International Journal of Research in Advent Technology (IJRAT) Special Issue
E-ISSN: 2321-9637
Sharadchandra Pawar college of Engineering, Dumbarwadi, Pune 410504, Organizes
National Conference "MOMENTUM-17", 14th & 15th February 2017
Available online at www.ijrat.org

Secured Online Social Network: A Review Study

Nitish Baste [1], Amar Dhumal [2], Akshay Gavade [3], Vaibhav Wagh[4]
1,2,3,4 Student, SPCOE, Department Of Computer Engineering, Dumbarwadi, Otur

Email: nitishbaste72@gmail.com [1], *amardhumal13@gmail.com* [2] , *akshay.gavade@yahoo.in* [3], *vaibhavwagh8331@gmail.com* [4]

Abstract- One fundamental issue in today's Online Social Networks (OSNs) is to give users the ability to control the messages posted on their own private space to avoid that unwanted content is displayed. Up to now, OSNs provide little support to this requirement. To fill the gap, in this paper, we propose a system allowing OSN users to have a direct control on the messages posted on their walls. This is achieved through a flexible rule-based system, which allows users to customize the filtering criteria to be applied to their walls, and a Machine Learning-based soft classifier automatically labeling messages in support of content-based filtering.

Index Terms- Flexible rules; Message Filtering; Online Social Networks; Short Text .

1. INTRODUCTION

On-line Social Networks (OSNs) are today one of the most popular interactive medium to communicate, share and disseminate a considerable amount of human life information.
An OSN is a web-based service that allows individuals to:
1) Construct a public or semi-public profile within the service,
2) Articulate a list of other users with whom they share a connection,
3) View and traverse their list of connections and those made by others within the service.

Daily and continuous communications imply the exchange of several types of content, including free text, image, and audio and video data. According to Facebook statistics average user creates 90 pieces of content each month, whereas more than 30 billion pieces of content (web links, news stories, blog posts, notes, photo albums, etc.) are shared each month. The huge and dynamic character of these data creates the premise for the employment of web content mining strategies aimed to automatically discover useful information dormant within the data. They are instrumental to provide an active support in complex and sophisticated tasks involved in OSN management, such as for instance access control or information filtering. Information filtering has been greatly explored for what concerns textual documents and, more recently, web content [2], [3]. However, the aim of the majority of these proposals is mainly to provide users a classification mechanism to avoid they are overwhelmed by useless data. In OSNs, information filtering can also be used for a different, more sensitive, purpose. This is due to the fact that in OSNs there is the possibility of posting or commenting other posts on particular public/private areas, called in general walls.

Information and communication technology plays a significant role in today's networked society. It has affected the online interaction between users, who are aware of security applications and their implications on personal privacy. There is a need to develop more security mechanisms for different communication technologies, particularly online social networks. Information filtering can therefore be used to give users the ability to automatically control the messages written on their own walls, by filtering out unwanted messages. Today OSNs provide very little support to prevent unwanted messages on user walls. For example, Facebook allows users to state who is allowed to insert messages in their walls (i.e., friends, friends of friends, or defined groups of friends). However, no content-based preferences are supported and therefore it is not possible to prevent undesired messages, such as political or vulgar ones, no matter of the user who posts them.

The aim of the system to propose and experimentally evaluate an automated system, called Filtered Wall (FW), able to filter unwanted messages from OSN user walls. The key idea of the proposed system is the support for content based user preferences. This is possible thank to the use of a Machine Learning (ML) text categorization procedure able to automatically assign with each message a set of categories based on its content. We believe that the proposed strategy is a key service for social networks in that in today social networks users have little control on the messages displayed on their walls. In contrast, by means of the

proposed mechanism, a user can specify what contents should not be displayed on his/her wall, by specifying a set of filtering rules. Filtering rules are very flexible in terms of the filtering requirements they can support, in that they allow to specify filtering conditions based on user profiles, user relationships as well as the output of the ML categorization process. In addition, the system provides the support for user defined blacklist management, that is, list of users that are temporarily prevented to post messages on a user wall. This System we design to show the effectiveness of the developed filtering techniques. Finally, we have provided a prototype implementation of our system having Facebook as target OSN, even if our system can be easily applied to other OSNs as well. To the best of our knowledge this is the first proposal of a system to automatically filter unwanted messages from OSN user walls on the basis of both message content and the message creator relationships and characteristics [4].

The rest of the paper has been organized as: section 2 indicates motivation, section 3 highlights the related work along with their downsides, section 4 discusses the proposed system modules, section 5 gives the development algorithm of the system. Section 6 shows the mathematical model of the system, section 7 displayed applications, section 8 shows result followed by conclusion and references.

2. MOTIVATION

Indeed, today OSNs provide very little support to prevent unwanted messages on user walls. For example, Facebook allows users to state who is allowed to insert messages in their walls. However, no content-based preferences are supported and therefore it is not possible to prevent undesired messages, such as political or vulgar ones, no matter of the user who posts them. However, no content-based preferences are supported and therefore it is not possible to prevent undesired messages, such as political or vulgar ones, no 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 ad hoc classification strategies. This is because wall messages are constituted by short text for which traditional classification methods have serious limitations since short texts do not provide sufficient word occurrences. It inspects every message before rendering the message to the intended recipients and makes immediate decision on whether or not the message under inspection should be dropped. The aim of the present work is therefore to propose and experimentally evaluate an automated system, called Filtered Wall (FW), able to filter unwanted messages from OSN user walls model.

3. RELATED WORK

M. Vanetti [5] proposes a system enforcing content-based message filtering conceived as a key service for On-line Social Networks (OSNs). The system allows OSN users to have a direct control on the messages posted on their walls. This is achieved through a flexible rule-based system, that allows a user to customize the filtering criteria to be applied to their walls, and a Machine Learning based soft classifier automatically producing membership labels in support of content-based filtering. They have presented a system to filter out undesired messages from OSN walls. The system exploits a ML soft classifier to enforce customizable contentdepended filtering rules. Moreover, the flexibility of the system in terms of filtering options is enhanced trough the management of BLs. The proposed system may suffer of problems similar to those in the specification of privacy settings in OSN. As future work, They said that to exploit similar techniques to infer BL and filtering rules.

Gediminas Adomavicius [6] gives an overview of the field of recommender systems and describes the current generation of recommendation methods that are usually classified into the following four main categories: content-based, collaborative, Policy-based personalization and hybrid recommendation approaches. This paper also describes various limitations of current recommendation methods and discusses possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications. In this paper, they reviewed various limitations of the current recommendation methods and discussed possible extensions that can provide better recommendation capabilities. These extensions include among others, the improved modeling of users and items, incorporation of the contextual information into the recommendation process, support for multicriteria ratings, and provision of a more flexible and less intrusive recommendation process.

Bharath Sriram [7] states microblogging services such as Twitter, the users may become overwhelmed by the raw data. One solution to this problem is the classification of short text messages. As short texts do not provide sufficient word occurrences, traditional classification methods such as ―BagOf-Words‖ have limitations. To address this problem, they propose to use a small set of domain-specific features extracted from the author's profile and text. The proposed approach effectively classifies the text to a predefined set of generic classes such as News, Events, Opinions, Deals, and Private Messages. They have proposed an approach to classify tweets into general but important categories by using the author information and features within the tweets. With such a system, users can subscribe to or view only certain types of tweets based on their interest.

Michael Beye [8] discussed, In recent years, Online Social Networks (OSNs) have become an important part of daily life for many. Users build explicit networks to represent their social relationships, either existing or new. Users also often upload and share a plethora of information related to their personal lives. The potential privacy risks of such behavior are often underestimated or ignored. For example, users often disclose personal information to a larger audience than intended. Users may even post information about others without their consent. A lack of experience and awareness in users, as well as proper tools and design of the OSNs, perpetuate the situation. This paper aims to provide insight into such privacy issues and looks at OSNs, their associated privacy risks, and existing research into solutions.

Josie Maria [9] discussed Effective Web content filtering is a necessity in educational and workplace environments, but current approaches are far from perfect. They discuss a model for text-based intelligent Web content filtering, in which shallow linguistic analysis plays a key role. In order to demon strate how this model can be realized, they have developed a lexical Named Entity Recognition system, and used it to improve the effectiveness of statistical Automated Text Categorization methods. They have performed several experiments that confirm this fact, and encourage the integration of other shallow linguistic processing techniques in intelligent Web content filtering. They discussed that shallow linguistic analysis in general, and Named Entity Recognition in particular, can be used to improve the effectiveness of text classification in the framework of intelligent Web content filtering.

4. MODULE

Proposed system divide into modules are as follows:

1. Framework:
This module provides Graphical User Interface to the user who wants to post his messages as a input. In this module Filtering Rules (FR) are used to filter the unwanted messages and provide Black list (BL) for the 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.

2. Text classification:
In this module established techniques used for text classifications work well on datasets with large documents but suffer when the documents in the quantity are tiny. In this perspective critical features are the description of a set of characterizing and discriminant features allowing the representation of underlying concepts and the collection of a complete and consistent set of supervised examples. We evaluate various representation technique in combination with a neural learning strategy to semantically categorize short texts.

3. Threshold estimation and post action:
By conceiving and implementing within FW, an Online Setup Assistant (OSA) procedure, we address the problem of setting thresholds to filter rules. OSA presents the user with a set of messages selected from the dataset. For each message, the user expresses the system the decision to accept or reject the message. The collection and processing of user decisions on an adequate set of messages distributed over all the classes permits to calculate customized thresholds representing the user attitude in accepting or rejecting certain contents.

4. Blacklist generation:
BLs are directly managed by the system, and should be able to determine the users to be inserted in the BL and decide user's retention in the BL is finished. Such information are given to the system through a set of rules, called BL rules.

5. ALGORITHM

5.1 Preprocessing

The primary aim of the pre-processing phase is to remove from the input message all characters and terms that can possibly affect the quality of group descriptions.

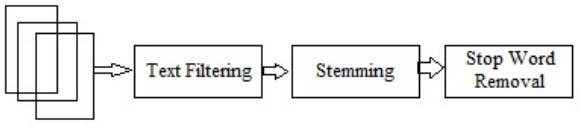

Fig. 2 Pre-processing of Message

5.1.1 Pre-processing steps

Algorithm:
1: d← input message
{STEP 1: Preprocessing}
2: for all d € D do
3: perform text categorization
4: if d!=null then
Filter text for unwanted symbols
5: apply stemming and mark stop-words in d;
6: end for

There are three steps to the preprocessing phase: Text filtering, Stemming and Stop words marking.

(a) Text filtering:
In the text filtering step, all terms that are useless or would introduce noise in filtering process are removed from the input message. Among such terms are: 1.HTML tags (e.g. <table>) and entities (e.g. &) if any.
2. non-letter characters such as "$", "%" or "#" (except white spaces and sentence markers such as '.', '?' or '!') Note that at this stage the stop-words are not removed from the input.

(b) Stemming:
Stemming algorithms are used to transform the words in texts into their grammatical root form, and are mainly used to improve the Information Retrieval System's efficiency. To stem a word is to reduce it to a more general form, possibly its root. For example, stemming the term interesting may produce the term interest. Though the stem of a word might not be its root, we want all words that have the same stem to have the same root.

(c) Elimination of Stop Words:
After stemming it is necessary to remove unwanted words. There are 400 to 500 types of stop words such as, of, and, the etc., that provide no useful information about the message. Stop-word removal is the process of removing these words. Stop-words account for about 20% of all words in a typical document. These techniques greatly reduce the size of the searching and matching each word in message. Stemming alone can reduce the size of an index by nearly 40%.

6. MATHEMATICAL MODEL

A. User Module:
Set (P) = {p0, p1, p2, p3, p4, p5, p6, p7}

p0=User Registration
p1=User Login.
p2=Create account.
p3=Post text message.
p4=Post images on wall.
p5=Communication.
p6=Maintain friend list.
p7=Apply filtering rules.

B. Text classification:
Set (K) = {p4, k0, k1, k2, k3}

k0= Stopwords removal.
k1= Neutral-Non Neutral Classification.
k2= Probability Calculation.
k3= Vulgar words classification.

C. Threshold estimation and post action:
Set (D) = {p2, p3, p4, d0, d1, d2, d3}

d0=Skin detection algorithm.
d1=Train image classification.
d2=Threshold value calculation.
d3=Skin and non skin pixel detection.

D. Blacklist generation:
Set(C) = {p5, p6, d0, d1, d3, p7, c0}

C0= Block unauthorized user

Union and Intersection of project:-

Set (P) = {p0, p1, p2, p3, p4, p5, p6, p7}
Set (K) = {p4, k0, k1, k2, k3}
Set (D) = {p2, p3, p4, d0, d1, d2, d3}
Set (C) = {p5, p6, d0, d1, d3, p7, c0}

7. APPLICATIONS

1. Security purpose.

2. To prevent misuse of such social networking sites.

3. This application is useful for common people who don't want to write any unwanted messages like vulgar, political, unwanted messages on his\her own wall by any third person.

4. Mostly, this type of activities are happen with some famous personalities, So if this facility will provide with OSN sites then people can protect his wall from this type of malpractices.

8. SCREENSHOTS

Fig. 2. Login Form

Fig. 3. Home Page

9. CONCLUSION

We have presented a system to filter unwanted messages from OSN walls. The system exploits a ML soft classifier to enforce customizable content-dependent FRs. Furthermore, the flexibility of the system in terms of filtering options is enhanced through the management of BLs. The first concerns the extraction and/or selection of contextual features that have been shown to have a high discriminative power. The second task includes the learning phase. As the underlying domain is dynamically changing, the collection of pre-classified data may not be representative in the longer term.

Acknowledgments

We express our sincere thanks to our project guide Prof. Deokate G. S**.** who always being with presence & constant, constructive criticism to made this paper. We would also like to thank all the staff of Computer Department for their valuable guidance, suggestion and support through the project work, who has given co-operation for the project with personal attention. Above all we express our deepest gratitude to all of them for their kind-hearted support which helped us a lot during project work. At the last we thankful to our friends, colleagues for the inspirational help provided to us through a project work.

.

REFERENCES

[1] Marco Vanetti, Elisabetta Binaghi, Elena Ferrari, Barbara Carminati, and Moreno Carullo, "A System to Filter Unwanted Messages from OSN User Walls" VOL. 25, NO. 2, FEBRUARY 2013.

[2] A. Adomavicius, G.and Tuzhilin, Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions,‖ IEEE Transaction on Knowledge and Data Engineering, vol. 17, no. 6, pp. 734–749, 2005.

[3] 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. 482–494, 2008.

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

[5] M. Vanetti, E. Binaghi, B. Carminati, M. Carullo E. Ferrari Content-based Filtering in On-line Social Networks.

[6] Gediminas Adomavicius, Member, IEEE, and Alexander Tuzhilin, Member, IEEE, Toward the Next Generation of Recommender Systems: A Survey of the State-of-the Art and Possible Extensions, IEEE Transactions On Knowledge And Data Engineering, Vol. 17, No. 6, June 2005.

[7] Bharath Sriram, David Fuhry, Engin Demir, Hakan Ferhatosmanoglu Murat Demirbas-Short Text Classification in Twitter to Improve Information Filtering

[8] Michael Beye, Arjan Jeckmans, Zekeriya Erkin, Pieter Hartel, Reginald Lagendijk and Qiang

Tang, Literature Overview - Privacy in Online Social Networks.

[9] Josie Maria Giomez Hidalgo, Francisco Carrero Garcia, and Enrique Puertas Sanz, Named Entity Recognition for Web Content Filtering.

[10] Hongyu Gao Yan Chen Kathy Lee Diana Palsetia Alok Choudhary, Towards Online Spam Filtering in Social Networks.

[11] Jennifer Golbeck, ―The Twitter Mute Button: A Web Filtering challenge‖, CHI 2012, May 5-10, 2012, Austin,Texas, USA.

[12] George Forman, An Extensive Empirical Study of Feature Selection Metrics for Text classification‖,Journal of Machine Learning Research 3(2003)1289-1305,Hewlett-Packard Labs Palo Alto,CA,USA.