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Developing System to Filter Unwanted Texts and Images from Social Network User Wall

Ravindra Takalikar #1, Mahesh Jadhav *2, Subhash Pingale # 3

Department of Computer Science and Engineering, Solapur University
SKN Sinhgad College of Engineering, Pandharpur, Maharashtra,India

* *Department of Computer Science and Engineering, Solapur University*
SKN Sinhgad College of Engineering, Pandharpur, Maharashtra,India

***Abstract*— In these days, internet is spreading worldwide. One of the chief purpose of use of internet is online social networks (OSNs). OSNs are used on large basis to market products, promote brands, connect people with their family, friends, & society through online communication. But, due to the deficiency of categorization & filtering tools, user acquires all messages which are published on his private space. so, user do not have whole control on the contents that are being posted. So, proposed work explains rule based system that gives permission to users to channelize the filtering criterion applied to their private space, and machine learning classifier able to title the messages automatically based on their content. Unwanted images are possible to filter by extracting and classifying their features like edge, color and shape.**

***Keywords*— Online Social Networks (OSNs), Machine Learning, Information Filtering.**

I. INTRODUCTION

OSNs is becoming indispensible thing in today's modern internet generation. People can easily convey the information (photos, ideas, thoughts) to their members of household, friends and society. A lot of content is shared at each day and month. Due to this vast and variety of data ,secrecy of osn user can be violated ,i.e. User may receive unrequired content on his private space. Information filtering & access control is required to acquire selective information. Main motive of information filtering is to avoid user from useless data. But, in osns information filtering is required to use in different manner since unwanted content like vulgar ,offense, hate etc. can be published on user private space. So ,in case of osns, information filtering should give users entire and automatic control on the contents that are written on their private space. Most popular osns are facebook , twitter, google+ etc. Main point in question about todays osns is that they are not able to provide contentwise filtering of messages. Also ,most of the wall messages are built up of short texts that are difficult to categorize by traditional categorization methods, since they consists of low standard terms with smaller extent of occurrences. In this work, customized filtering rules specifies the filtering criteria which are applied to user private space in order to control the posting of unwanted contents. Filtering rules use attributes of user profile to specify filtering criteria. Machine learning classifier is trained with contents and their respective category (neutral, vulgar, political, offense etc.) So that it can autonomously categorize new input content into proper category based on training of preclassified contents. Also a lot of messages shared between users of osn are in the form of images. To filter unwanted images first it is required to extract features from it by using various descriptors. Then compute the euclidean distance between input image feature and preclassified images features by using knn classifier. Based on euclidean distance input image can be recognized into proper category. Once category of image is recognized then we can take proper action (block, notify) on it.

II. RELATED WORK

Proposed work consists of system which can filter out unrequired messages from OSN user private space. So , we have to focus on job done in information filtering for web contents. In OSNs, a flow of information is generated varyingly by different users. User perhaps recieves improper content on his private space. So, activity of classifying such diverse data and presenting only that data to user which is according to his need is known as information filtering [6]. There are 4 types of information filtering i.e. collaborative filtering , content based, hybrid filtering, social filtering. In contentwise filtering , based on content to content mutual relation a new document is suggested to user[8]. Details of content like its features ,treatments etc. are used for contentwise filtering. R.J.Mooney and L.Roy [3] proposes content based book recommendation to suggest books to user from features like author, publisher, genere etc. of books which are previously preferred by user. Dumais and Foltz [2] suggest technical memos based on previous technical subjects that are liked by people. Depending on the likes of user (history) and ratings of other people with similar likes, collobrative filtering filters the information [2]. Amazon.com ,eBay are the examples of collaborative filtering. Hybrid filtering systems [2] uses the characteristics of both content based and collaborative system. In social filtering , filtering is done by organizing discussions into groups. First work done in information filtering is in case of email for filtering of spam. But then it covers other fields like online news and other web resources [9] [10]. For machine learning classification, feature extraction of content is important , as it is applied to the training stage of machine learning algorithm. Out of many text representation techniques bag of words is shown better semantics and statistical quality [16][17][18]. Neural networks [20][21], support vector machines [22] are the efficient methods of machine learning based classification over other methods such as Naïve Bayesian [24]. Major part of work in information filtering is done for long text, but in OSN most of the messages are of short length which are difficult to classify as they are not properly spelled and their representation is not proper. Sokolova [26] proposed statistical learning approach for short text classification. But proposed approach is for hard classifier and not for soft classifier that consider multimembership of content into classes. Filmtrust [28] is an application that customize the visit to website based on history data and social graph of user. But still here user cannot decide by how and upto which amount unrequired information is filtered out. Access control models [29] are also major part of proposed work. So, to apply filtering criteria we use relationship of message creator with resource owner and description of message content.

III. SCOPE

Through OSNs people can communicate with each other contentiously through exchange of contents like video, audio and text. Scope of this system is that it can control the contents that are published on user private space.

IV. OBJECTIVES

- To apply customized filtering criteria to the messages that are published on user private space.
- To consider the challenges in short text classification.
- Once filtering system is deployed, then inspect each message before message is received by an intended recipient in order to take a decision whether the message is published or not.

V. FILTERED WALL ARCHITECTURE

It consists of three layers i.e. graphical user interface (GUI), social network application (SNA), social network manager (SNM).

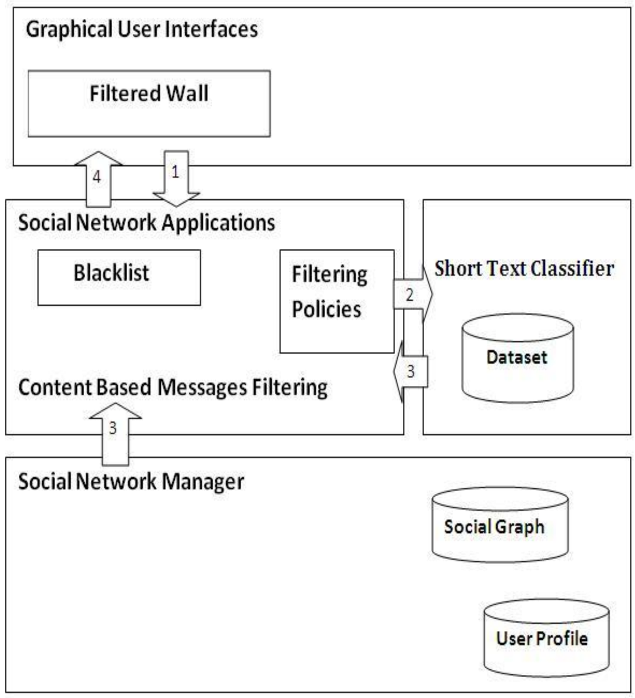

Fig. 1 Filtered wall architecture

SNM handles user profiles and their social graphs. SNA layer support various applications. In our system short text classifier and contentwise message filtering are two components deployed in this layer. Interaction with applications of social network is possible through GUI layer. Filtered wall is there in our system at GUI layer. Flow of message in our system is as follows-

Let Ram and Raj are friends on OSN. When raj opens the wall of Ram and post the message on his private space, then firstly that message is inspected by filtered wall as shown by 1. Machine learning categorization technique categorize that message by comparing its features with features of preclassified messages that are stored in dataset as shown by 2. Then filtered wall applies filtering criteria based on categorization of message performed by short text classifier and information extracted from social graph of user as shown by 3. Finally filtering criteria decides the message will be blocked or display on user private space as shown by 4.

VI. METHODOLOGY

Components of text message filtering system are shown in fig.2 as-

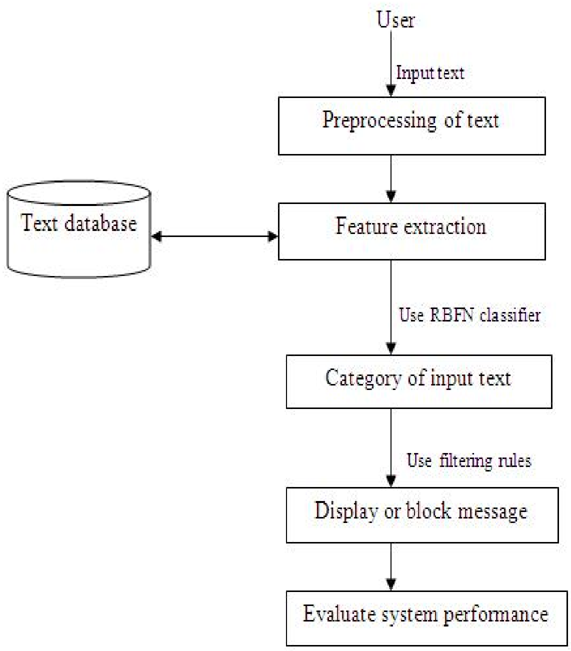

Fig.2 Text message filtering system

A. *Preprocessing of Information*

To classify any information, it is necessary to preprocess that information so that it is easy to recognize semantics of that message. Preprocessing of text involves following tasks-

1) Tokenization: Here, information in document is separated into individual words. e.g. we're reading a book now. After tokenization we get = we 're reading a book now.

2) *Stop Word Removal:* Here, words that are not helpful for classification are removed. e.g.- 'a','an','the','he',etc are stop words.

3) *Stemming:* Here, suffix of words in document are removed to make each word as a root word in order to classification more accurately. e.g. Punishing->punish, teaching->teach.

4) *Text Representation:* It is the process of extraction of feature from information and representation of that information in the form of feature vector. It influences overall execution of classification. Feature of information can be extracted by different methods like bag of words, vector space model, document properties, contextual features. Bag of words treat each term in document as a word which is used as feature for classification. e.g. Document is- Bob watch cricket. John also watch cricket. So ,in context of above documents list of non-identical words can be build as- { "Bob","watch","cricket","John","also"}. By using index of list , above document is possible to represent as 5- entry vector- [1,2,2,1,1] . Each entry in vector represents no of times term appear in document. Finally weightage of each term t_k in document d_j can be calculated by tf-idf [30] standard method of information retrieval.Document properties [1] represents statistics of message i.e. no of correct words, bad words, question marks etc. in that message so as to retrieve the features from it. Contextual features considers surrounding where the message is published.

B. Learning and Classification Procedure

Learning is the process of categorization of new information based on previous trained examples. We select neural network algorithm i.e. radial basis function network algorithm , since it is robust to hacker, quick and provides nonlinear mapping.

C. Radial Basis Function (RBF) Network

Radial basis function [25] is neural network as shown in fig.3. There are three layers of network- input layer, hidden layer, output layer.

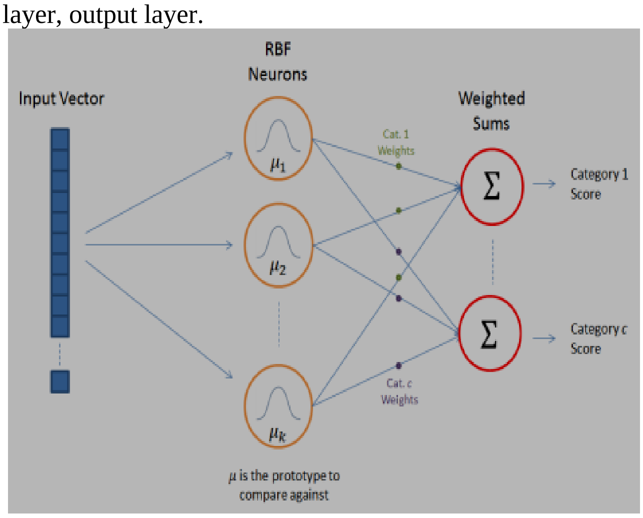

Fig.3 Radial basis function network architecture

Input layer bears feature vector of input message which is to be categorized. It is nonprocessing layer. Hidden layer bears a set of RBF neurons. RBF Neurons are there which are trained with precategorized examples from training set. Each neuron have its precategorized example (prototype) vector i.e. µ. Each hidden neuron finds the Euclidean distance [25] between the feature vector of input data and its precategorized example vector. Each neuron gives activation value based on this Euclidean distance by employing Gaussian function [25]. If input is more similar with class c example than class d example, then it is categorized as class c. If input is more similar with neuron example then hidden unit gives response close to 1. As the distance increases , then response exponentially drops towards 0. Shape of response of neurons is belly type curve as shown in fig.4 below.

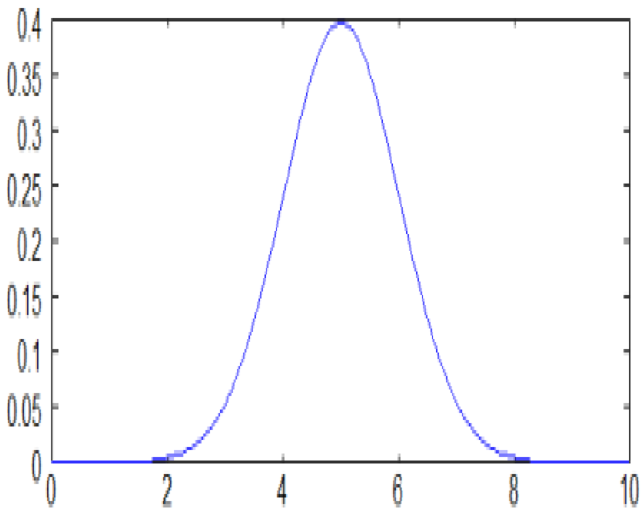

Fig.4 Response curve of RBF neuron

Neurons example vector is nothing but center of belly curve , since it's value is at center of belly curve. Output node bears nodes where every output node bears one category with a score. Input data is classified into that category which has highest score. Every output node receives activation value from every neuron and take their weighted sum to calculate its score. Output node assign positive weight to RBF neurons that belongs to its category and negative weight to remaining neurons . Every output node multiplies neurons activation value by this weight in order to calculate total response or weighted sum [25].

D. Filtering Rules

Filtering rules [1] are used to apply filtering criteria to incoming categorized messages on user private space. User can decide which content from whom is to be filtered. Filtering rules consists of fields as author ,creatorspecification, contentspecification and action. Author is user who defines the rule. Creatorspecification specifies OSN users. It have two forms as- i) an OP av, where an is attribute name of userprofile, an is attribute value and op is comparison operator. ii) (m,rt,mindepth,maxtrust) denotes all users that have relationship of type rt i.e. friend of, parent of etc. with user m and having depth greater than or equal to mindepth , trust level is less than or equal to maxtrust. For direct relationship mindepth value is 1. Increment and decrement of trust value [31] depends on message creator behaviour.

Contentspecification is of the form (c, ml) denotes minimum membership level threshold (ml) [27] required for message inorder to classify in class c. Action is {notify,block} denotes action taken on incoming messages. e.g. Let Ram want to block vulgar messages from friends whose trust value is below 1. For vulgar class threshold is set to 0.80. To block such messages filtering rule can be given as-((Ram, friendof, 1,1),(vulgar,0.80),block). Similarity between document and category can be determined by using two parameters i.e. membership value of each term of document into that category and membership value of each term in that document. This process is known as fuzzyfication [32] by which we can calculate membership of document into respective categories.

E. *Image Filtering System*

Components of image filtering system are shown in fig.5 as-

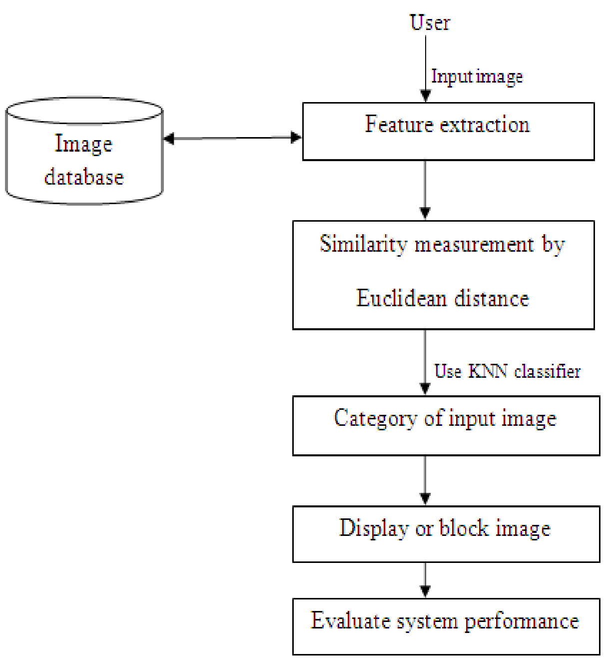

Fig.5 Image filtering system

For image classification , we have to preclassify the different images in different category. Then train the classifier with these preclassified images in order to categorize new incoming images. Features like color, shape, edge plays an important role to classify the image. So ,select appropriate feature extractor to extract features of image. Hue, Saturation , Value extractor [15] is used to extract color from image ,since each component of it directly considers the human virtual perception of colors. Shape of an image is an crucial feature which can be used to categorize image into proper category. GLCM extractor [15] accurately extracts properties of surface of image. Human eyes can easily sense edge feature of image. Edges accurately represent the content of image. By using EHD[15], we can accurately extract edge feature of an image, since edge histogram correctly represents frequency and ordering of brightness variations of image correctly. Once features are drawn from image, then find the Euclidean distance of input image feature from each preclassified image feature in database. Classify the input image into that image category from which it have minimum Euclidean distance.

VII. RESULTS

Performance of proposed system can be evaluated by three parameters i.e. Precision (P) , Recall(R), and F1-measure [13]-

Precision- Precision [13] represents the fraction of messages that are correctly classified by classifier out of total classified messages. It evaluates the number of false positives (FP).

P= True positives (TP) / TP+ FP

Recall- Recall [13] represents fraction of messages of a class that are correctly classified by classifier out of total messages that are actually present in that class. It evaluates the number of false negetives (FN).

R= TP/ TP + FN

F-measure- There is trade-off between precision and recall values. F-measure [13] is computed to keep balance between precision and recall values. F-measure is harmonic mean of precision and recall measures.

F1-measure= 2.P.R / P + R

TABLE I

RESULTS OF TEXT MESSAGES

Class	Precision	Recall	F1-measure
Hate	82%	90%	86%
Offensive	89%	80%	84%
Sex	100%	90%	95%
Vulgar	64%	70%	67%
Violence	89%	80%	84%
Neutral	83%	100%	91%

TABLE II

RESULTS OF IMAGES

Class	Precision	Recall	F1-measure
Good image	63%	71%	68%
Bad image	88%	78%	83%

VIII. CONCLUSIONS

In this paper, we have addressed the problem of customized and contentwise filtering of messages in OSNs by use of adaptable rule-based system, short text classifier and different feature extractors. Proposed system provides only functionalities that are needed in order to provide highly developed tool for content-based filtering of OSN messages. Building of complete system that can be easily used by normal user is beyond the range of this paper. We plan to develop tool for convenient specification of filtering rules, trust levels.

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