ISSN:0975-9646

Tambe Ujwala S et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5 (6) , 2014, 7339-7345

A Review Paper on Filter Unwanted Messages from OSN

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Abstract—**In the online social network such as Facebook, Twitter, etc., it is possible to display any type of data on the wall of the user. These data can contain unwanted messages such as: policy statement, vulgar data, account staff teasing, etc. other users can see the data and may also rule on such a position. Such a position can affect user social image. So, the safety of such personal wall is an important issue. To some extent face book allows users to specify which helped to put messages in their walls (i.e., friends, friends of friends, or defined groups of friends). However, no preferences based on content are supported, so it is impossible to prevent the display of these unwanted messages. To protect a spam message posted on the wall of the user and to protect the user social image is an important issue in the social networking site. To filter out unwanted messages, we offer three levels architecture containing a message classifier based on the content and use of machine learning technique. The user is able to customize the filtering rule according to their preferences and / also set the filter on different user privileges i.e. subsidies to allow the user to insert messages in his / her wall.**

We propose a system that allows the user to restrict particular user based on his social reputation also user can extract tags from images displayed and filter accordingly and make the decision whether to allow such content or not.

*Keywords- **online social network, learning machine, short text classification, reputation.***

I. INTRODUCTION

Online Social Networks (OSN) are now one of the most popular interactive media to communicate, share and disseminate a considerable amount of information of human life. Daily and continuous communications involve the exchange of various types of content, including free text, image, audio and video data. According average Facebook user creates 90 pieces of content each month, while more than 30 billion pieces of content (web links, news stories, blogs, notes, photo albums, etc.) shared each month. [1] In the online social network such as Facebook, Twitter, etc., it is possible to display any type of data on the wall of the user. These data can contain unwanted messages .Posting unwanted content on the users wall of social network account can corrupt the social image of the user. So, the safety of this wall is an important issue. In many social networking systems such issue is addressed by providing easy remove content, blocking the installation of the user, which makes post private institution, etc.

But if the user's posts on another user's wall and a
nother user not touch social account for so many days so it can accommodate post on his wall for a long time and can cause corruption of the social image and even if the locking system of the user. Content based on the content of the wall filter does not yet have any system of online social networking. OSN today offer little support to prevent unwanted messages on the walls of the user. For example, Facebook users are only allowed to say who is allowed to insert messages in their walls (i.e. Direct and indirect friends) .Therefore friends the objective of this work is to propose and evaluate experimentally a automated system, called filtered wall (FW), capable of filtering spam walls of OSN user. To automatically assign each text message short a set of categories based on their content, we use machine learning (ML) technical text categorization.

II. LITERATURE SURVEY

Filtering depends on individual preferences explanations or information typically represents long-term interest group. Users get only the data that is extracted. Filtering systems designed to classify information flow of information dynamically generated and presented to the user that the information is likely to meet the needs of users [2]. This document has been primarily focused on the similarity between the information filtering and retrieval of information. In this paper, the technique used to filter information is applied to unstructured or semi-structured, as opposed to database applications that use structured data. PW Foltz and ST Domains use's a technique that analyzes the interests of the user by analyzing user feedback and keywords provided by the user. Keyword matching technique and latent semantic indexing is used in it. In this user with a similar preference are considered. Also in the early stages of mail was the area of information filtering[3] .PJ Hayes, PM Andersen, IB Nirenburg, LM Schmandt and invented new idea is discussed with respect to the text categorization. Text Categorization Shell (TCS). He also explained that the application of text categorization developed TCS consists of run-time TCS and a rule base system.A. Adomavicius, Tuzhilin G.and discussed an advanced recommendation systems concept, also discussed methods of current recommendation generation are classified into three main categories collaboration, and hybrid recommendation approaches based on the content. But these approaches do not consider the process of understanding of users and items [5]. "The automatic learning of decision rules for text categorization" C. Apte, F. Damerau, SM Weiss, Sholom D., and Weiss discussed ideas to automatically discover classification models that can be used for General categorization of documents or

custom filter free text [6] .J. Golbeck proposed application, called FilmTrust to customize access to the site. But these systems do not provide a layer of filtering policy by which the Users can use the result of the classification process to determine the extent and filter unwanted information [7]
The proposed approach effectively classifies the text to a predefined set of generic classes such as news, events, reviews, offers and private messages. So in this article there was attention to classify news, views and messages according to their categories.

According Mindi McDowell and Damon Morda, social networking is a way to connect millions of people and share information with each other online. Thousands of people using these social networking services worldwide quickly. When you share information between users of social networking sites, you must follow the potential risks. And you need to be wary of what you're sharing [4].

In the opinion of Aaron Beach, Mike Gartrell, and Richard Han, social network information is now being used in a manner for which it may not have been originally proposed. In particular, the increased use of smartphones capable of running applications that access social network information enable applications to be aware of the location and user preferences. However, current models for the exchange of this information, users must compromise their privacy and security [1]. We present several of these privacy issues and security, as well as our design and implementation of solutions to these problems [5]. Our work allows location-based query local mobile devices for users of the information on social networking services without disclosing the identity of the user or compromising users' privacy and security. We argue that it is important that these solutions are accepted as mobile social networks continue to grow exponentially.

Online social networks are now used by hundreds of millions of people and have become an important platform for communication and interaction between users [2, 4]. This led to a wealth of information for application developers that develop over these networks. Any relationship and social information enables a unique breed of application that has not previously existed. In addition, the social network information is now correlated with the physical locations of users, allowing the user information and preferences of social relations interact in real time with their physical environment [5].

Giles Hogben, ENISA said, social networking is the (end-users) a privileged way to manage personal data. It is an area where people take an active interest in how their personal information is managed and displayed rather than holders of accounts as liabilities in most identity management systems. Social engagement is a necessary incentive for end users to engage in processes such as defining the rules of confidentiality and provide feedback on spammers [7]. As previously mentioned, social networking is the world's largest organization of personal data.

As said Ted Demopoulos, social networking is one of the social networking sites such as Facebook, Twitter, Google+, Pinterest and LinkedIn are powerful, allowing you to meet, discuss and share with people around the world . However, with all these capabilities are risks; not only you but your family, friends and employer. In this newsletter we will discuss what the dangers are and how to use these sites more safely.

Based content filtering is an existing system. Where systems information filtering are designed to classify a stream of information generated dynamically transmitted asynchronously by an information producer and present the user with the information that is likely to meet its requirements [3].

2.1 Content-based Filtering

Content Based filtering selects one based on the interests of the user element. It uses previously preferred by the user items, and suggests the best suitable item. Each user is independent of the system based content. This kind of system selects an item, according to the relationship between point of content and users against the recommendations collaboration system that selects article based on the relationship between people with similar preferences [7].The system based on content created profile of a system based on the basis of the rated user of user Content. Articles features are weighted according to characteristics preferred by the user and recommendations are given by the system accordingly. In content filtering function, the main question is whether the system is able to learn user actions related to a particular content source and use them for other types of content. Text classification is similar to the content based filtering material covered in this type of system are primarily textual. Social profile online social network user must be taken into account, which makes the content-based filtering system difficult to apply in the field of OSN as a standalone system. Systems information filtering are designed to classify a stream of Information generated dynamically dispatched asynchronously by an information producer and present the user with the information that is likely to meet its requirements [6].

In the filtering based on the content of each user is assumed to operate independently. Therefore, a filter system based on the contents of a selected data element based on the correlation between the content items and the user preferences as opposed to a system which chooses collaborative filtering items based on the correlation between the persons having similar preferences [7].While the email was the original early work on information filtering domain, the following documents have focused on a variety of fields, including articles north, "news" articles and Internet resources wider network. Treated in filtering based on textual content documents are mostly in nature, which makes the content-based classification of text near filtering. The activity of filtering can be modeled, in fact, as a case of the single label binary classification, partitioning incoming documents into relevant categories and irrelevant.

More complex filtering systems include multi-label text categorization automatic labeling messages thematic Cate partial-Categories.

Content-based filtering is based primarily on the use of one paradigm ML classifier that is auto-matically induced learning a set of pre-classified examples. A remarkable variety of related work has recently appeared, which differ for feature extraction methods adopted, learning style, and the collection of samples, [1], [3].The extraction of text features maps procedure into a compact representation of its content and is uniformly applied to training and generalization phases. Several experiments show that bag of words (Bow) ap-approaches provide good performance and generally outweigh more sophisticated text representation which may have a higher semantics, but the lower statistical quality . As regards the model of learning is concerned, there is a number of approaches depending on the main-wire Tering content and text classification typically showing the mutual disadvantages and advantages according to the issues that rely on the application. In [4] a detailed comparative analysis was performed to confirm the superiority of Stimuler- classifiers, neural networks and Support Vector Machines on other popular methods such as Rocchio and naive Bayes However, it is interesting to note that most of the work related to text filtering was applied by ML long text form and evaluated methods for text classification performance strictly depends on the nature of textual documents.

The application of filtering based on the content of messages posted on the walls of OSN users pose additional challenges given the short duration of these messages other than the wide range of topics that can be discussed. Short text classification has so far received little attention in the scientific community. Recent work highlights The difficulty of defining robust features, mainly due to the fact that the description of the short text is concise, with many spellings, non-standard terms and noise errors. Zelikovitz and Hirsh to try to improve the classification of short text strings developing semi supervised learning strategy based on a combination of labeled training data plus a secondary corpus of documents related but unlabeled more. This solution is inapplicable in our area where short messages are not abstract or part of the documents more semantically related. A different approach is proposed by Bobicev and Sokolova that bypass the problem of the construction function of errors by adopting a statistical learning method that can perform reasonably well without engineering option. However, this method, the forecast called partial application, produces a language model that is used in probabilistic classifiers text classifiers that are hard in nature and do not easily integrate soft, multi-membership paradigms. In our scenario, we consider the gradual accession of the classes key to the definition of personalization strategies based on flexible rules.

2.2 Policy-based personalization of OSN contents

Recently, there have been some proposals operator clas-classification mechanisms to customize access in OSN. For example, in a classification method was proposed to classify short text messages to avoid overwhelming users of micro blogging services in the raw data. The system described in and Twitter2 focuses on a set of categories associated with each describing updates its contents. The user can then see that certain types of tweets on the basis of his / her interests. However, Kuter and Golbeck [7] propose an application called Film Trust, which operates OSN relationships of trust and provenance information to customize access to the site. However, these systems do not provide a layer of filtering policy by which the user can exploit the results of the classification process and decide how to filter unwanted information. However, our political language filter allows adjustment of MRF in a variety of criteria, which considers not only the results of the classification process, but also the relationship of the owner of the wall with other OSN users as well as information on the user's profile. In addition, our system is complemented by a flexible mechanism for BL management that provides an additional opportunity to customize the filtering procedure.

The only social networking service, we are aware provide filtering capabilities for its users is MyWOT, social networking service that allows its subscribers the ability to: 1) the rate of resources in relation to four criteria: reliability, vendor reliability, privacy and child safety; 2) set preferences that determine whether the browser should block access to a particular resource, or should send a warning message based on the specified value. Although there are some similarities, the AP-MyWOT approach is quite different from ours. In particular, it supports the filtering criteria that are much less flexible than Filtered wall because they are based on the four criteria mentioned above. In addition, no mechanism for automatic classification is provided to the end user.

III. PROPOSED SYSTEM

In this section, we describe the architecture of the wall filtered with short text classifier users interact with the system through a graphical interface to configure and manage their FRS / BLS. Online social networks extend the process in different situations for people to access services within their walls in a single user environment of the situation [6].

As shown in Figure 1, the architecture of the wall filter consists of the following to access effective in real-time applications such as face book and other social networks. First layer in the OSN generally provides basic functionality with the profile and relationship management and also specifies many other network services externally in real time process generations.[1]

A.Filtered Wall Architecture

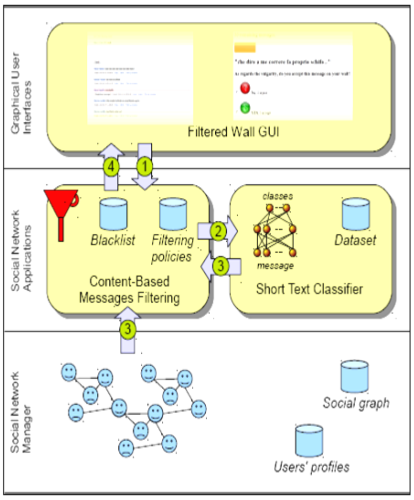

Fig.1. Wall conceptual architecture and filtered stream messages follow, writing for publication .

The first layer, called the Social Network Manager (SNM), it provides the basic Functionality OSN (i.e., profile and Relationship Management), while the second layer provides support for external applications Social Network (SCN). SNA supported in turn may need an extra layer to their graphical user interfaces necessary (GUI).

To protect a spam message posted on the wall of the user and to protect the user social image is an important issue in the social networking site. To filter out unwanted messages, we offer three levels architecture containing a message classifier based on the content and use of machine learning technique. The user is able to customize the filtering rule according to their preferences and / also set the filter on different user privileges i.e. subsidies to allow the user to insert messages in his / her wall.

B.Objective:

1: To provide a filtered current wall (FW) mechanism that is able to filter out unwanted messages wall present in the online social network

2: Provide classification mechanism to prevent unnecessary data overwhelmed present in Wall position of the user.

3: Improve the quality of classification

This system is proposed automated system called filtered wall (FW), capable of filtering spam wall of OSN user. This system uses machine learning (ML) technique for text categorization automatically assigned to each short text message a set of categories based on their content. With this classification of text filtering and blacklist users of the facility is also available. As mentioned above figure, it is a three-tier architecture. Social network manager layer provides basic functionality OSN. Second layer provides support for external social network application and needs of the graphical user interface. Hence our system operates majorly in the second and third layer where you can categorize and filter text.

Standard measures of classification:

1. The user when trying to post a message on the wall details, then it is first introduced into the wall filtered

2. A machine learning text-based classifier to retrieve the metadata of the message content

3. After this process filtered wall returns the metadata provided by the classifier. With metadata and user profile Black List rules and filtering criteria is applied

4. According to this forum post the output will be filtered or filtered published by wall

Here are some strategies text representations

C. Representation of Text:

The extraction of an appropriate set of features that represent the text of a given document is a crucial task that greatly affects the overall performance of the clas-cation strategy. Different sets of features for authorization cate-text have been proposed in the literature [4], but all of the most appropriate features and functionality representation for short text messages have not yet been sufficiently studied. Based on these considerations and on the basis of our experience [5], we consider three types of features, bow, and document properties (Dp) and contextual characteristics (CF). The first two types of devices, already used in [5], are endogenous, meaning that they are entirely derived from the information contained in the message text. Text representation using indigenous knowledge has a good general applicability, but in a business context, it is also legitimate to use exogenous

Knowledge, namely, sources of information outside of my body-wise but directly or indirectly related to the message itself. We introduce information modeling CF char-acterize the environment in which the user is viewing. These features play a key role in understanding the deterministic semantics of messages [4]. All the features offered were analyzed in the phase of experimental evaluation to determine the combination that best suits short message classification (see Section IV).

There are two types of functions as follows

*a. BOW (bag of words), Document Properties***:**

These are endogenous, meaning that they are entirely derived from the information contained in the message text. Text representation using indigenous knowledge has a good general applicability, but in a business context, it is Also legitimate to use exogenous knowledge i.e., sources of information outside of the message body, but directly or indirectly related to the message itself.

In Document Properties the following are the categories that we can apply to the particular text

1. Good words we do know the words to our set and the corresponding document.
2. Bad words we do know our dirty words together and in the corresponding document.
3. Words of capital: it expresses the amount of words, mostly written in capital letters.
4. Punctuation Character: We calculate punctuation and remove game message.
5. Exclamation Point: We calculate the exclamation and remove game message.
6. Question Mark: We calculate the question mark and remove game message.

b. Contextual characteristics:
This feature characterizes the environment where the user is viewing. They play a key role in semantic understanding of messages features based on exogenous knowledge .Regarding, CF, instead of being calculated on the body of the message, they are designed as a representation of VSM text that characterizes environment where messages are displayed (the topics of discussion, the group name or any other relevant surrounding text messages). SFC are not very different from the bow features describing the nature of the data. Therefore, all the formal definitions introduced for functions arc also apply to the SFC.

IV. SHORT TEXT CLASSIFIER

Techniques used for text classification works well on data sets with large documents such as News corpus established [10], but suffer when the documents in the corpus are short. In this context, the key issues are the definition of a set of discriminative features and characterization for the representation of the underlying concepts and the collection of a comprehensive and coherent set of supervised examples.

Our study aims to develop and evaluate different representation techniques in combination with neural learning strategy to classify semantically short texts. From the point of view ML, we approach the task in defining a strategy to two hierarchical levels assuming it is best to identify and eliminate penalties "neutral" and classify "non-neutral" sentences by the class of interest instead of doing everything in one step. This choice is motivated by the work showing the associated benefits in the text classification and / or short texts using a hierarchical strategy [1]. The first task level is designed as a hard classification in which the short texts are tagged with net neutral and non-neutral labels. The soft second level classifier is the crisp set of non-neutral and short texts for each of them, "enough" estimated relevance or "progressive membership" for each class designed product, without deciding "hard" on one of them. This list of categories is then used by subsequent phases of the filtering process.

A. Text classification
Text classification is the study of the classification of text documents into predefined categories. The subject has been studied extensively at conferences SIGIR and evaluated on standard benchmarks. There are a number of main approaches. For example, naive Bayes has been widely used. It uses the joint probabilities of words and categories to estimate the probability that a given document belongs to each category. Documents with a probability greater than a certain threshold are considered relevant for this category. The method most k-nearest neighbor is another popular approach to text classification. For a given document, the neighbor's k most similar to a given document is first identified. The categories of these neighbors are then used to decide the class of a given document. A threshold is used for each category. Programs of neural networks, designed to model the human nervous system and learning models by modifying the weights between nodes from training examples have also been applied to text classification. Feedforward / back propagation neural network (FF / BP NN) is generally used. Frequencies of TFIDF term or terms are used as input to the network. Based on the training examples, the network can be trained to predict the category of a document. Another new technique used in text classification is called support vector machine (SVM), an approach that tries to find a hyper plane that separates two classes better. Joachims SVM first application to a problem of text classification. It has been shown that the best performance SVM among different classifiers throughout Reuters-21578 data. In addition to the general text documents, pages classification ofWeb was also studied.Web pages are often noisy, but they provide additional information about each document. For example, the terms marked with different HTML tags (such as titles or headings) can be assigned a higher than normal text weight. Conditions of Web pages neighborhood were also used in attempt to improve the performance of classification. However, it is worse performance because there are often too many words and too many neighbors' crosslinks between different classes [5]. The use of other information on the Web pages of area has been proposed. Examples of such information include Predicted category of neighbors of a page [5.], anchor text pointing to a page or outbound links from page to page all other documents. It has been shown that the Use of this additional information improves the classification results.

a. Text Representation
Text representation of a given document is an important task that greatly affects the performance of classification process. It is done by extracting features for a given document. The survey [7] suggest three types of important features for the representation of text. They are bags of words, the document properties (DP) and contextual factors (CF) .The first two types of features derived entirely from information contained in the message text [7] that the background characteristics are exogenous. Text representation using endogenous. Bag of words in terms of representation are identified by words. It is also important to use entity which is extracted from the outside, but the content of the message in relation to the message itself. A contextual feature is introduced in which characterize the environment in which the user is viewing. According to [6] .It determines the semantics of messages [6] .Vector space is the text representation model by which a text document is represented as a binary vector or actual weight. These three characteristics are experimentally evaluated for short text classification in [8] for their relevance [5].

b. Machine Learning Based Classification:
In this section, we illustrate the evaluation study of the performance. We conducted modules classification and filtering. We begin by describing the dataset A [1]. The Problem and Dataset description. The analysis of related work has highlighted the absence of a publicly accessible reference for comparing different approaches to content-based classification of short texts OSN[6]. To deal with this shortcoming, we have built and made available a dataset D

message from Facebook. The data set called WmSnSec is available online at 1266 messages from publicly Italian groups were selected and extracted using an automated procedure that removes unwanted spam messages and for each message stores the message body and the name of the group of which it is derived[2]. The messages come from the section of the Web page of the group, where all registered users can post a new message or reply to messages already posted by other users. We address short text categorization as a process of classification two hierarchical levels. The top level classifier performs a hard binary categorization that labels messages as neutral and non-neutral. The task of the first level filtering facilitates following second level of the task in which a finer classification is performed [3]. The second level classifier performs a soft partition of non-neutral messages attributed to a given message progressive composition to each non-neutral classes. Among the variety of Multi-Class ML models well suited for text classification, we choose the Radial Basic network functions (RBF) model[3],[5] for its robustness proven in the treatment of imprecision inherent in missions and class for the experienced competitive behavior compared to others on the state of the art classifiers. The first graders and second-level are then structured as regular RBF conceived as hard and soft classifier respectively [7].

V. Filtering Rules And Blacklist Management

In the proposed system, we model a social network as a directed graph, where each node corresponds to a network user and edges represent relationships between different users. In particular, each edge is marked by the type of the relationship (eg, a friend, colleague, mother), and possibly the corresponding level of confidence, which is how a given user considers trustworthy to respect of this specific kind of relationship the user that he / she establishes the relationship. Black management is to prevent unwanted messages creators, regardless of their content. BL'S are directly managed by the system, which should be able to determine who the users are inserted in the BL and decide when the user retention in the BL is finished. BL rules are the owner of the wall can identify users to be blocked based on their profiles, and their relations in the SVO. Therefore, using a rule of BL, wall owners are eg able to prevent the walls from users they do not know directly (i.e. with whom they have indirect relations), or users who are friends of a particular person, because they can have a bad opinion of that person. The ban can be adopted for an indefinite period of time or for a specific time window.

A. Filtering Rules

OSN allows users to express constraints on designer's message. Creators on which FR apply can be selected based on several different criteria; one of the most relevant is by imposing conditions on the attributes of their profile. In this way, it is for example possible to define rules applicable only to young designers and creators for religious / political data. Creators can also be identified by the use of information on their social graph. This implies conditions state the type, depth and confidence values of the relationship (s) designers must be involved in order to apply the rules defined. FR is dependent on following factors

- Author
- Creator Spec
- Content Spec
- Action

An author is a person who defines the rules. Creator Spec denotes the set of OSN user and Content Spec is a Boolean expression defined on content. Action denotes the action to be performed by the system on the messages matching content Spec and created by users identified by creator Spec [1].

B.Basic Machine Learning Classification

In this section, we illustrate the evaluation study of the performance. We conducted modules classification and filtering. We begin by describing the dataset. The Problem and Dataset description. The analysis of related work has highlighted the absence of a publicly accessible reference for comparing different approaches to content-based classification of short texts OSN. To deal with this shortcoming, we have built and made available dataset D messages from Facebook. The data set called WmSnSec is available online at 1266 messages from publicly Italian groups were selected and extracted using an automated procedure that removes unwanted spam messages and for each message stores the message body and the name of the group of which it is derived. The messages come from the section of the Web page of the group, where all registered users can post a new message or reply to messages already posted by other users. In the definition of the specification language for the FRS, we consider three main issues that we believe should influence a decision filtering messages. First, in the OSN as in everyday life, the same message can have different meanings and relevance in terms of writing. Therefore, FRS should allow users to express constraints on designer's message. Creators who apply FR can be chosen based on several different criteria; one of the most relevant is by imposing conditions on the attributes of their profile. In this way, it is for example possible to define rules applicable only to young designers and creator's data for religious / political. Given the scenario creators of social networks can also be identified by the use of the information on their social graph. This implies conditions state type values, depth and confidence in the relationship (s) designers must be involved to implement the specified rules. All these options are formalized by the notion of designer specification, defined as follows.

C. Setup Wizard 5.3 online for FRS thresholds

As mentioned in the previous section, we address the problem of defining thresholds for filtering rules, the design and implementation of FW, a process line configuration assistant (AOS). For each message, the user tells the system the decision to accept or reject the message. Collection and treatment decisions of the user on an appropriate set of broadcast messages on all classes to calculate custom thresholds representing the attitude of the user to accept or reject certain content. Such messages are selected according to the following process. Taken a number of a fraction of the data set and not belonging to sets of training / testing non-neutral messages are classified by the ML to have, for each message, the values belonging to the second class level.

D.Blacklists

Another component of the system is a mechanism to prevent spam BL creators, regardless of their content. BL'S are directly managed by the system, which should be able to determine who the users are inserted in the BL and decide when the user retention in the BL is finished. To improve flexibility, this information is in the system by a set of rules, the rules on BL. These rules are not defined by the NPS, so they are not intended as guidelines for high level will be applied to the entire community. Instead, we decided to let the users themselves, ie, the owners of the wall to clarify the rules of BL control should be banished from their walls and for how long. Therefore, a user may be excluded from a wall, at the same time, the ability to publish in the other walls. Similar to the MRF, our rules make the owner wall BL able to identify users to be blocked according to their profiles and their relationships in the OSN. Therefore, using a rule of BL, wall owners are eg able to prevent the walls from users they do not know directly (ie with whom they have indirect relations), or users who are friends of a particular person, because they can have a bad opinion of that person. The ban can be adopted for an indefinite period or for a specific time window. In addition, the prohibition of criteria may also take into account the behavior of users in the OSN. Specifically, bad behavior information indicating potential users, we have focused on two main measures. The first is related to the principle that if a user in a given time interval has been inserted into a BL repeatedly, for example greater than a given threshold, he / she can earn the BL stay for another such as his / her behavior has not improved. This principle is valid for users who have already been included in the BL considered at least once. However, to catch new bad behavior, we use the relative frequency (RF), which allows the system to be able to detect the users whose messages are not yet the FR. These two measures can be calculated locally, that is, considering only the messages and / or user specify the rule or BL BL in the world, that is, taking into account all the walls and / or BLS OSN users.

VI. CONCLUSION

In this article, we presented a system to filter out unwanted messages walls OSN. The system exploits a soft ML classifier to implement the content depends customizable FR. In addition, the flexibility of the system in terms of filtering options is enhanced by the direction of BLS. This system approach when the user decides to be inserted into a blacklist. The system developed GUI and a set of tools that make BLS and RNR easier and simpler specifications.

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