International Journal of Engineering Research in Computer Science and Engineering (IJERCSE) Vol 2, Issue 11, November 2015

Content Based Filtering In Online Social Networking

[1] ShalakhaPotdar, [2] Prof.P.V.Kulkarni
[1]Student, [2]Professor.,
Government College of Engineering Aurangabad
[1]shalakapotdar1@gmail.com,[2]pallavi.k11@gmail.com

***Abstract*- Nowadays in this internet world social networking sites are the most popular to everyone. One major problem in social networking sites are privacy and security policies. No social networking site has done much to control this issue. This paper proposes the system to filter unwanted messages through the use of content based filtering and ML techniques. This helps user to have direct control on messages posted on his private wall.**

***Index Terms*—Artificial Content Based Filtering, Filter Wall, Machine Learning, Online Social Networking**

I. INTRODUCTION

In recent years one of the most popular medium to communicate and share information are online social networking sites. Friends no matter how long they are, can communicate each other effortlessly. As the usage of OSN is spreading rapidly and widely, there is need of today to develop more security mechanism to prevent unwanted messages on user walls. The user receives all messages posted by the friends he follows as there is no classification of filtering tools.The filtering tools gives users the ability to control the messages automatically written on their own walls by filtering out unwanted messages. OSNs e.gFacebook, allows choosing who is permitted to insert message in their walls but content based preferences are not available and so it is not possible to prevent unwanted messages. This paper is an extension of my previous published paper in which the system to filter unwanted messages in OSN was described. Here in this paper we will see in detail how content based filtering helps in prohibiting malware messages on own wall. In next section we will see related work done on content based filtering.

II. RELATED WORK

M. Chau and H. Chen [5] proposed a machine-learning-based approach that combines Web content analysis and Web structure analysis. Each Web page is represented by them by a set of content-based and link-based features, which may be used as the input for many machine learning algorithms. This proposed method may be applied in topic-Specific search engine development and many other Web applications such as Web content management.

R.J. Mooney and L. Roy described that [7] recommender systems improve access to relevant products and information by creating personalized suggestions based on prior examples of a user's likes and dislikes. In content-based recommender methods information about an item itself is used to make suggestions. The benefit of this approach is that it helps in recommending previously unrated items to users with unique likes and dislikes, and to provide explanations for its recommendations.

M.Vanetti, E.Binaghi, B.Carminati, M.Carullo, and E. Ferrari [1] propose a system implementing content-based message filtering for Online Social Networks (OSNs). The system permits OSN users to have a direct control on the messages posted on their walls. This is done with the help of a flexible rule-based system, that allows a user to modify the filtering principles which are to be applied to his/herosnwall, and a Machine Learning based soft classifier automatically marking messages in support of content-based filtering.

Taking into consideration the learning model, there are many approaches in text classification and content-based filtering in general which shows mutual advantages and disadvantages in function of application dependent issues. From the detailed analysis it is proved that Boosting-based classifiers [12], Neural Networks [13],[14] and Support Vector Machines [15] are superior over other popular methods, such as Rocchio [16] and Na¨ıve Bayesian [17].Electronic mail is considered as the original domain of early work on information filtering but subsequent papers also addressed diversified domains which includes newswire articles, Internet "news" articles and broader network resources.

Several experiments proved that bag of Words (BoW) approaches give good performance and succeed in general over many sophisticated text representation that may have higher semantics but lower statistical quality. For short text classification a very different approach is proposed by Bobicev and Sokolova [18] that circumvent the problem of error-prone feature building by adopting a statistical learning method which can perform practically well without feature engineering. This method, called Prediction by Partial Mapping, produces a language model which is used in probabilistic text classifiers that are hard classifiers in nature and very hard to integrate soft multi-membership paradigms.

III. PROPOSED WORK:

The aim of this paper is to develop a system that allows OSN users to easily filter undesired messages according to content based criteria.

As shown in above figure there is three tier architecture in support of OSN. These three layers are

- Social Network Manager (SNM)
- Social Network Application (SNA)
- Graphical User Interface (GUI)

The first layer provides the crucial OSN functionalities. This layer also maintains all the data regarding to the user profile. Data is provided for second layer by applying Filtering Rule (FR) and Black List (BL) after maintenance and administration of all users

In the second layer(SNA) Content Based Message Filtering (CBMF) and Short Text Classifier is composed. This is the key layer for the message categorization according to its CBMF filtering. Black list is also maintained for the user who often sends bad words in message.

GUI is the third layer which provides Graphical User Interface to the user who wants to post his message as a input. In this layer Filtering Rules (FR) are used to filter the unwanted messages and use Black List (BL) for the user who are temporally prohibited to publish messages on user's wall.

As graphically shown in Fig. 1 the path pursued by a message, this can be summarized as follows:

- After entering the private wall of one of the owner's associates, the user attempts to post a message, which is captured by Filtered Wall.
- A ML-based text classifier extracts metadata from the content of the message.
- With the help of data exhorted from the social graph and user's profiles, FW uses metadata provided by the classifier to implement the filtering and BL rules
- Depending on the outcome of the previous step, the message will be available or filtered by FW.
- We will see in detail how content based filtering helps in our system to filter unwanted messages from OSN user wall.

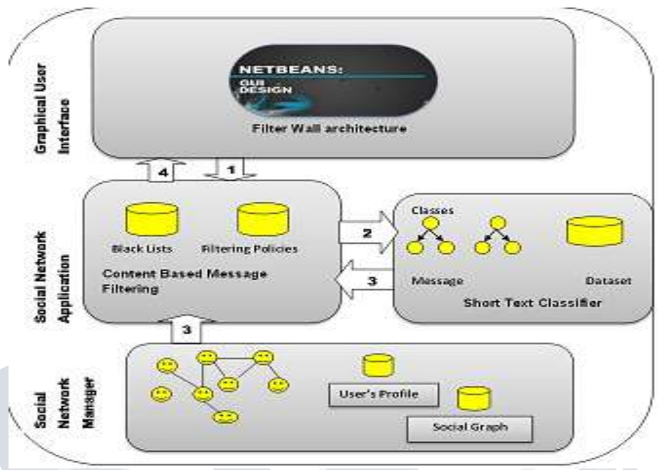

Fig. 1 Architecture of OSN Filter Wall

A. Content Based Filtering

Information required by user is likely to satisfy by information filtering systems which classify randomly generated information and present to the user in more meaningful and systematic way. Our proposed system mainly functions on content based filtering wherein each user is supposed to operate independently. As a result, a content-based filtering system selects information based on the correlation of content of the items with the user preferences as against with a collaborative filtering system which chooses items based on the correlation between people with similar preferences. This filtering is close to text classification as documents processed in content-based filtering are mostly textual in nature. Filtering activity can be modeled as a case of single label, binary classification which partitions incoming documents into relevant and non-relevant categories.

This content-based filtering is mainly based on the use of the Machine Learning paradigm in which a classifier is automatically induced by gaining knowledge from a set of pre-classified examples. The feature extraction method maps text into a compact representation of its content and is evenly applied to training and generalization phases. The practice of content-based filtering on messages posted on OSN user walls poses additional challenges given the short length of these messages as ML mostly has been applied for long-form text. Short text classification has received very little attention up to now in the scientific community.

According to latest work there are difficulties in defining robust features as description of short text is very concise, with many misspellings, non-standard terms and noise. This solution is not applicable in our domain wherein short messages are not summary or part of longer semantically related documents. In information filtering the delivery of items selected from a big collection that the user possibly find interesting or worthwhile and can be seen as a classification task. On the basis of training data a user model is induced which supports the filtering system to classify unseen items into a positive class a (relevant to the user) or a negative class b (irrelevant to the user). The training set comprises of the items that the user found interesting. These items then form training examples that all have a characteristic. This characteristic specifies the class of the item based on either the ranking of the user or on implicit proof. Formally, an item is described as a vector V = (v1,v2 ,...,vn) of n components. The components can be derived from either the content of the items or from data about the users preferences and can have binary, nominal or numerical attributes. The task of the learning method is to choose a function based on a training set of n input vectors that can categorize any item in the collection. The function y( ) X will either be able to categorize an unseen item as negative or positive at once by returning a binary value or a numerical value. In that case a threshold can be used to decide if the item is relevant or irrelevant to the user.

There are many ways in which terms can be represented so that it can be used as a basis for the learning component. A representation method here that is often used is the vector space model. In this model a document C is represented as an dimensional vector wherein each dimension corresponds to a distinct term and n is the total number of terms which are used in the collection of documents. The document vector is written as in the below given formula, where we is the weight of term t_i that indicates its importance. If document C does not contain term t_i then weight we is zero. The tf-idf scheme is used to determine the term weights. In this method the terms are given a weight that is based on how frequently a term appears in a particular document and how often it occurs in the entire document collection:

$$wi = tf_i . \log(\frac{n}{cf_i})$$

Where, tf_i is the number of occurrences of term t_i in document C, n the total number of documents in the collection and cf_i the number of documents in which term t_i appears at least once.

B. Filtering Rules and Blacklists Mechanism

In this section, we begin with the rules adopted for filtering unwanted messagesieFRs.Later we illustrate Blacklists mechanism.

a) Filtering Rules:

While defining the language for filtering rules specification, these filtering rules should permit users to state constraints on message creators. Hence, there should be different criteria to apply these filtering rules like, imposing conditions on user profile's attributes. It is likely to define rules applying to young creators also, to creators with a given religious or political view and also to creators who are not expert in the given field.Another important relevant issue to be taken into consideration in defining a language for filtering rule specification is thebacking for content based rules.This means messages will be identified by filtering rules according to constraints on their contents. With the help of content-based constraints it would be possible to identify messages that are neutral or non-neutral. An average OSN user may have difficulties in defining the precise threshold for the membership level. To solve this issue it is needed to make the user specify the membership level threshold more comfortably.We also believe it would be worthwhile allowing the specification of a tolerance value which is associated with each basic constraint and defines that how much the membership level should be lower than the membership threshold given in the constraint. The tolerance would help the system to handle the messages that are very close to satisfy the rule and hence they might deserve a special treatment. As an example, we might have a rule which would block messages with offensive class with a membership level greater than 0.7. As such messages with offensive class with membership level of 0.69 will be published, as they are not filtered by the rule. However, if tolerance value 0.05 is introduced in the previous content-based constraint it will allow the system to handle these messages automatically. The last section of a filtering rule is the action that the system has to take on the messages that satisfy the rule. The possible actions we are seeing are "block", "publish" and "notify", with the semantics of blocking/publishing the message, or we can notify the user about the message so to wait him/her decision.

b) Blacklist mechanism:

We make use of a BL mechanism to evade messages from undesired creators. BL is managed and maintained directly by the system, which according to our strategy is able to: (i) identify who are the users to be inserted in the BL, (ii) block all their messages, and (iii) decide when users retaining in the BL is finished. These tasks can be performed automatically by the system if the BL mechanism is instructed with some rules (BL rules). These rules aim to specify (a) how the BL mechanism will detect users to be banned and (b) for how long the banned users will retained in the BL, i.e., the retention time. As per our system design, above rules are not defined by the Social Network manager, which proposes that these rules are not anticipated as general high level directives to be applied to the whole community; instead we decide to let the wall owners to specify BL rules regulating who has to be banned from their walls. Thus, the wall owner is able to clearly define how the system has to detect users to be banned and alsoto specify time for the banned users to stay in the BL. According to this strategy, a user might be banned from a wall and at the same time, is able to post in other walls. While defining the language of BL rule specification we have mainlyconsidered issue of how to identify users to be banned. With the help of this specification, wall owners are able to ban from their walls, e.g., users they do not know directly or users that are friend of a given person as they might have a bad opinion of this person. This banning can be imposed for an uncertain time period or for a specific time window.

Moreover, banning criteria take in consideration also users' behavior in the OSN.The measure we define isthat if within a specific time interval a user if user's behavior is not improved ie he/she continues to post spam messages or bad words, he/she is considered to stay in the BL for another while. This principle is for those users who have been already inserted in the BL at least one time.

IV. IMPLEMENTATION :

Here we will see two main modules implemented in our OSN system:

A. *Training Module:*

- In this, admin give categories to the post document where categories are nothing but Valid Post and Invalid Post.
- Here we take at least 5 valid and 5 invalid posts then for each keyword the IDF(Inverse Document Frequency) is calculated for valid posts as well as invalid post. With this, valid weight for the keyword is found out based on the formula 1/IDF of Keyword.
- Probability is calculated for each post is as valid by following formula

$$\text{P(Each post/Valid)} = \frac{\text{Summation Weight of valid}}{\text{Summation Weight of valid} + \text{summation weight of invalid}}$$

- The training post with its probability is then stored in the database.

B. *Detection Module:*

- In this module post is detected whether it is valid or invalid.
- Here after receiving keywords from the post its IDF is calculated from train valid and invalid document. Then weight and probability of the post is found out.
- Then we take average probability of valid post and Invalid post.
- Later we compare the probability of entered post with average of valid posts and invalid posts. If entered post is near to the valid post's average probability, we declare it as valid post or else invalid post.

V. CONCLUSION

In this paper we have represented a system which filters unwanted messages in online Social Networks. This is done through content based message filtering which is mainly based on machine learning paradigm. The system here takes advantage of a ML soft classifier to enforce customizable content-dependent Filter Rules. We have also seen in detail the content based blacklist which bans user from posting on the owners OSN wall. We would like to mention that the system proposed in this paper represents just the basic set of functionalities needed to provide a sophisticated tool for OSN message filtering. The proposed system may experience problems similar to those encountered in the specification of OSN privacy settings. Furthermore we plan to study the development of a system which will filter unwanted images with the help of image retrieval system. This system has a huge future scope in the field of Online Social Networks as the security and privacy has become the main concern in the internet world.

REFERENCE

[1] M.Vanetti, E.Binaghi, B.Carminati,M.Carullo, and E.Ferrari, "Content-Based Filtering in On-Line Social Networks," proc. ECML/PKDD Workshop Privacy and Security Issues in Data Mining and Machine Learning (PSDML'10), 2010.

[2] Measuring semantic similarity between words using web search engines. In www.'07: Proceedings of the 16th international 757{766, New York, NY, USA, 2007.

[3] A.Adomavicius and G.Tuzhilin, "Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions,"

IEEE Trans. Knowledge and Data Eng., vol. 17, no. 6, pp. 734-749, June 2005.

[4] F.Sebastiani, "Machine learning in automated text categorization," ACM Computing Surveys,vol.34,no. 1, pp. 147,2002.

[5] M. Chau and H. Chen, "A Machine Learning Approach to Web Page Filtering Using Content and Structure Analysis," Decision Support Systems, vol.44, no.2, pp.483-494, 2008.

[6] N.J.Belkin and W.B.Croft, "Information filtering and information retrieval: Two the sides of the same coin?" *Communications of ACM*, vol.35 , no.12,pp.29-38,1992.

[7] R.J.Mooney and L.Roy, "Content-Based Book Recommending Using Learning for Text Categorization," Proc. Fifth ACM Cpnf.Digital Libraries,pp.195-204,2000.

[8] Boykin, P.O., Roychowdhury, V.P.: Leveraging social networks to fight spam. IEEE Computer MagaZine 38, 61-67(2005).

[9] P. J. Hayes, P. M. Andersen, I. B. Nirenburg and L. M. Schmandt, "Tcs: a shell for content-based text categorization,"in Proceedings of 6th IEEE Conference on Artificial Intelligence Applications (CAIA-90). IEEE Computer Society Press, Los Alamitos, US, 1990, pp.320-326.

[10] M. J. Pazzani and D. Billsus, "Learning and Revising User Profiles: The Identification of InterestingWeb Sites,", Machine Learning, vol. 27, no. 3, pp. 313-331 1997.

[11] Uszok, J.M. Bradshaw, M. Johnson, R.Jeffers, A. Tate, J. Dalton, and S. Aitken, "Kaos Policy Management for Semantic Web Services," IEEE Intelligent Systems, vol.19, no.4, pp.32-41, July /Aug.2004.

[12] R.E. Schapire and Y. Singer, "Boostexter: a boosting –based system for text categorization," Machine Learning, vol.39, no.2/3, pp.135-168, 2000

[13] H. Sch¨utze, D. A. Hull, and J. O. Pedersen, "A comparison of classifiers and document representations for the routing problem," in Proceedings of the 18th Annual ACM/SIGIR Conference on Resea. Springer Verlag, 1995, pp. 229–237.

[14] E. D. Wiener, J. O. Pedersen, and A. S. Weigend, "A neural network approach to topic spotting," in Proceedings of 4th Annual Symposium on Document Analysis and Information Retrieval (SDAIR-95), Las Vegas, US, 1995, pp. 317–332

[15] T. Joachims, "Text categorization with support vector machines Learning with many relevant features," in Proceedings of the European Conference on Machine Learning. Springer, 1998, pp. 137–142.

[16] "A probabilistic analysis of the rocchio algorithm with tfidf for text categorization," in Proceedings of International Conference on Machine Learning, 1997, pp. 143–151

[17] S.E.Robertson and K.S.Jones, "Relevance weighting of search terms," Journal of the American Society for Information SCIENCE, VOL.27, NO.3, PP.129-146, 1976.

[18] Bobicev and M. Sokolova, "An effective and robust method for short text classification," in AAAI, D. Fox and C. P. Gomes, Eds.AAAI Press, 2008, pp. 1444-1445.