

# Filtering Restricted Messages through OSN User Walls

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*Abstract* – Online Social Network users are facing a giant problem today that is they are not able to control the messages posted on their walls. Today, existing Online Social Network are providing little support to prevent unwanted messages on user walls. So in this paper we are going to block up the space and providing the OSN users a tool through which they can set constraints and define what kind of messages they allow on their walls. This is achieved through content based message filtering rules, short Text classifiers, Black Lists, Machine Learning based classification.

*Keywords* – On-line Social Network, Filtering wall, Short text classifier, Black Lists, Machine Learning-Based Classification, Content-Based Messages Filtering.

## I. INTRODUCTION

As we know to communicate and share any kind of human information we use On-line Social Network which is one of the most interactive medium today. These sharing include several types of text, image, audio and video data. Billions of content are shared each month as per the OSNs information that create a big problem for mining strategies. Now short texts are also used in massive form which is not able to recognize by the existing system. So in this proposal we are mainly focus on classification mechanism to avoid useless data. Information filtering is done in OSNs for different purposes so that variety of comments and posts can be possible.

## II. EXISTING SYSTEM

### A. Existing System

Some OSNs allows users to state who is permitted to put in messages in their walls such as friends, friends of friend etc. But there is no content-based preferences are supported and prevent unnecessary messages. Now Wall messages are constituted by short text so traditional classification methods are not able to catch them.

### B. Existing Algorithm

- *Inductive Learning Algorithm*

#### 1) Find similar

Find similar method is a alternative of Rocchio's technique for significance feedback which is a popular for expanding user doubt on the basis of relevance judgments. In this method the weight assigned to a expression is a combination of its weight in an original query and judged relevant and irrelevant documents.

#### 2) Decision Tree

The decision trees were grown-up by recursive insatiable splitting and splits were selected using the Bayesian subsequent possibility of model structure. A class probability not only a binary decision but also retained at each node.

#### 3) Naive Bayes

Naive Bayes is defined as the set up training data to calculate approximately the prospect of each class given the document feature values of a new instance. We use Bayes method to approximate the possibility :

$$P(C = c_k | \vec{x}) = \frac{P(\vec{x} | C = c_k) P(C = c_k)}{P(\vec{x})}$$

### C. Existing System Drawbacks

- It is machine based classifier used for this system.
- It has only the classifier so after compare to contents message will be displayed on the public wall.
- User cannot handle spam messages directly.

### III. PROPOSED SYSTEM

#### A. Proposed System

The proposed system provides an automated system that will be able to filter undesired messages from OSN user walls. As well as we use Machine Learning-based text categorization techniques to automatically assign with each and every short text message and label it. Classification strategies will be based on Radial Basis Function Network (RBNF) for their proven capabilities in acting as soft classifiers, to overcome noisy data and intrinsically vague classes. Also the system provides a powerful rule layer to specify Filtering Rules by which users can state what contents should be displayed on their walls.

#### B. System Architecture

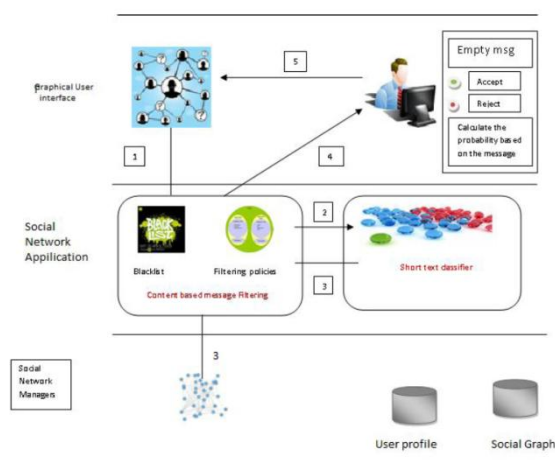


Fig. 1. System Architecture

The OSN have three layers - graphical user interface, social network application and social network managers. The social network managers handle the basic functionalities like profile management, network based function etc. But in this project we mainly focused on other two layers and apply some new condition. Application layer have short text classifier and content based message filtering. Short text classifier classifying the messages based on the content. Content based message filter have black list and filtering policies. First, find relationship between the user and message senders and it will filter and calculate the probabilities using classifier. And then send a empty message below the probabilities result to the user. So our proposed system will give the direct control to the user that what kind of messages displays on their wall.

#### C. Short text classifier

##### 1) Text Representation

We consider three types of features in the text Representation- 1) Bag of Words (BoW) 2) Document properties (DP) and 3) Contextual Features. The first two types of features are already used and they are entirely derived from the information contained within the text of the message. We introduce CF modeling information that characterizes the environment where the user is posting.

##### 2) Machine Learning-based Classification

Short text categorization is a two level classification process. The first level performs a hard categorization and labels the messages as Neutral and Non-Neutral. The first-level task provides facility to the second-level task in which advanced classification is performed then second-level performs a flexible partition of Non-Neutral messages and assign a given message a regular membership to each of the Non-Neutral classes.

##### 3) Radial Basis Function Network (RBFN)

RBFNs have a single concealed layer of processing units with local, restricted activation domain: a Gaussian function is commonly used, but any other locally tunable function can be used. They were introduced as a neural network evolution of exact interpolation, and are demonstrated to have the universal approximation property.

#### D. Filtering policy and Blacklist Management

##### 1) Filtering Policy

###### a) Creator prototype

It involves to state circumstances on trust values, depth and type of the relationship of the message creator in order to apply specified rules. A *cp* (creator prototype) implicitly denotes a set of OSN users

- A set of attribute constraints of the form  $pan\ cop\ pav$ , where  $pan$  is a user profile attribute name,  $pav$  and  $cop$  are, respectively, a profile attribute value and a comparison operator, compatible with  $pan$ 's domain.
- A set of relationship constraints of the form  $(n, v, minDepth, maxTrust)$  denoting all the OSN users participating with user  $n$  in a relationship of type  $v$ , having a trust value less than or equal to  $maxTrust$  and a depth greater than or equal to  $minDepth$ .

## b) *Filtering Policy*

A filtering Rule is set of creator, contentSpec, creatorSpec and action where

- creator is the user who specify the rule;
- *creatorSpec* is a creator specification, specified according to Definition 1;
- contentSpec is a Boolean expression defined on content constraints of the form  $(c, mml)$  where  $c$  is a class of the first or second level and  $mml$  is the minimum membership level threshold required for class  $c$  to make the constraint satisfied;
- action  $a$  indicates the action performed on the messages by the system which is identified by creatorSpec.

## 2) *Blacklists*

A Blacklists rule is a tuple (creator, creatorSpec, creatorBehavior, t), where :

- creator is the user or wall owner who specifies the rule;
- creatorSpec is a creator specification, specified according to Definition 1;
- creatorBehavior consists of two components RFBlocked and minBanned.
- $t$  denotes the time period the users identified by creatorSpec and creatorBehavior have to be banned from author wall.

## E. *Advantages*

- The system employs a powerful rule layer to specify Filtering Rules.
- The central part of the proposed system is Short Text Classifier and Content-Based Messages Filtering.
- BL system is used to avoid messages from undesired authors, independent from their contents.

## IV. CONCLUSIONS

We have presented a system in which user can have direct control and block unwanted messages on their social

network wall. The system using the machine language soft classifier to label the contents as Neutral and Non-Neutral. And then applying the Filtering Rules based on the creators. In addition, BL Rule is also used to enhance in terms of filtering options.

## V. FUTURE ENHANCEMENT

In future work, we plan to deal with this difficulty by inspecting the use of online learning prototype that will be able to label feedbacks from users. In addition, we plan to advance our system with a more refined approach to decide when a user should be inserted into a BL.

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