International Journal of Scientific Engineering and Science
Volume 2, Issue 1, pp. 33-36, 2018. ISSN (Online): 2456-7361

Blocking Adult Account in OSN's Using Iterative Social Based Classifier Algorithm

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Abstract— *Now a days, usage of Online Social Network among the users are increasing worldwide. With this, sexual explicit content is also spreading in wide range. In order to provide security in this particular area, we have used an Iterative Social Based Classifier Algorithm to detect and block the adult content in Online Social Network. The username, email id and follow-ups which contain any spam content will be blocked by the administrator and it will not be visible by the other user. If a particular network address (IP address, mac address) continuously posts such content will be blocked permanently. In this way, the user can be benefited from viewing adult posts in Online Social Network.*

Keywords— *Classifier Algorithm, Entity based collective, IP address, Link based collective, MAC address*.

I. INTRODUCTION

Social networking gives people an opportunity to meet new people around the world. Users of these sites have access to millions of profiles from around the world. Before the advent of social networking sites, chat rooms were the only way to meet new people on the internet. But, the main drawback of chat rooms was that you may not know the person with whom you are interacting with. The introduction of profiles on social networking sites allowed people to know more information about a person before they interact with them. Most of the popular social networks allow users to create groups. These groups allow likeminded people to share their interests and hobbies. People may later regret posting pictures or comments that they thought funny at the time. Online bullying can be a problem if someone posts unkind or untrue things about you. Some people may use a fake profile - just because they say they are 16 years old does not mean that is true. Be careful when you choose to be friends with someone you have never met in real life.

With over 200 million monthly active users and half a billion tweets sent per day , online social networks like twitter, face book has become an increasingly influential platform for real-time information sharing. However, OSNs at the same time has become an attractive platform for the adult entertainment industry to conduct social marketing campaigns.

A large number of accounts have been created on OSN for the purposes of promoting services related to adult entertainment, propagating sexually explicit materials, and even recruiting performers for the adult entertainment industry. The wide spread of adult content is an emerging yet critical problem faced by twitter and other online social networks (OSN). An increasing number of users who are not interested in adult content have started complaining about the uncontrolled spread of adult content.

To make the problem even worse, a fair amount of Twitter users are underage minors, whose exposure to such adult content may cause legal problems. Although many OSNs, requires that users must be older than 13, there is no effective enforcement preventing users under 13 from using OSNs. A recent report shows that millions of Facebook members in the U.S. are under 13.

II. RELATED WORK

"Graph Regularized Transductive Classification on Heterogeneous Information Networks [10]"
M. Ji, Y. Sun, M. Danilevsky, J. Han, and J. Gao Ieee transaction 2010

This paper consider the transductive classification problem on heterogeneous networked data which share a common topic. Only some objects in the given network are labeled, and we aim to predict labels for all types of the remaining objects. A novel graph-based regularization framework, GNetMine, is proposed to model the link structure in information networks with arbitrary network schema and arbitrary number of object/link types.

"Analyzing Spammer's Social Networks for Fun and Profit [5]"
Chao Yang, Robert Harkreade, Jialong Zhang A&M University Seungwon Shin, GuofeiGu IEEE transaction 2012

This paper reveal three categories of accounts that have lose friendships with criminal accounts. Through these analyses, we provide a novel and effective criminal account inference algorithm by exploiting criminal accounts' social relationships and semantic coordination.

"Understanding and Combating Link Farming in the Twitter Social Network[9]"
SaptarshiGhosh, BimalViswanathyFarshadKooti MPI-SWS, Naveen K. Sharma IIT Kharagpur, GautamKorlam IIT Kharagpur, India FabricioBenevenuto UFOP, Brazil NiloyGanguly IIT, Krishna P, IEEE transaction 2012.

It find that link farming is wide spread and that a majority of spammers' links are farmed from a small fraction of Twitter users, the social capitalists, who are themselves seeking to amass social capital and links by following back anyone who follows them. Our findings shed light on the social dynamics that are at the root of the link farming problem in Twitter network and they have important implications for future designs of link spam defenses.

"ISC: An Iterative Social Based Classifier for Adult Account Detection on Twitter [1]"
Hanqiang Cheng, Xinyu Xing, Xue Liu, and Qin Lv, IEEE transaction 2015

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As adult Twitter accounts are mostly connected with normal accounts and post many normal entities, which makes the graph full of noisy links, existing graph based classification techniques cannot work well on such a graph. To address this problem, we propose an iterative social based classifier (ISC), a novel graph based classification technique resistant to the noisy links. Valuations using large-scale real-world Twitter data how that, by labeling a small number of popular Twitter accounts, ISC can achieve satisfactory performance in adult account detection, significantly outperforming existing techniques.

III. Problem Definition

Problem in existing system is that if any user post any adult contents in their post it will be shown to their follower's table also, and we could not detect any adult users' as well, and also user can register with any adult name.

IV. Proposed Methodology

In this section, we first introduce the link-entity graph constructed based on social links on Twitter and entities in tweets. Then we present an overview of the iterative social based classifier which identifies adult accounts on the link entity graph.

A. Graph Construction

The link-entity graph has two types of nodes and two types of edges. Fig. 2 shows an example of the link-entity graph. The two types of nodes are accounts and entities (i.e., hashtags, URLs, and mentioned users) contained in tweets. We use entities instead of the plain text because of the following observations.

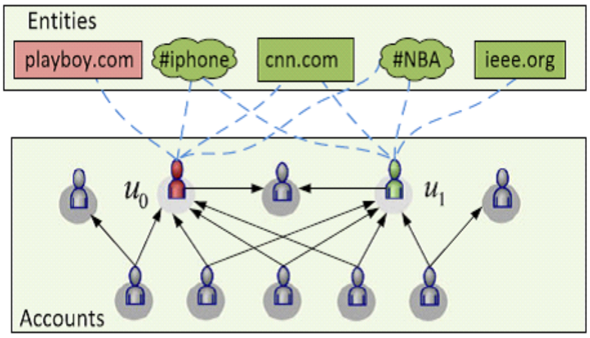

Fig. 1. Link entity graph example.

First, the meaning of hash tags is more focused and can serve as a better clue in detecting adult accounts. This is particularly true for those vulgar slang text which might be used by both normal accounts and adult accounts. Many normal accounts would simply use untagged version slang word to express a certain emotion and have no intention themselves in propagating adult materials. In contrast, many adult accounts will intentionally tag some slang words to increase the chances that their tweets can be read by users who search for such text [1]. For example, "sexy" may be used by normal accounts to express adoration, while "#sexy" are more often used by adult accounts for the purpose of propagating some adult materials. Second, it is difficult to detect adult accounts who frequently mention other adult accounts or just post adult URLs when using plain text.

Motivated by the observation that adult accounts are mostly followed by users who are interested in adult content, the first type of relationships we considered in link entity graph is the "following" relationship between accounts which is represented by directed solid edge as shown in figure 1.The second type of relationships we considered is the "posting" relationship between accounts and entities which is represented by undirected dotted edge as shown in the figure 1. All the edges in the link-entity graph are assigned the same weight. The reason why we do not weigh the "posting" relationship by the number of times an entity is mentioned is due to the fact that many popular normal entities (e.g., "facebook.com" or "instagram.com") are frequently posted by adult accounts for many times, whereas adult entities might be posted for just several times[1].

B. Iterative Social Based Classifier

Based on the link-entity graph, we design iterative social based classifier. Algorithm 1 describes the overall procedure of ISC. At a high level, ISC uses an iterative classification procedure. Before presenting details about ISC, we first define some notations.

Gsdenotes the "following" relationships between all accounts. Ge denotes the "posting" relationships between accounts and entities. Two types of collective correlation features, link based collective correlation (LCC) and entity based collective correlation (ECC), are extracted from Gs and Ge, respectively. We use XA and XB to denote these two types of features. L denotes the training set. ^ L denotes the automatically labeled set generated by ISC during the iterative classification procedure. _ is a constant between 0 and 1, which is used to combine two decision functions learned in ISC [1].

Algorithm 1. Iterative social based classifier.

```
Input: Gs;Ge; L;_
Output: y
1: MA ¼ 0 ;
2: ^ L ¼ L ;
3: while MA increases do
4: XA CCM (Gs, ^ L) ;
5: XB CCM (Ge, ^ L) ;
6: yA; yB SDC (XA;XB; L; _) ;
7: y ¼ _yA þ ð1 _ _ÞyB ;
8: ^ L UpdateLabelSet(y, _, ^ L);
9: MA JaccardðyA
þ; yB
þÞ ;
10: end
```

In each iteration, we perform the following operations. First, we update both LCC and ECC based on Gs, Ge and the automatically labeled set ^ L using the collective correlation model introduced in Section 4 (lines 4-5). Initially, ^ L is set to L. Second, we train a social driven classifier based on the

Volume 2, Issue 1, pp. 33-36, 2018. ISSN (Online): 2456-7361

newly updated features XA and XB. Two decision functions, one for LCC and the other for ECC, are jointly learned in SDC. Details about SDC are presented in Section 5. The prediction values of these two decision functions for all accounts are denoted by yA and yB, respectively.
Third, we update the automatically labeled set ^ L based on the combined prediction of yA and yB (line 7 _ 8).

Each time ^ L is expanded by adding a certain number of accounts that have not been placed in this set before. In particular, we add those accounts which have the highest likelihood of being either adult or normal accounts. In our implementation, we first divide all accounts into adult class and normal class in terms of their prediction values, then we calculate the ranking scores for accounts in each class. Based on the ranking scores of all accounts, we double the size of ^ L in each iteration by adding those accounts which are ranked on the top [1].

Lastly, we calculate the mutual agreement (MA) on adult account prediction between the two decision functions learned in SDC (Line 9). Suppose yAþ and yB þ represent adult accounts predicted by the two decision functions of SDC, respectively.

The mutual agreement is defined as the Jaccard similarity between yA þ and yB þ, which can be calculated as kyA þ\yBþkkyAþ[yBþk [19]. Here k _ k denotes the size of a set. If the mutual agreement starts to decrease, we stop the iterative classification procedure.

V. IMPLEMENTATION

A. User's Process

While registration user want to give the details like name, password. User has to enter the one time password for first time login. Admin no need to register. User can directly login with username and password. After registration process user can enter into their log in. After log in they can post the new post and also they can upload their profile picture as well. And every searched can also search the friends from their account and if they want they can follow, and also they can do un follow any other user.

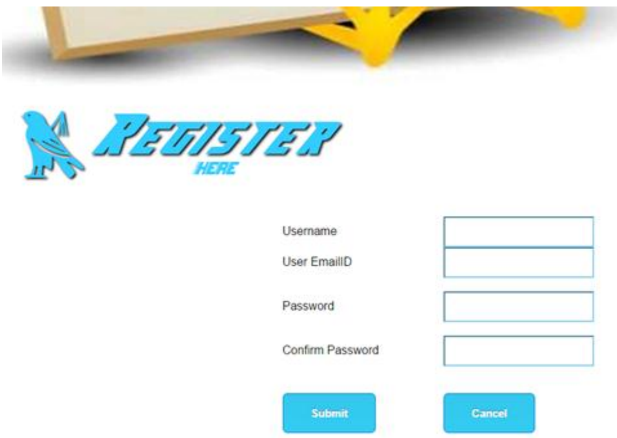

Fig. 2. User registration.

User can suggest the adult word to the admin. For example: if admin from the another country and application user from another country means admin may not know the user's language. So application users' can suggest the bad words to the admin from his local language. Admin will analyze and will add it to the application form at end. Added words will consider as the adult words.

User will get the new notification from the their followers, if any user post the new post that would automatically will show it to the all followers and also if any user post the adult content post that post automatically will get filter. So that user will not get the new notification for adult post. That post only will view in the post owner timeline only.

B. Admin Process

Admin can able to view the adult account in graph view and also he can view that adult user's adult counts, like how many adult counts they posted , in their post. And admin can unblock the adult user. And also he can add the suggested word as well as they can also reject that word.

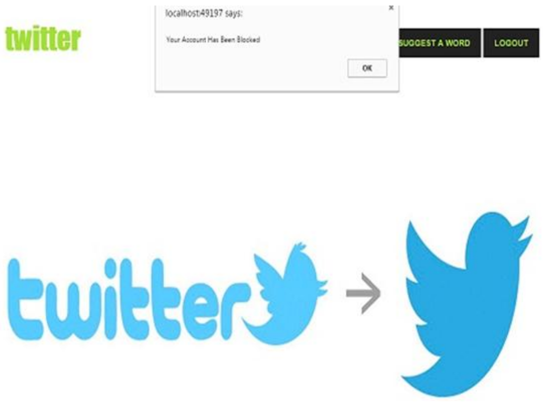

Fig. 3. Blocking the account.

C. Network Address Filtration

User can also post the adult content, only that will show up into his account and if any posted adult content more than three time that user will be automatically get blocked by admin. After blocking user has to give the request to the admin for unblock their account. If any user post adult content that post automatically will get filter. The IP address of the particular user is get through the network interface card and the MAC address of the system is Blocked by the admin if the user registered with any spam words. Then the user cant able to use this application on the particular system.

Fig. 4. Blocking using MAC address.

VI. Conclusion

All the adult account user will be detected by admin, and normal user also cannot post the adult post, user has to give the user name as the normal name without adult content user name. If any user post any adult content more than three time that user will be block by admin.

VII. Future Enhancement

In future we will concentrate on adult video posted on this application. We will detect and block the adult contents on videos. Though we only demonstrate the effectiveness of our proposed solution on Twitter in this article, the proposed solution is applicable to many other OSNs. In our future work, we plan to evaluate the effectiveness of our proposed solution on other popular social networks such as Facebook and SinaWeibo, etc.

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