Risk Evaluation to Filter Unnecessary Messages from OSN User Walls using Trustworthines

Jeyageetha.V, Assistant Professor,
Department of Computer Science and Engineering,
Nandha College of Technology, Erode, Tamilnadu, India.
Email:jeyageetha.v@gmail.com

Abstract: The core problem in the current Online Social Networks (OSNs) is to assign clients the expert to covenant with the messages posted on their confidential space to revolve away that unlikable substance. The disagreeable information may contain political, repellent, nonneural and message sifting frameworks are designed for formless or semi-organized information, instead of database applications, which exploit structured information. In this work we anticipated a System with the malleable guidelines to channel the disagreeable messages posted on client divider. In the rouse of round about limit the warning message is forward to that client. It enables clients to adjust the enlightening criteria to be allied to their dividers, and a Machine Learning-based classifier subsequently characterize the messages and naming messages in help of essence based separating.

Keywords: Adaptable guidelines, message sifting, online interpersonal organizations, short content grouping

I. INTRODUCTION

Online Social Networks (OSNs) are today a standout amongst the most well known bright medium to convey, share, and scatter a lot of human life data.

An OSN is an electronic administration that enables people to:

1) Construct an open or semi-open profile inside the administration,
2) Articulate a rundown of different clients with whom they share an association,
3) View and cross their ramshackle of associations and those made by others inside the administration.

Every day and ceaseless interchanges infer the trading of a few sorts of substance, including free content, picture, and sound and video information. As per Face book insights client makes 90 bits of essence every month, while in more than 30 billion bits of substance (web joins, news stories, blog entries, notes, photograph collections, and so forth.) are shared every month.

The tremendous and dynamic character of this information makes the reason for the work of web content mining procedures intended to obviously find supportive data lethargic within the in sequence. They are instrumental in giving a functioning help in perplexing and advanced errands engaged with OSN the board, for example, get to control or data to sift.Data separating has been significantly investigated for what concerns literary reports and, all the more as of late, web content [2], [3]. Be that as it may, the point of most of this proposition is, for the most part to give clients a grouping system to maintain a strategic distance from they are beaten by futile information. In OSNs, data separating can likewise be utilized for an alternate, increasingly delicate, reason. This is because of the way that in OSN there is the likelihood of posting or remarking different posts on specific open/private regions, brought all in all dividers.

Data and correspondence innovation assumes a critical job in the present organized society. It has influenced the online collaboration between clients, who know about security applications and their suggestions on close to home protection. There is a need to grow better security systems for various correspondence advancements, especially online informal communities. Data sifting can hence be utilized to enable clients to naturally control the messages composed without anyone else dividers, by sifting through unattractive messages.

Today OSNs give next to no help to avert undesirable messages on client dividers. For instance, Facebook enables clients to state who is permitted to embed messages in their dividers (i.e., companions, companions of companions, or characterized gatherings of companions). In any case, no substance-based inclinations are bolstered, and subsequently it is absurd to expect to anticipate undesired messages, for example, political or obscene ones, regardless of the client who posts them.

The point of the framework to propose and tentatively assess a robotized framework, called Filtered Wall (FW), ready to channel undesirable messages from OSN client dividers. The key thought of the proposed framework is the help for substance-based client inclinations. This is conceivable thank to the utilization of a Machine Learning (ML) content classification system ready to naturally allocate with each message a lot of classes dependent on its substance. We trust that the proposed methodology is a key administration for interpersonal organizations in that in today informal communities clients have little control over the messages showed on their dividers. Conversely, by methods for the proposed system, a client can determine what substance ought not to be shown on his/her divider, by indicating a lot of separate rules. Separating rules are entirely adaptable regarding the sifting prerequisites they can bolster, in that they permit to determine to separate conditions dependent on client profiles, client connections just as the yield of the ML arrangement process. Also, the framework gives the help to client characterized boycott the board, that is, rundown of clients that are incidentally averted to post messages on a client divider.

This System we configuration to demonstrate the adequacy of the created separating strategies. At long last, we have given a model execution of our framework having Face book as target OSN, regardless of whether our framework can be effectively connected to different OSNs too. To the finest of the insight it is the first proposition of a framework to consequently channel undesirable messages from OSN client dividers based on both message content and the message maker connections and characteristics [4].

II. Literature Survey

M. Vanetti [5] proposes a framework implementing content-based message sifting imagined as a key administration for Online Social Networks (OSNs). The framework permits OSN clients to have immediate control on the messages posted on their dividers. This is accomplished through an adaptable principle-based framework, that enables a client to alter the sifting criteria to be connected to their dividers, and a Machine Learning based delicate classifier naturally creating enrollment marks in help of substance based separating. They have introduced a framework to sift through undesired messages from OSN dividers. The framework misuses an ML delicate classifier to authorize adjustable substance depended on sifting rules. Besides, the adaptability of the framework as far as separating choices are improved through the administration of BLS. The proposed framework may endure issues like those in the determination of protection settings in OSN. As future work, They said that to misuse comparable methods to derive BL and sifting rules.

Gediminas Adomavicius[6] gives a diagram of the field of recommender frameworks and depicts the present age of suggestion strategies that are characterized into the accompanying four principle classes: content-based, community-oriented, Policy-based personalization and cross breed proposal approaches. This paper additionally depicts different confinements of current suggestion strategies and examines conceivable augmentations that can enhance proposal capacities and make recommender frameworks relevant to a considerably more extensive scope of utilizations. In this paper, they checked on different confinements of the present suggestion techniques and examined conceivable augmentations that can give better proposal capacities. These expansions incorporate among others, the enhanced displaying of clients and things, consolidation of the relevant data into the suggestion procedure, support for multi criteria evaluations, and arrangement of an increasingly adaptable and less nosy proposal process.

Bharath Sriram[7] states micro blogging administrations, for example, Twitter, the clients may progress toward becoming overpowered by the crude information. One answer to this issue is the arrangement of short instant messages. As short posts don't give adequate word events, conventional arrangement techniques, for example, ―Bag-Of-Words‖ have restrictions. To address this issue, they propose to utilize a little arrangement of space explicit highlights removed from the creator's profile and content. The proposed methodology viably groups the content to a predefined set of nonexclusive classes, for example, News, Events, Opinions, Deals, and Private Messages. They have proposed a way to deal with order tweets into general however critical classes by utilizing the creator data and highlights inside the tweets. With such a framework, clients can buy in to or see just specific kinds of tweets dependent on their advantage.

Michael Beye [8] examined, lately, Online Social Networks (OSNs) have turned into a vital piece of day by day life for some. Clients fabricate express systems to speak to their social connections, either existing or new. Clients additionally regularly transfer and offer plenty of data identified with their own lives. The potential security dangers of such conduct are frequently thought little of or disregarded. For instance, clients frequently unveil individual data to a bigger gathering of people than planned. Clients may even post data about others without their assent. An absence of experience and mindfulness in clients, just as appropriate devices and plan of the OSNs, sustain the circumstance. This paper intends to give understanding into such protection issues and takes a gander at OSNs, their related security chances, and existing examination into arrangements.

Josie Maria [9] talked about Effective Web content separating is a need in instructive and work environment conditions, yet current methodologies are a long way from impeccable. They talk about a model for content-based canny Web content separating, in which shallow phonetic investigation assumes a key job. To evil spirit state how this model can be acknowledged, they have built up a Lexical Named Entity Recognition Framework, and utilized it to enhance the adequacy of measurable Automated Text Categorization strategies. They have played out a few tests that affirm this reality, and energize the integration of other shallow semantic preparing systems in shrewd Web content separating. They examined that shallow semantic investigation when all is said in done, and Named Entity Recognition specifically, can be utilized to enhance the adequacy of content order in the structure of smart Web content sifting.

III. IMPLEMENTATION DETAILS

A. Filtering Types

1) Content-based:

Content-based sifting framework suggests a record by coordinating the archive profile with the client profile, utilizing usual data recovery methods such as Term Frequency and Inverse Document recurrence (TF-IDF). Client qualities are assembled after some time and profiled consequently dependent on a client's earlier input and decisions. The framework utilizes thing to thing connection in prescribing the archive to the client. The framework begins with the way toward gathering the substance insights concerning the thing, for example, medicines, manifestations and so on for sickness related thing and creator, distributor and so on for the book things. In the subsequent stage, the framework requests that the client rate the things. At last, the framework matches unrated thing with the client profile thing and dole the score to the unrated thing and the client is given things positioned by the scores relegated.

News dude, is one of the instances of substance based sifting framework which utilizes present moment TF-IDF strategy and long haul Bayesian classifier for learning on an underlying arrangement of archives given by the client. Content-based data separating frameworks are not influenced by the virus begin issue and new client issue, as the framework centers around the individual client needs Content-based data sifting frameworks are not reasonable for interactive media things, for example, pictures, sound, video. Sight and sound records must be characterized with a semantic depiction of the asset which will be a tedious procedure. Content-based separating strategies can't channel reports dependent on quality and importance.

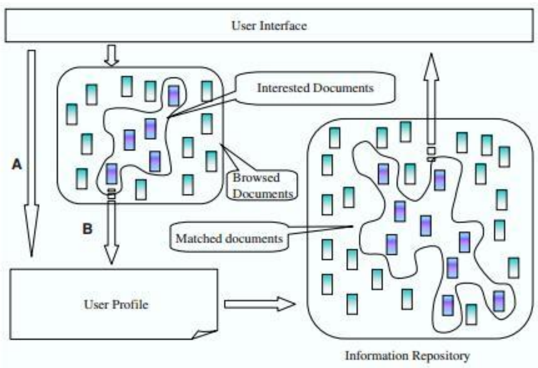

Figure 1: Content-based filtering

Limitations: Albeit content-based separating has turned out to be viable in prescribing printed things pertinent to a subject, it additionally has its confinements:

Content-based separating more than regularly gives suggestion in an exacting sense, since all the data is chosen and prescribed dependent on a printed substance. Despite the fact that an item was basically helpful, it may be underestimated in view of the vague and along these lines deluding appearance of the printed substance. Moreover, it is vague in nature of the suggested items. This is on the grounds that the term vector for an item essentially catches the recurrence of each term in an article, and an inadequately worded article can well have an equivalent or much higher comparability esteem than a finely kept in touch with one.

Content-based separating for the majority part functions admirably with adequate printed data. Be that as it may, other interactive media records, for example, pictures, sound, and video streams are not relevant if the metadata don't have enough printed data.

2) Collaborative filtering:

Communitarian separating frameworks channels data dependent on the interests of the client (previous history), and the evaluations of different clients with comparative interests. It is broadly utilized in many sifting frameworks or recommender frameworks, particularly in online business applications. One of the instances of such a framework is Amazon.com and e-Bay, where a client's past shopping history is utilized to make suggestions for new items.

B. Proposed Work

In spite of the endeavours in the fields referenced above, other vital issues have been investigated incorporate client security, dependability and setting mindful suggestion. One of the clients worries to utilize recommender frameworks openly and easily is client protection. Clients are typically hesitant to reveal their private data, for example, buy, perusing, perusing records. Notwithstanding, most current separating calculations need to get client private data for further investigation and suggestion administrations. Some work has contemplated on the most proficient method to ensure client security in recommender frameworks. Current sifting procedures expect that client evaluations are trustable and treat all clients similarly. Nonetheless, some may contend that the assessments of specialists ought to be more underlined than that of fledglings.

The fundamental objective of the framework is to plan an online message separating framework that is sent at the OSN specialist organization side. Once sent, it reviews each message before rendering the message to the expected beneficiaries and settles on prompt choice on regardless of whether the message under assessment ought to be dropped. The point of the present work is consequently to propose and tentatively assess a robotized framework, called Filtered Wall (FW), ready to channel undesirable messages from OSN client dividers. We abuse Machine Learning (ML) content classification systems to consequently dole out with each short instant message a lot of classes dependent on its substance.

1) Hybrid filtering systems:

The cross type separating frameworks join highlights of both the substance and communitarian sifting frameworks. The mixture framework conquers the issue of the virus begin and early rather issue by utilizing the substance-based methodology in the underlying stage. The first is the straightforward blend demonstrates, which joins results from the shared and substance-based channels.

Filtering Rules: The framework gives an incredible principle layer misusing an adaptable language to indicate Filtering Rules (FRs), by which clients can state what substance ought not to be shown on their dividers.

Online setup assistant for FR's thresholds: OSA presents the client with a lot of messages chose from the dataset talked about. For each message, the client advises the framework of the choice to acknowledge or dismiss the message. The accumulation and handling of client choices on a sufficient arrangement of messages dispersed over every one of the classes permit to figure tweaked edges speaking to the client mentality in tolerating or dismissing certain substance. Such messages are chosen by the accompanying procedure. A specific measure of no impartial messages taken from a small amount of the dataset and not having a place with the preparation test sets, are characterized by the ML to have, for each message, the second dimension class participation esteems.

Assume that Bob is an OSN client and he needs to dependably square messages having a high level of revolting substance. Through the session with OSA, the edge speaking to the client frame of mind for the vulgar class is set to 0.8. Presently, assume that Bob needs to channel just messages originating from backhanded companions, while for direct companions such messages ought to be blocked just for those clients whose trust esteem is underneath 0.5. These separating criteria can be effectively indicated through the following FRs5:

- ((Bob, friend, 2, 1), (Vulgar, 0.80), block)
- ((Bob, friend, 1, 0.5), (Vulgar, 0.80), block)

2) Blacklists:

A further segment of our framework is a BL instrument to maintain a strategic distance from messages from undesired makers, autonomous from their substance. BL's are specifically overseen by the framework, which ought to most likely figure out who are the clients to be embedded in the BL and choose when client's maintenance in the BL is done. To upgrade adaptability, such data are given to the framework through a lot of standards, henceforth called BL rules.

BL rule:- A BL rule is a tuple (creator, creatorSpec, creatorbehavior, T) where the creator is the

OSN client who indicates the standard, i.e., the divider proprietor;

• creatorSpec is a maker detail;

• creatorBehavior comprises of two segments RFBlocked and man Banned**.**

RFBlocked = (RF, mode, window) is characterized such that:– RF = #bMessages/#tMessages, where #tMessages is the absolute number of messages that each OSN client distinguished by creatorSpec has attempted to distribute in the creator divider (mode = Wall) or all the OSN dividers (mode = SN); though #bMessages is the number of messages among those in #tMessages that have been blocked; window is the time interim of production of those messages that must be considered for RF calculation; minBanned = (min, mode, window), where min is the base number of times in the time interim determined in window that OSN clients recognized by creatorSpec must be embedded into the BL due to BL rules indicated by creator divider (mode = myWall) or all OSN clients (mode = SN) so as to fulfil the limitation.

T means the time span the clients recognized by creatorSpec and maker Behaviour must be prohibited from creator divider.

C. Algorithm

1) Pre-processing:

The essential point of the pre-preparing stage is to expel from the information message all characters and terms that can influence the nature of gathering portrayals.

2) Pre-processing steps:

/** Phase 1: Pre-processing */

for each document

{

do text filtering;

identify the document's language;

apply to stem;

mark stop words;

}

Algorithm :

1: d← input message

{STEP 1: Pre-processing}

2: **for** all d € D do

3: perform text categorization

4: **if** d!=null **then**

Filter text for unwanted symbols

5: apply to stem and mark stop-words in d

6: **end for**

There are three ladders to the pre-processing phase: Text filtering, Stemming and Stop words marking.

Text filtering: In the content sifting step, all terms that are pointless or would present commotion in the separating process are expelled from the info message. Among such terms are:

• HTML tags (e.g. <table>) and entities (e.g. &) if any.
• The 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.

Stemming:

Stemming calculations are utilized to change the words in writings into their syntactic root-structure, and are essentially used to enhance the Information Retrieval System's proficiency. To stem a word is to diminish it to a progressively broad structure, perhaps its root. For instance, stemming the term fascinating may create the term intrigue. In spite of the fact that the stem of a word probably won't be its root, we need all words that have a similar stem to have a similar root.

Elimination of Stop Words:

In the wake of stemming it is important to evacuate undesirable words. There are 400 to 500 sorts of stop words, for example, ―of‖, ―and‖, ―the,‖ and so on., that give no helpful data about the message. Stop-word evacuation is the way toward expelling these words. Stop-words represent about 20% of all words in a run of the mill record. These systems incredibly diminish the extent of the seeking and coordinating each word in the message. Stemming alone can lessen the measure of a file by almost 40%.

D. Mathematical Model

1) For Filtering Rules:

Input: Sifting Rules are adaptable by the client. The Client can have an expert to choose what substance ought to be blocked or showed on his divider by utilizing Filtering rules. For indicating a Filtering rules client profile just as client social relationship will be considered.
FR= {Trustier, SOUs, Rule, TuV}

FR is dependent on the following factors • Trustier

• Set of Users (SOUs) • Rule

• Action

Trustier is a person who defines the rules. SOUs denote the set of OSN user.

The Rule is a Boolean expression defined on content.

Process: FM= {SOUs, Rule==category (Violence, Vulgar, offensive, Hate, Sexual), TuV}

- FM
- SOUs
- Rule
- TuV

Here, FM Block Messages at the basic level.

SOUs Denotes set of users

Rule Category of specified contents in the message.

TuV is the trust value of the sender.

In handling, in the wake of giving information message, the framework will contrast the content and the diverse classes which are forestalled. In the event if message found in that forestalled sort of class, at that pointed message will show to the client that ―can't send this kind of messages‖, and still the client needs to send the message he/she can proceed with sending the message. The Trustier, who gets the message, the words which are protected in the standard are sent in **** position. In the wake of getting the message, the Trustier will give the Feedback (FB) to the sender and the sender will pick up the TuV as needs are. Procedure indicates the activity to be performed by the framework on the messages coordinating Rule and made by clients recognized by SOUs.

E.g. FM== {Friends, Rule==category (Vulgar, Sexual), TuV>50}

i.e. Trustier will acknowledge the message from companions yet message ought not to contain foul or sexual words. The Message containing such words will influence the TuV of the sender. Presently the inquiry emerges, estimation of TuV.

2) Trust Value Calculations:

The trust estimation of any client in OSN is reliant on the input they gain by the client to whom they communicated something specific. The Input from the client should likewise be trusted commendable. That is the reason the FB can be sorted into the following:-

Positive with content (PC) - Good FB, the message is worthy with questionable substance. This will expand the TuV of the sender.

Positive without content (PWC) - Good FB, the message is worthy as this message does not contain shocking substance. This will expand the TuV of the sender.

Negative with content (NC) - Bad FB, such messages must not be sent once more, which are against the Rule. This will diminish the TuV of the sender.

Negative without content (NWC) - Bad FB, the message doesn't contain any frightful substance yet the Trustier is giving negative FB. Such kind of FB from Trustier will influence the TuV of its own, and the TuV of the sender will stay the same.
So, based on over categories the TuV will be intended as follows:-

FB as 1 and 2 TuV= TuV+ abs [(PC+PWC)/ (NC+NWC)] FB as 3 TuV= TuV-[1+ (NC+NWC) / (PC+PWC)] for [(NC+NWC) / (PC+PWC)] <1

Otherwise, send system-generated message to the sender, FB Negative with content exceeds the limit of Threshold Value (ThV) and deduct 5 points from TuV, so ThV=TuV-5.

FB as 4 TuV= TuV of sender, but TuV= TuV-[1+ (NC+NWC) / (PC+PWC)] for Trustier.

Output: PFM= {Rule, M||Y}

PFM Percentages of the separated message in a year or month.
As a rule, more than a separating guideline can apply to a similar client. A message is in this way distributed just on the off chance that it isn't hindered by any of the siftings decides that apply to the message maker.

3) Blacklists: BLs are specifically overseen by the framework. This ought to most likely decide the clients to be embedded in the BL and choose when to hold client once again from the BL. To improve adaptability, such data is given to the framework through a lot of guidelines, in the future called BL rules.

BL rules: INPUT = {Sender, FB, TuV, ThV} Where • Sender is the OSN user who is sending the message;

• FB is the FeedBack expand by the sender after sending the message

• TuV is the new Trust Value considered as formulas specified in A.3.
• ThV is a Threshold Value.

BL Rules: ThV = PC+ PWC when, PC+PWC=NC+NWC. For the sender, when 5 points are deducted by the system, which means sender cross the ThV put sender into BL for a specific duration.

For Trustier, after giving feedback, check that, if true, put Trustier in BL for the specific duration.

E. Performance Study*:*

As we can see here the graph of accuracy. Our proposed method i.e. Trust value computation gives more accuracy (93%) than existing RBFN algorithm (85%).

Results for Message Neutrality:

Table 1: Result for message neutrality

Classification		***Neutral***			***Non-Neutral***		
RBFN	**TV**	**P**	**R**	**F1**	**P**	**R**	**F1**
84%	94%	93%	90%	95%	95%	92%	93%
85%	95%	86%	98%	93%	89%	97%	94%

Here P is Precision, R is Recall and F1 is F-measure. We have calculated these values by using the following formula:

Precision=(No. of True Positives)/(No. of true positives +No. of false positives)

Recall=(No. of True Negatives)/(No. of True Negative + No. of false positive)

F1-measure=(2*(Precision*Recall)/(Precision+Recall)).

Results for Non-neutral Classes Identification:

Table 2: Result for non-neural classes identification

Violence			***Vulgar***			***Hate***		
P	**R**	**F1**	**P**	**R**	**F1**	**P**	**R**	**F1**
87%	93%	90%	88%	94%	91%	90%	97%	94%
98%	84%	83%	94%	82%	84%	89%	92%	95%

IV CONCLUSION

In this report, we have talked about the writing overview of the sifting framework. We are building up a framework to channel undesired messages from OSN dividers. The divider that limits the undesirable message called as the Filtered Wall (FW). In this report we talked about the thought regarding the framework. Also, we contemplated procedures and methods restricting the inductions that a client can do on the authorized separating rules with the point of bypassing the sifting framework, for example, for example haphazardly advising a message that ought to rather be blocked.

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