interactions between different parts of a system without primitive order. If the automation converges to non-display action, it means that the repost probability of this post is very low, and the selection of display action does not lead to the repost by the user (in the environment). In this case, this ineffective post is detected and removed from the system display.

If the learning automata belongs to the display-action post, another action is selected in the next step by learning automata and this post will remain in the system until the convergence occurs towards the display action. The probability of selecting a display action at any time determines the probability of post repost. On the other hand, if it does not converge over time, the above steps are repeated from the second step to convergence. During the lifecycle of a post, online learning is performed continuously and the probability of each action is updated consequently.

Figure. 3 shows the flow chart of the suggested method for the self-organizing post. Initially, a learning automata is considered for each post, which selects an action from the display or not-display actions based on its probability vector c. A reward and penalty are considered for each action, considering the environment's reinforcement signal (user's decision to repost or not to repost). Then, the convergence of learning automata is investigated and the post is deleted from the system's display cycle when the convergence is towards the not-display action. This method provides the possibility to select posts for display that their repost probability is not close to zero, which is very effective in solving the information overload problem.

This process is spontaneous and does not require to be controlled by an external factor. Generally, this process begins with stochastic fluctuations and is reinforced with positive feedback. The proposed method has also this feature and as a result, this method is completely decentralized and distributed across all components of the system. In this way, this method is generally powerful and has the ability to save itself after significant disturbances. Due to the dynamic nature of the environment, the feedback received from each of the actions are applied in an online way and the results are updated. The self-organizing feature presents many applications in online communities. Using self-organizing posts can be effective in solving the information overload problem. Posts with negligible epidemic probability are automatically removed from the system's display loop.

3.6. Learning Automata Convergence

The entropy concept is used to understand the learning automata convergence. Entropy is a criterion for measuring the amount of information generated by a source or received by the observer. This idea was first presented by Shanon in 1948. Entropy in information theory is a numerical criterion for the amount of information or the randomness of a random variable. In fact, the entropy of a random variable is the mathematical expectation of the amount of information obtained from its observation. The entropy of a discrete random variable X is represented by the probability mass function P(X) with the symbol H(X) and defined by (8).

The information obtained from observing an event is defined as the negative logarithm of its occurrence probability. Therefore, the information obtained from observing a definite event (i.e. with probability 1) is zero. Consequently, $p(x_i)$ refers to the probability of the random variable X at the time t, which is shown in (9).

$$H(X) = \sum_{i=0}^{n-1} p(x_i)\log_b(1/p(x_1) \tag{8}$$

$$p(x_i) = prob\{X_i = a_i\} \tag{9}$$

In equation (8), the parameter b can take values such as $b = e = 2.718$, or $b = 10$, and or $b = 2$.

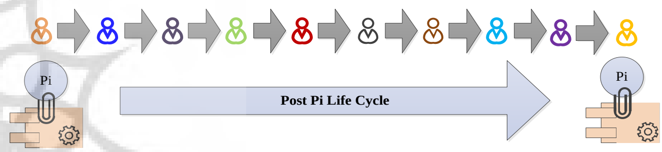


Fig. 2. The proposed method for estimating the epidemic of a post

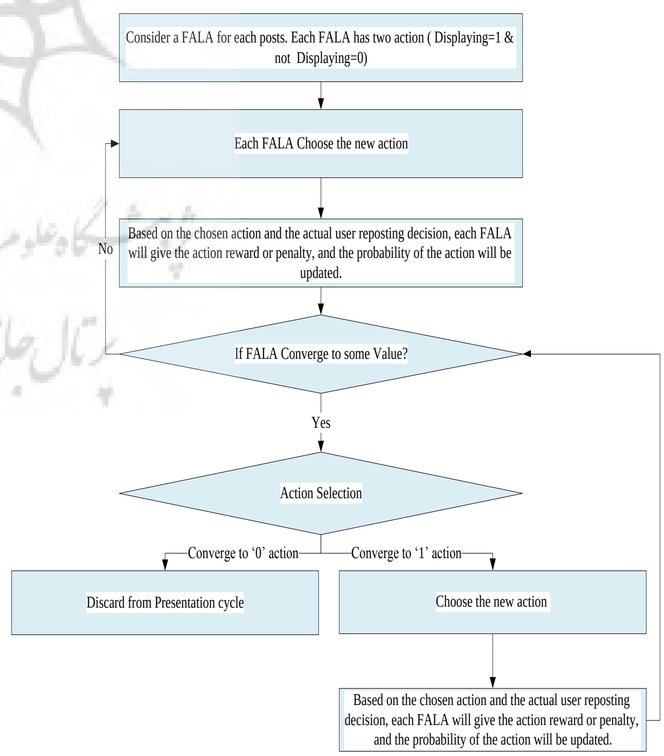


Fig. 3. Self-organizing post

In learning automata method, entropy can be used as a criterion for measuring system efficiency. The entropy of each environment indicates its uncertainty; the higher the randomness of the environment, the greater the amount of uncertainty and vice versa. When an environment is able to find optimal action, the entropy of the automata and hence, the entropy of the environment decreases. The threshold T_{min} is used to evaluate the convergence. Determining the threshold is performed as a compromise between efficiency and accuracy. In this paper, the amount of $T_{min} = 0.02$ was used for the entropy threshold after several evaluations.

4. EVALUATION AND RESULTS

This section of the article evaluates the proposed method. For this purpose, three relatively large datasets of the Twitter community were selected and several experiments were carried out on the datasets and the proposed method.

4.1. Dataset Specifications

The required datasets were collected given the issues raised in a systematic process and according to the requirements of the problem. In this study, three datasets were collected with different characteristics. Table 1 presents the characteristics of these three datasets.

There are several applicational tools to collect Twitter data: 1) Twitter Search Application; 2) Twitter Streaming Application; 3) Twitter Firehouse Application. The Twitter streaming application provides access to public posts close to the test time. In order to use this application, it is first necessary to register and then, determine the stream profile. Criteria such as keyword, user names, location, or place name can be determined by the user and these applications collect the posts on Twitter based on these characteristics. However, this tool only provides samples of activities occurred on Twitter, which is the main disadvantage of this tool for collecting requested data.

Based on the description provided by Twitter, this tool can collect up to 40% of the recent public posts. Twitter Firehouse application assures the 100% collection of posts. Unfortunately, this tool was not free and it was not possible to use it in tests, due to sanctions. Accordingly, this article has used free services provided by the Twitter streaming application.

Twitter search application is based on the REST architecture (web service architecture). This application allows developers to create their own programs by applying changes to the main application. Searching names, verbs, user profile, user timeline, posts, posts location, followers, and followings are among the capabilities of this application.

These applications support different types of input and output, which the former can be a wide range of search features while the latter is provided in various templates such as XML and JSON. The JSON template is a very simple text format that allows to read and write. This template is extensively used in data exchanges between machines, due to its simplicity of processing and creation. In this research, a relational database was used to maintain the JSONs output, in order to facilitate the implementation of multiple queries.

TABLE 1. PREPROCESSING STEPS FOR A POST

Different steps	Text
Original text from retweet	**RT @xfl2020: This is *great* football reimagined. This is the XFL. Watch the official announcement — LIVE NOW! #XFL2020 https://t.co/KFX5oLmkHw**
Convert to lower case	**rt @xfl2020: this is *great* football reimagined. this is the xfl. watch the official announcement — live now! #xfl2020 https://t.co/kfx5olmkhw**
Remove rt, http and all special characters	**this is *great* football reimagined this is the xfl watch the official announcement live now xfl2020**
Remove stop words	***great football reimagined xfl watch official announcement live xfl2020***
Tokenize	**[“great”,"football","reimagined","xfl","watch","official","announcement","live","xfl2020"]**
Is there any hashtag?	**1**
Is there any URL?	**1**

In order to collect data, users-related identifiers (nine-digit) were randomly generated and collected using the application, their posts, and reposts by their followers. Regarding the issue addressed in this essay, the collected dataset was divided into two groups of positive and negative samples for some evaluations. Positive samples are related to the states that the user attempts to repost after observing the post while the negative samples are related to the state in which the user does not take action by observing the post. The API_user_timeline command is applied to collect the dataset and the tweepy package is used to load Twitter posts. In order to use this package, a personal key is first registered to connect to Twitter. Using this personal key, it is possible to upload the information of posts and users for free. However, Twitter has a specific supervisory on loading information and thus, considers limits for calling within a specified time period; for example, more than two hundred posts of a user cannot be observed on this online community.

After collecting the data, it is necessary to process the posts. Table 1 briefly reports the processed steps on posts. In the first step, the original text of the reposted posts is specified. In some cases, users use the UPPERCASE to write the English letters of the posts to emphasize or transfer some of the concepts. Given the proposed method, the uppercase fails to affect the repost decision. Therefore, all posts are considered lowercase when processing the text of the reposted posts. The stop word refers to words that can be found in most texts and are not part of the keywords. For example, in Persian, prepositions (such as "به", "از", and ...), conjunctions (such as "که", "پس" and ...), and pronouns (such as "من", "او" "and ...) are among the stop words. In English, prepositions, conjunctions, pronouns, etc. are included in stop words, which should be deleted in the next step.

Based on the proposed method, the text of a post should be tokenized to calculate similarities and related processes. This tokenization is performed by the tools available at the MATLAB Library. As mentioned in the proposed method, the existence of hashtag and the link address are very effective in reposting posts. In order to simplify the calculation of the proposed method, two binary variables are used to declare the hashtag and the link address. The value of this variable is 1 in the case of hashtag and link address; otherwise, it is zero.

After the above steps, a relational database is used to store JSON document information for better performance and easier implementation. For this purpose, six tables were created in this database. These tables include posts, reposts, users, user-follower, following network of users, and entities. Figure 4 shows the schema of this relational database.

As observed in Table 2, these three datasets have different sizes and are suitable for evaluating the proposed method.

Figure 5 depicts the distribution of posts per user, in which the horizontal axis indicates the number of posts created by users and the vertical axis represents the percentage of this category of users among all users. For example, users with one to ten posts account for about 50% of users in the first dataset. In other words, 50% of users have created only five or fewer posts according to more accurate estimates.

As illustrated in Figure 5, the distribution of posts number per user is not according to the normal distribution. Similarly, users with two hundred posts

TABLE 2. SPECIFICATIONS OF THE EVALUATION DATASETS

#	Dataset	#Tweet	#Users	#Retweet
1	Steve Jobs Death	19834	11155	**158133**
2	US Election	253680	57267	**741064**
3	:)	13956	1162	**21578**

account for a very small percentage of users. In this regard, the limitations of data collection tools are the reason for the limited range of the horizontal axis to two hundred posts. As mentioned earlier, these tools allow the retrieval of the maximum amount of two hundred posts per user in the free version. As observed, the distribution of the number of posts is very similar in all three Figures, such that a high percentage of users have very little activity. In contrast, a small percentage of users shows the most activity in online communities.

Figure 6 displays the results of the previous diagrams in a different form. In these diagrams, the horizontal axis shows the logarithm of the number of reposts while the vertical axis presents the frequency of posts. Due to the size of the evaluation datasets, the logarithm of the values is used instead of the real values. The reason for using

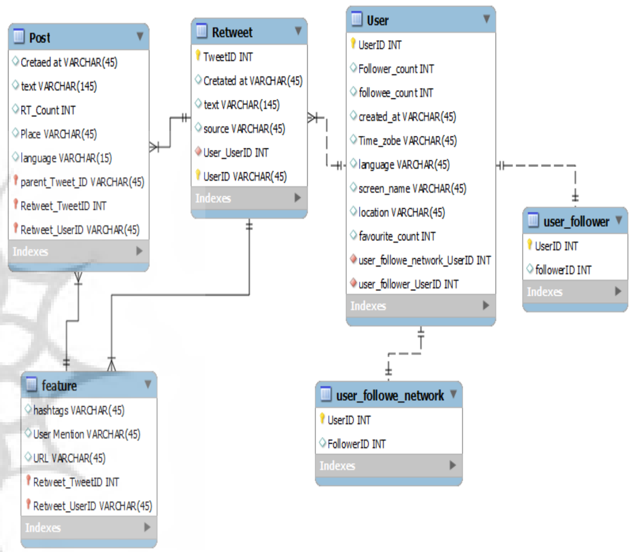


Fig. 4. Relational database schema

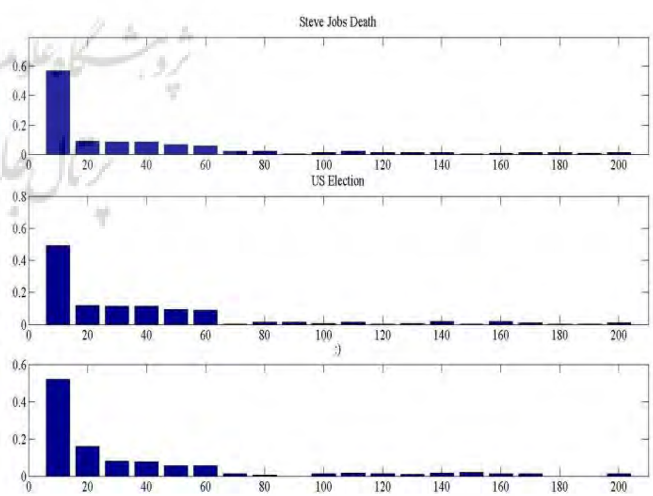


Fig. 5. The frequency percentage of users in relation to the number of posts created in the three evaluation datasets

logarithm in these diagrams is to show a denser and better result of the studies.

As depicted in Figure 6, a large part of the posts have a repost number less than two, although the frequency of posts with more than a thousand reposts is very small. Due to the size difference between the three datasets, the number of post reposts is also different in these three graphs. The number of posts after point 3 (i.e. eight reposts) sharply decrease across all three graphs, indicating that a large portion of the posts has less than ten reposts. In Figure 6, the blue, green, and red graphs belong to three datasets of 1 to 3, respectively.

The convergence feasibility of the proposed method was first examined to evaluate it in sub-problem 1. Then, the experiment conducted to determine the convergence rate of the method was assessed on all three evaluation datasets. The convergence diagram of the method for this evaluation dataset is drawn in various steps.

As observed in Figure 7, the suggested method converges rapidly for all three datasets. In order to interpret these graphs, the convergence rate was measured in all three graphs after the first 50 steps, which were required for the initial learning of the proposed method. The convergence rate of all three graphs was about 50% after 50 steps. In other words, this method converged in half of the cases and was able to present an accurate estimation. However, the convergence rate of the method increases by passing the 50th step. The proposed method was able to achieve a convergence rate of around 90% after about a hundred steps (this number is different in various datasets). For 1% of the posts with a high rate of repost, our method provided a correct estimation for about 90% of the cases. Considering the entropy threshold, the convergence rate has not changed significantly in the next steps after a certain step.

In order to represent the effect of the entropy threshold, three different colors were used in the convergence of each method. The larger the threshold value of convergence, the faster the convergence rate will be. In this experiment, three thresholds were used as follows: a) 0.05, b) 0.03, and

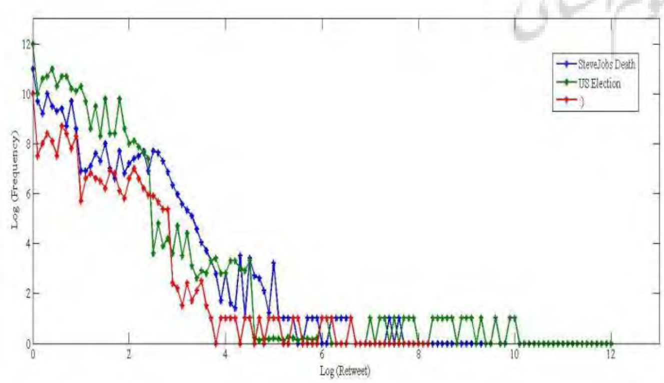


Fig. 6. The frequency ratio of posts to the number of reposts

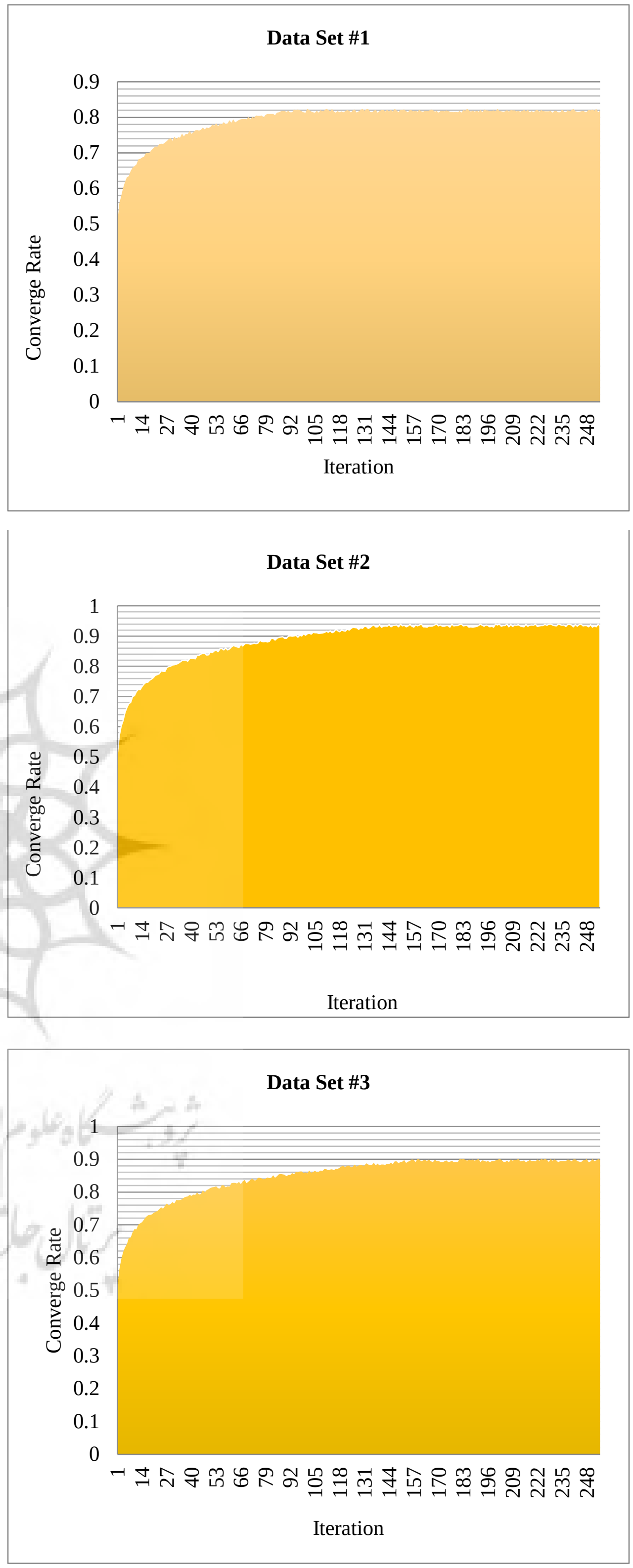


Fig. 7. Convergence rate for all three datasets

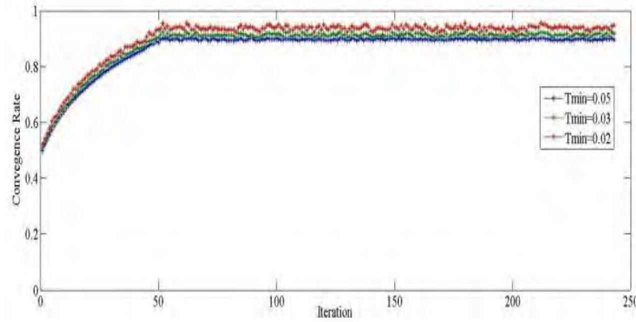
c) 0.02. The graphs for each of these states are indicated in red, green, and blue colors, respectively. As observed, the red-color graph, which shows the highest threshold, converges faster than that of the other two graphs.

As illustrated in Figure 8, the effect of the entropy threshold on the convergence rate of the proposed method has been investigated in these three graphs. The higher amount of the threshold represents the higher rate of the convergence. In other words, the threshold value acts as a convergence condition, and the high values of this factor increase the probability of convergence. On the contrary, the lower the amount of this rate, the lower the rate and the probability of convergence of the method will be. It should be noted that the dataset is effective; as an example, there is no significant difference between the different threshold values for convergence rates, as observed in dataset 2. In some datasets, the users' repost behavior is performed uniformly and with low volatility. The higher level of the uniformity of the behavior increases the convergence rate and different variations in the entropy threshold do not make a remarkable difference.

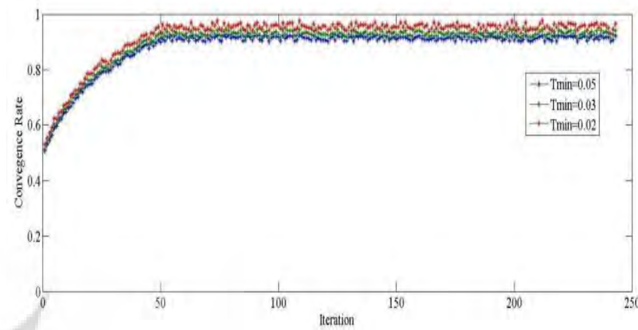
The changes in entropy can be used to illustrate the learning process in the proposed method [33]. Figure. (4-12) shows the diagram of the process of entropy changes in the environment in all three datasets with different colors. The graphs for each of the datasets 1, 2, and 3 are specified with blue, red, and green, respectively. In this diagram, the horizontal axis represents the various steps of learning with a factor of ten. The vertical axis of this graph is related to the entropy of the environment in these three datasets. This graph shows the first 100 steps of the learning process of all three datasets. As mentioned in Section 3.2, the amount of entropy in the initial state is equal to one, which is decreased by learning the method. For the convergence condition, an entropy threshold is determined which the value of 0.02 is considered in this article.

As indicated in Figure 9, the entropy changes process of the method is demonstrated in the three datasets. In learning methods using learning automata, the entropy is used as a tool for measuring the efficiency of the method. Generally, the more the randomness of the environment, the more the efficiency will be. Further, the entropy of the learning automata and consequently, the entropy of the environment is reduced if the environment is able to find optimal action.

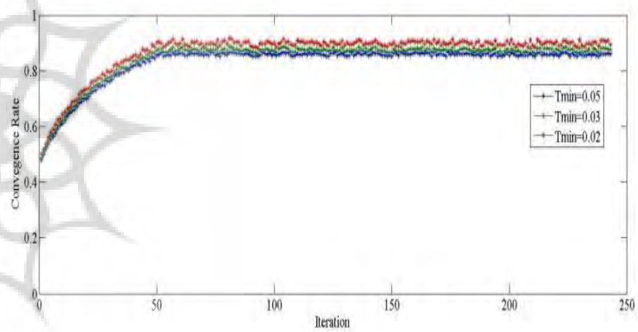
The degree of entropy in absolute disorder state is equal to one, which is decreased and approached to zero by moving towards learning. This trend is also found in Fig. 9. In each of the three datasets, the entropy rate of the proposed method is initially equal to one and then, it reaches below the "0.1" in each of the three datasets after about 100 steps. The problem's environment is completely random and the entropy rate in the method is one in the initial state. The proposed method has two actions, which the probability of each of these two actions is the same and



c) Data Set #1



c) Data Set #2



c) Data Set #3

Fig. 8. The effect of the entropy threshold on the convergence rate

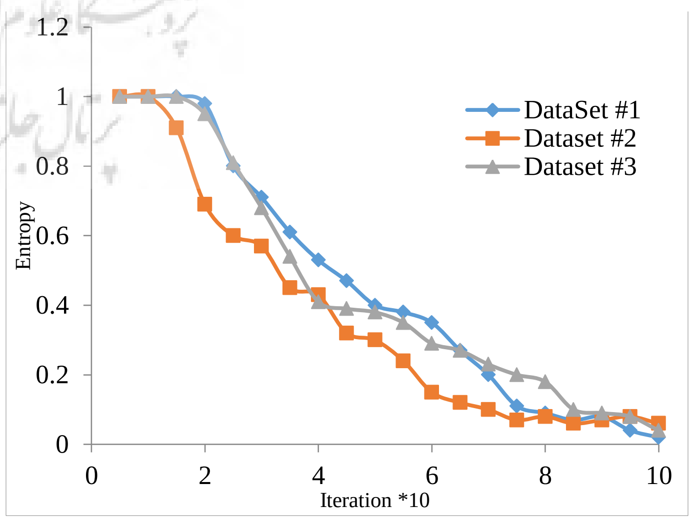


Fig. 9. Entropy changes process in all three evaluation datasets after passing the learning steps

equal to "1/2" in the initial state. The entropy calculation method was shown in equation (8). Based on calculations:

$$H(X) = -\sum_{i=0}^{n-1} p(x_i)\log_b(1/p(x_1) = -\sum_{i=0}^{n-1}(1/2)\log_b(1/2) = 1$$

If the learning automata has complete certainty and the probability of action is equal to one and the probability of another action is zero, then, according to the equation (8), we have:

$$H(X) = -\sum_{i=0}^{n-1} p(x_i)\log_b(1/p(x_1) = -[0*\log_b(0) + 1*\log_b(1)] = 0$$

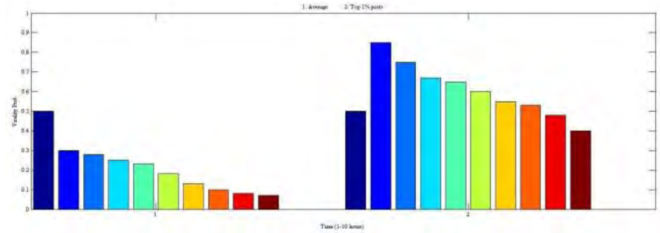
As discussed in Section III, the entropy of the method is equal to 1 in the initial state. With each step, the learning automata chooses an action and considers reward and penalty for the related action, considering the environment bookmark. This reward and penalty make the learning automata to gradually convergent to an action.

As addressed in the proposed method, the epidemic probability of a post tends to zero after a certain period of time, such that it attenuates and is removed from the cycle.

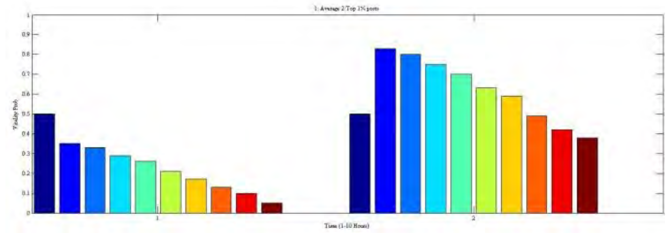
If the entire life cycle of a post is considered, then, this graph is gradually attenuated and tends to zero after converging to the epidemic. To this end, an experiment was arranged and conducted to demonstrate this issue. Fig. 10 shows the graph of changes in the epidemic probability of posts after ten hours of creation. The right-side graph represents 1% of posts with high repost while the left-side graph is for all posts in the dataset.

In Figure. 10, as observed on the left-side diagrams, the epidemic probability of posts is about 50% at the time of the start, although this value declines over time. This experiment confirms the results of the research [33, 34]. The epidemic probability of posts in the datasets 1 to 3 has almost a similar trend. After ten hours of creating a post, the pandemic probability of the post has significantly dropped below 10%. However, the variation trend is slightly different in the right-side diagrams. These graphs are related to the posts with a high rate of repost for datasets 1 to 3 and the study of these graphs is useful for illustrating the overall lifecycle pattern of a post. Based on the results, the first hour plays a key role in the epidemic probability of a post, which is increased as much as a post is reposted at that time (first hour). Posts with many reposts reach their maximum epidemic probability at the first hour; an increase in repost and the users' encounters rapidly increases the repost probability of a post. As expected, the epidemic probability of a post quickly decreases over time and drops below 50% (in all three datasets).

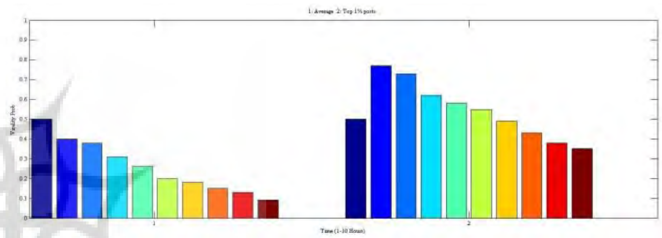
The purpose of this study was to dynamically estimate the epidemic probability of a post. In order to better understand the epidemic probability of a post on an online community, another test was conducted to evaluate the relationship between the repost rate of a post by users and



c) Data Set #1



c) Data Set #2



c) Data Set #3

Fig. 10. Changes in epidemic probability within 10 hours of post creation. The right graph corresponds to 1% of the posts with high repost and the left one represents the total average of posts.

the estimated epidemic probability of posts. As mentioned earlier, the epidemic probability of a post is a dynamic quantity over time, so that the proposed method begins to measure this probability by creating a post. In a comprehensive perspective, the epidemic probability of a post decreases over time; i.e. each post has an epidemic value in [0, 1] during its life cycle. In order to test the relation of this probability with the number of reposts, the epidemic probability of a post was considered after ten hours of publication. In addition, the logarithm of the repost number was used in this experiment for better illustrating the number of reposts. Figure 11 shows the relationship between the estimated epidemic probability of a post and the logarithm of the repost number of that post. The horizontal axis represents the epidemic probability of posts in the interval 0 to 1. The vertical axis indicates the logarithm of the repost number of a post.

As specified in Figure 11, posts with high epidemic probability are reposted more and the epidemic probability of posts is directly related to the repost rate of posts, although this relationship varies in different datasets. The reason for this difference is that each of these datasets has different distributions of the number of reposts, the number of users, and the number of posts, making the difference

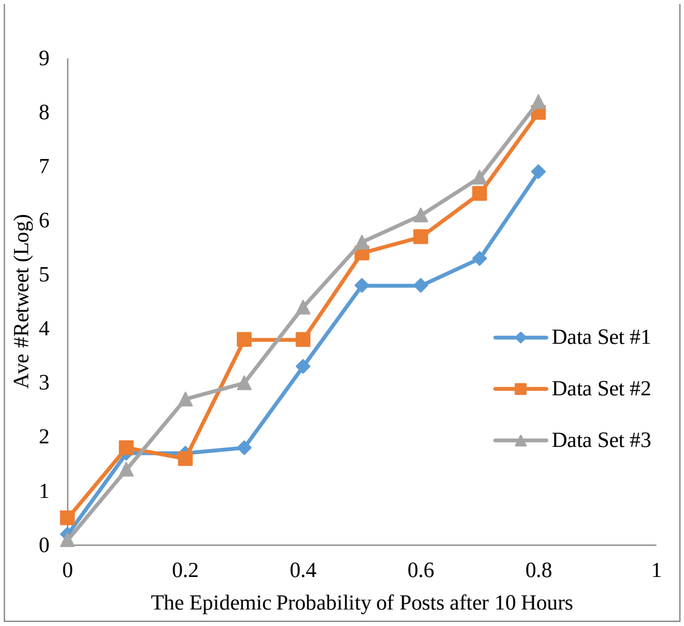


Fig. 11. Changes in the repost number of post with respect to the epidemic probability of a post

inevitable in the variation graph. Figure 11 highlights the high rate of reposts for posts with high epidemic probability.

5. CONCLUSION

The present study introduced the concept of the life cycle of a post in online communities for the first time. The life cycle is related to the epidemic probability of a post from the moment of creation until its attenuation. For this purpose, a learning automata-based approach was presented in this paper, which was capable of estimating the epidemic probability of posts in online communities.

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