IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 1, May 2023

Unwanted Message Filtering on Social Network Sites User Wall

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Abstract: *In the present day scenario online social networks (OSN) are very popular and one of the most interactive medium to share, communicate and exchange numerous types of information like text, image, audio, video etc. All thesepublicly shared information are explicitly viewed by connected people in the blog or networks and having an enormous social impact in human mind. Posting or commenting on particular public/private areas called wall, may include superfluous messages or sensitive data. Information filtering can therefore have a solid influence in online social networks and it can be used to give users the facility to organize the messages written on public areas by filtering out unwanted wordings. In this paper, we have proposed a system which may allow OSN users to have a direct control on posting or commenting on their walls with the help of information filtering. Whenever user posts a message it will be intercepted by the filtered wall, and applies Filtering and Black List Rules to the message. If it is not violated by filtering and black list rules, then the message will be displayed on user walls.*

Keywords: Content Based Message Filtering, DemographicFiltering, Collaborative Filtering

I. INTRODUCTION

A social networking service is a platform to build socialnetworks or social relations among people who, for example, share interests, activities and distribute a considerable amount of human life information. Daily and continuous communications imply the exchange of several types of content, including free text, image, audio, andvideo data. With the rapid growth of social media, users especially adolescents are spending significant amount of time on various social networking sites to connect with others, to share information, and to pursue common interests. OSNs provide very little support to prevent unwanted messages on user walls. A main part of social network content is constituted by short text, a notable example are the messages permanently written by OSN users on particular public or private areas, called in general walls. With the lack of classification or filtering tools, the user receives all messages posted by the users he follows.In most cases, the user receive a noisy stream of updates. There is a need to develop more security mechanisms for different communication technologies, particularly online social networks. Therefore a major task of today's Online Social Networks (OSN) is information filtering. Information filtering has been greatly explored for textual documents and more recently, web content[1][2][3]. Filtering messages can be used to give users the ability to automatically control the messages written on users walls, by filtering out unwanted messages.

Filtered wall is proposed for OSN users to have a direct control on the messages posted on their walls. For filtering mechanism filtered wall uses Machine Learning technique for assigning categories to each message, and also uses Filtering rules so that user canexplicitly specify which contents should not be displayed on their walls. Filtered wall also contains Black List Rules for blocking particular user up to certain period of time.The proposed system gives security to the On-line Social Networks.

II. EXISTING SYSTEM

Online social Networks (OSNs) provide very little support to prevent unwanted messages on user walls. For example, facebook allows people to post any kind of messages and can also share and upload photos to the user wall i.e., from friends, friends of friends or defined groups. Although it does not provide any content-based support and therefore itis not possible to avert undesired messages, such as political, general advertisements, product based advertisements, no

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matter of the user who posts them. Providing this service is not only a matter of using previously defined web content mining techniques for a different application, rather it requires to design adhoc classification strategies. This is because wall messages are composed by short text for which traditional classification methods have serious limitations since short texts do not provide adequate word occurrences. In Existing Systemthere is no mechanism for filtering unwanted content in user walls.

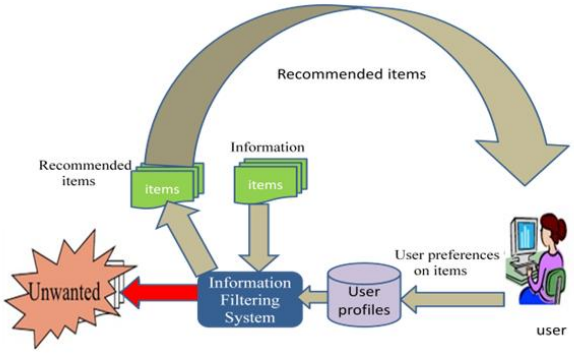
III. PROPOSED SYSTEM

Filtered Wall (FW) architecture has been proposed for filtering unwanted messages from OSN user walls. Filteredwall architecture utilizes Machine Learning (ML) techniques for text categorization to automatically assign a category to each message according to its content. The prime efforts in building a resilient short text classifier (STC) are concentrated in the extraction and selection of a set of characterizing and distinguish features. Filtered wall uses neural learning model, which is today recognized as one of the most efficient solutions in text classification.

The overall short text classification strategy is based on Radial Basis Function Networks (RBFN)[5][10].Besides classification facilities, the system present a powerful rule layer exploiting a flexible language to specify FilteringRules (FRs), by which users can specify what contents, should not be unveil on their walls. In addition, the system furnish the support for user-defined Blacklists (BLs), that is, the list of users that are temporarily halt to post any kindof messages on a user wall. Different semiology for filtering rules to better fit the considered domain, an online setup assistant (OSA) is used to help users in FR specification. The main components of Proposed System are Short Text Classification (STC), Content Based Message Filtering (CBMF), Collaborative Filtering, Filtering Rules (FRs), and Black list Rules (BLs)[12].In addition to text Filtering this paper also implements how to filter the text of a given image[17][19][20], and also Insertsparticular objects in the Black list for avoiding specific advertisements.

IV. WHAT IS INFORMATION FILTERING ?

An Information filtering system is a system that removes unwanted information from an information streamusing (semi) automated or computerized methods prior to presentation to a human user. In social networking sites user may get different types of messages which may be unrelated or may have different meanings, so user does not have any use with that type of messages, so user should have one mechanism for avoiding unwanted messages i.e., Information Filtering. Information Filtering first stores the user preferences of items, based on the preferences it filters unwanted data and accepts only recommended items. These recommended items are only displayed on the user wall. Why we need Information Filtering means it saves user time and accepts only user interested items.



Information Filtering

V. FILTERED WALL ARCHITECTURE

Filtered wall architecture filters the unwanted messagesfrom online social networks. It consists of three layers.

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

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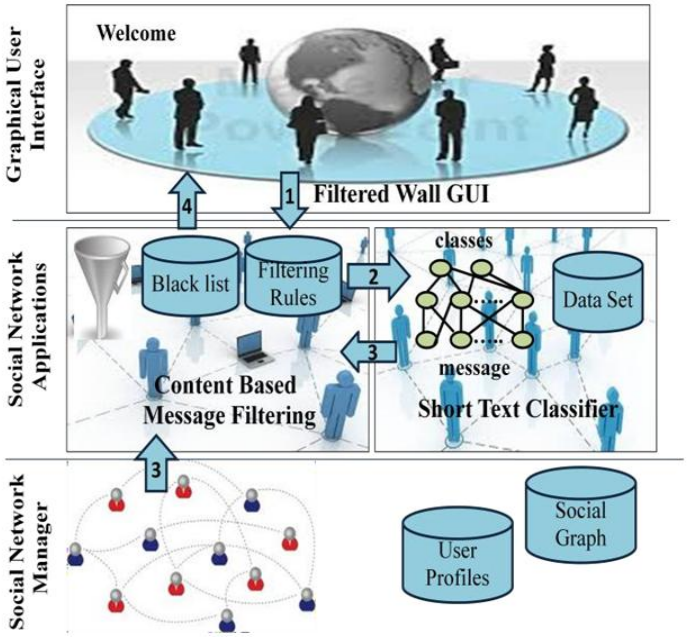

Filtered wall architecture

Social Network Manager (SNM) provides basic OSN functionalities, and it represents the user profile as a social graph i.e., each node represents network user and edges represents relationship between two users. It maintains the data related to user profile and provides the data to the second layer for applying filtering rules (FR) and Blacklists(BL). Second layer composed of Content Base Message Filtering (CBMF) and a short text classifier (STC).Third layer consists of graphical user interface by which user provide his input and is able to see published wall messages. Additionally GUI provides user the facility to apply filtering rules for his wall messages and helps to provide list of BL user who are temporally prevented to publish messages on user's wall. The GUI also consists of Filtered Wall (FW) where the user is able to see his desirable messages.

As per the filtered wall architecture, when the user post a message on a private wall of his or her contact it is intercepted by the filtered wall. Then a short text classifier categories a message according to its content and CBMF applies FR and BL as per the data provided by the third layer. Based on the result of above step the message is published or filtered by FW.

5.1 Short Text Classifier (STC)

Short text classifier consists of two components.

- Text Representation
- Machine Learning Classification

In Text Representation Short Text Classifier extracts the features of text by using vector space model. Machine Learning Classification classifies messages based on RadialBasis Function Network Method

Text Representation

In automatic text classification, it has been proved that the term is the best unit for text representation and classification [6].Though a text document expresses vast range of information, unfortunately, it lacks the imposed structure of traditional database. Therefore, unstructured data, particularly free running text data has to be transformed into a structured data [15]. To do this, many preprocessing techniques are proposed in literature [7,8].After converting an unstructured data into a structured data, we need to have an effective document representation model to build an efficient classification system.

Text representation extracts three types of features, Bag of Words (Bow), Document properties (Dp) and Contextual Features (CF)[4][8][9][10]. The first two types of features are endogenous, that is, they arecompletely derived from the

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information contained within the text of the message. Bag of Word (Bow) is one of the basic methods of representing a document. The Bow is used to form a vector representing a document using the frequency count of each term in the document.

The underlying model for text representation is the Vector Space Model (VSM)[16][11].In the vector space model a document *D* is represented as an *m*- dimensional vector, where each dimension corresponds to a distinct term and *m* is the total number of terms used in the collection of documents. The document vector is written as, where $\mathbf{w_i}$ is the weight of term $\mathbf{t_i}$ that indicates its importance. If document *D* does not contain term $\mathbf{t_i}$ then weight $\mathbf{w_i}$ is zero. Term weights can be determined byusing the *tf-idf* scheme. In the Boolean vector approach

the terms are assigned a weight that is based on how often aterm appears in a particular document and how

frequently it occurs in the entire document collection. Value 1 is assigned to the term if it does occurs in a document, otherwise value 0 is assigned to the term. A more sophisticated measure is the *tf-idf* scheme. *tf* is called the term frequency $\mathbf{tf_i}$, i.e., the number of occurrences of term $\mathbf{t_i}$ in document *D*. *idf* is called the inverse document frequency and is calculated as follows.

$$idf_i = \log(n/ df_i)$$

where *n* is the total number of documents in the collection and $\mathbf{df}_i$ the number of documents in which term appears at least once. The weighting factor $\mathbf{w}_i$ of document **i** is determined by the product of the term frequency and the inverse document frequency. In the Bow representation, terms are identified with words. In the case of nonbinary weighting, the weight wkj of term tk in document dj is computed according to the standard term frequency inverse document frequency (tf-idf) weighting function, defined as

$$tf-idf(t_k,d_j) = \#(t_k, d_j).\log. |Tr| / \#Tr(t_k)$$

where #(tk, dj) denotes the number of times tk occurs in dj, and #T r(t_k) denotes the document frequency of term t_k, i.e., the number of documents in Tr in which t_k occurs.

Machine Learning Classification

Short text classification is a hierarchical two level classification. In the first level Radial Basis Function Network (RBFN) classifies whether a message is neutral ornon neutral, in the second level, Non neutral messages are classified producing gradual estimates of appropriateness toeach of the considered category.

RBFNs have a single hidden layer of processing units with local, restricted activation domain, a Gaussian function is commonly used[12]. RBFN main advantages are that classification function is nonlinear, the model may produce confidence values and it may be robustto outliers. The first-level classifier is then structured as a regular RBFN[13]. In the second level of the classification stage, a modification to the standard use of RBFN[6]. Its regular use in classification includes a hard decision on the output values, according to the winner-take-all rule[14], a given input pattern is assigned with the class corresponding to the winner output neuron which has the highest value. In proposed approach it considers all values of the outputneurons as a result of the classification task and interpret them as gradual estimation of multi membership to classes. The collection of preclassified messages presents some critical aspects greatly affecting the performance of theoverall classification strategy.

The overall classificationstrategy as follows. Let Ω be the set of classes to which each message can belong to.

Each element of the supervised collected set of messages $D=\{(m_i,y_i) \ldots (m_{|D|},y_{|D|})\}$

is composed of the text mi and the supervised label $yi \in \{0,1\}^{|\Omega|}$ describing the belongingness to each of the defined classes. The set D is then split into two partitions, namely the training set TrSD and the test set TeSD. The performance of two levels are calculated by using training set.

5.2 Content Based Message Filtering (CBMF)

Content-based filtering, also referred as cognitive filtering, recommends items based on a comparison between the user profile and content of the items. Each items content isrepresented as a set of descriptors or terms, typically the words that occur in a document [7][18]. There are several ways in which terms can be represented in order to be used as a basis for the learning component. A representation method that is often used is the vector space model. In addition to this We use another approach i.e., categorizing text in a Local Language (Natural LanguageProcessing)[21][22][23].

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5.3 Collaborative Filtering

Unlike content-based recommendation methods, collaborative recommender systems [2][18] (or collaborative filtering systems) try to predict the utility of items for a particular user based on the items previously rated by other users. More formally, the utility u(c, s) of item *s* for user *c* is estimated based on the utilities u(cj, s) assigned to item *s* by those users cjЄC who are similar to user *c*.

5.3 Demographic Filtering

Demographic filtering allows users to establish criteria to sort information by age, gender and education to identify the types of users that like a certain item [18].

5.4 Filtering Rules (FRs)

Filtered wall provides a powerful rule layer that uses a flexible language to define Filtering Rules (FRs), by which users can specify which contents should not be present on their walls. users can create their own rules[1].This implies to specify conditions on depth, type and trust values of the relationship(s) creators should be involved in order to apply them the specified rules.

Definition 1 (Creator Specification)

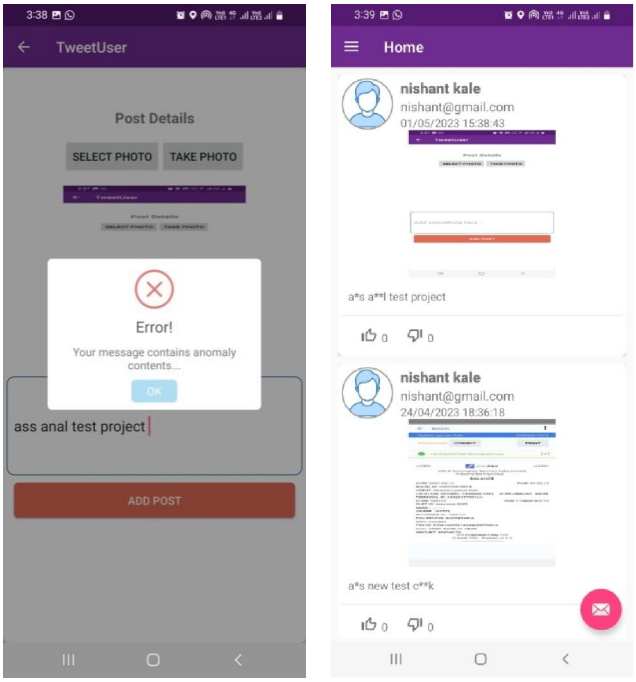
A creator specification creatorSpec absolutely denotes a set of OSN users. It can have one of the following forms, possibly combined [1].

A set of attribute constraints of the form {an OP av}an is a attribute name of user profile.

OP is a comparison operator, compatible with an'sdomain. av is a attribute value of user profile.

Relationship constraints of the set consists of (m, rt, minDepth,maxTrust) denotes all participating OSN users with user m of relationship type rt having depth greater than or equal to minDepth, and trust value lessthan or equalto maxtrust.

VI. RESULT



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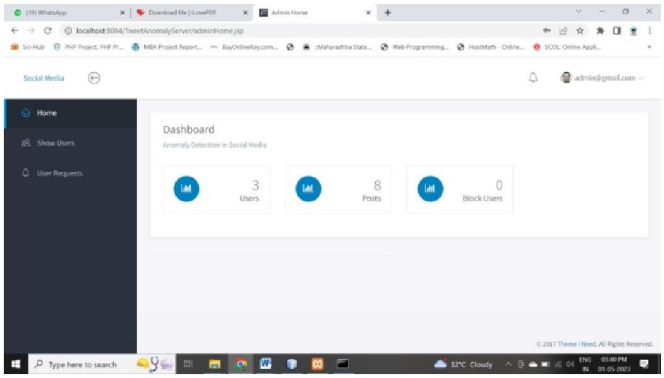

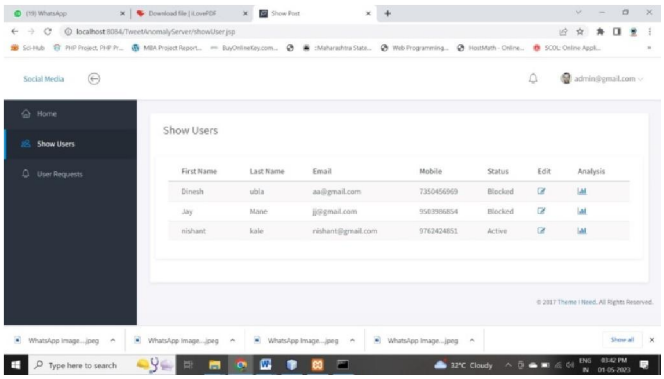

VII. CONCLUSION

Users will use online social networks for many purposes but it may have disadvantages by getting unwanted data, sofor avoiding unwanted data we have proposed filtered wall. In this Filtered wall architecture it consists of Short Text Classifier (STC), Content Based Message Filtering (CBMF), Filtering and Black list Rules. Whenever user gets a message it is intercepted by the filtered wall, then Short Text Classifier (STC) extracts the metadata and classifies the message, then Content Based MessageFiltering (CBMF) assigns a category to the message based on the content. Based on the result of STC and CBMF Filtered wall applies filtering and black list rules. Finally message will be displayed on the user wall, if it does not violates the filtering and black list rules. By using thisFiltered wall architecture performance will be improved. Proposed system allows OSN users to have direct controlon the messages posted on their walls. Additionally we plan to enhance our system by filtering data in videos.

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