

4.2. Machine Learning-Based Text Classification

Short text classification is a hierarchical two-level classification process. The first-level classifier accomplishes a binary hard classification that labels messages as Neutral and Non-Neutral. In second-level task a finer-grained classification is performed. The second-level classifier accomplishes a soft-partition of Non-neutral messages assigning a given message a gradual membership to each of the non-neutral classes. With respect to other state of the art classifiers we select the RBFN model, among the variety of multi-class ML models well-suited for text classification. Let Ω be the set of classes to which each message can belong to. Each element of the supervised collected set of messages $D = \{(m_i, \vec{y}_i), \dots, (m_{|D|}, \vec{y}_{|D|})\}$ is composed of the text m_i and the supervised label $\vec{y}_i \in \{0,1\}^{|\Omega|}$ describing the belongingness to each of the defined classes. The set D is then into two partitions, namely the training set TrSD and the test set TeSD. Let $M1$ and $M2$ be the first and second level classifier, respectively, and y_i be the belongingness to the Neutral class. The learning and generalization phase works as follows:

- 1) we extract the vector of features \vec{x}_i from each message m_i . The two sets TrSD and TeSD are then converted into $\text{TrS} = \{(\vec{x}_i, \vec{y}_i), \dots, (\vec{x}_{|\text{TrSD}|}, \vec{y}_{|\text{TrSD}|})\}$ and $\text{TeS} = \{(\vec{x}_i, \vec{y}_i), \dots, (\vec{x}_{|\text{TeSD}|}, \vec{y}_{|\text{TeSD}|})\}$, respectively.
- 2) for $M1$, a binary training set $\text{TrS1} = \{(\vec{x}_i, y_i) \in \text{TrS} \mid (x_i, y_i), y_i = \vec{y}_{j1}\}$ is created.
- 3) for $M2$, a multi-class training set $\text{TrS2} = \{(\vec{x}_i, y_i) \in \text{TrS} \mid (x_i, \vec{y}_i), \vec{y}_{jk} = \vec{y}_{j(k+1)}, k=2, \dots, |\Omega|\}$ is created.
- 4) to distinguish whether or not a message is non-neutral, $M1$ is trained with TrS1. The performance of the model $M1$ is then calculated using the test set TeS1.
- 5) to calculate the gradual membership to non-neutral classes, $M2$ is trained with the non-neutral TrS2 messages. Then the performance of the model $M2$ is calculated using the test set TeS2. Therefore, the hierarchical system is composed of $M1$ and $M2$, where the overall computed function $f: R^n \rightarrow R^{|\Omega|}$ is able to map the feature space to the class space, that is, to recognize the belongingness of a message to each of the $|\Omega|$ classes.

5. Filtering Rules and Blacklist

Here, we introduce the rules adopted for filtering unwanted messages. We model a social network as a directed graph. In this directed graph each node denotes a network user and edges denotes relationships between two different users. Each edge is labeled by the type of the established relationship (e.g., friend of, colleague of, parent of) and, possibly, the corresponding trust level, which represents how much a given user is trustworthy. We believe that trust levels are rational numbers in the range $[0; 1]$. There exists a direct relationship of a given type RT and trust value X between two users, if there is an edge connecting them having the labels RT and X . More than one edge connecting two users represents an indirect relationship.

5.1. Filtering Rules

The same message may have different meanings and depends on who writes it. Message creators on which a FR are to be applied can be selected on the basis of several different criteria, like imposing conditions on their profile's attributes.

Creator specification, defined as follows.

Definition 1. (Creator specification). A creator specification creatorSpec implicitly specifies a set of OSN users. It can have one of the following forms, possibly combined:

- 1) A set of attribute constraints of the form $an \text{ OP } av$, where an is a user profile attribute name, av and OP are, respectively, a profile attribute value and a comparison operator, compatible with an 's domain.
- 2) A set of relationship constraints of the form $(m; rt; \text{minDepth}; \text{maxTrust})$, indicating all the OSN users participating with user m in a relationship of type rt , having a depth greater than or equal to minDepth , and a trust value less than or equal to maxTrust .

Example - The creator specification $\text{CS1} = \{\text{Age} < 17; \text{Sex} = \text{male}\}$ denotes all the males whose age is less than 17 years, whereas the creator specification $\text{CS2} = \{\text{Dipika}; \text{colleague}; 2; 0.4\}$ denotes all the users who are colleagues of Dipika and whose trust level is less than or equal to 0.4. Finally, the creator specification $\text{CS3} = \{(\text{Dipika}; \text{colleague}; 2; 0.4); (\text{Sex} = \text{female})\}$ selects only the female users from those identified by CS2.

For content-based filtering criteria, we make use of the two-level text classification to identify messages that, with high probability, are neutral or non-neutral.; as well as, in a similar way, messages dealing with a particular second level class. The last component of a FR is the action. The possible actions are "block" and "notify", with the obvious semantics of blocking the message, or notifying the wall owner and wait him/her decision. A FR is therefore formally defined as follows.

Definition 2. (Filtering rule). A filtering rule FR is a tuple (author, creatorSpec, contentSpec, action), where:

- 1) author is the user who shapes the rule;
- 2) creatorSpec is a creator specification, specified according to Definition 1;
- 3) contentSpec is a Boolean expression defined on content constraints of the form (C, ml) , where C is a class of the first or second level and ml is the minimum membership level threshold necessary for class C to make the constraint satisfied;
- 4) action $\in \{\text{block}; \text{notify}\}$ represents the action to be performed by the system on the messages matching contentSpec and created by users recognized by creatorSpec.

More than one filtering rule can apply to the same user. A message can be published only if it is not blocked by any of the filtering rules that apply to the message creator.

5.2. Online Setup Assistant for FRs Threshold Calculation

By Online Setup Assistant (OSA) procedure, we solve the problem of setting thresholds to filter rules. Messages selected from the dataset is presented to the user through OSA. For each message, the user states the system the willingness or the decision to accept or reject the message. The collection and processing of user decisions on sufficient set of messages distributed over all the classes permits to compute customized thresholds signifying the user attitude in accepting or rejecting certain contents.

Following process is used to select such messages. A particular amount of non-neutral messages taken from a fraction of the dataset and not belonging to the training/test sets. These messages are categorized by the ML in order to have, the second level class membership values. Then class membership values are quantized into a number of qC discrete sets. And, for each discrete set, we select a number nC of messages, obtaining sets MC of messages with $|MC|=nCqC$, where $C \in \Omega - \{\text{Neutral}\}$ is a second level class. For instance, for the second level class Violence, we select 6 messages belonging to 8 degrees of Hate, for a total of 48 messages. For each second level class C , messages belonging to MC are shown. For each displayed message m , the user is asked to tell the decision $ma \in \{\text{Filter, Pass}\}$. This decision indicates the readiness of the user to filter or not filter the message. Together with the decision ma the user is asked to express the degree of certainty $mb \in \{0, 1, 2, 3, 4, 5\}$ with which the decision is taken, where $mb = 5$ represents the highest certainty, and $mb = 0$ shows the lowest certainty. Example 1. Suppose that Dipika is an OSN user and she wants to always block messages having a high degree of hate content. Through the session with OSA, the threshold representing the user attitude for the hate class is set to 0.7. Now suppose that Helen wants to filter only messages coming from indirect friends, whereas for direct friends such messages should be blocked only for those users whose trust value is below 0.3.

5.3. Blacklists

Blacklists (BLs) are directly managed by the system, which should be able to decide the users to be inserted in the BL and decide user's retention in the BL is finished. Such information is provided to the system through a set of rules, called BL rules. We let the wall's owners to state BL rules regulating who has to be banned from their walls and for how long. Therefore, a user might be banned from a wall, by, at the same time, being able to post in other walls.

Like FRs, our BL rules make the wall owner able to recognize users to be blocked based on their profiles as well as their relationships in the OSN. Therefore, by means of a BL rule, wall owners can be able to bar from their walls users they do not directly know BL for another while, as his/her behaviour is not improved. This principle works for those users that have been already inserted in the considered BL at least one time.

Definition 3. (BL rule). A BL rule is a tuple (author, creatorSpec, creatorBehavior, T), where:

- 1) author is the OSN user who states the rule, i.e., the wall owner;
- 2) creatorSpec is a creator specification, specified according to Definition 1;
- 3) creatorBehavior consists of two components RFBlocked and minBanned. RFBlocked = (RF, mode, window) is defined such that:
 - $RF = \frac{\#bMessages}{\#tMessages}$, where $\#tMessages$ is the total number of messages that each OSN user recognized by creatorSpec has tried to publish in the author wall (mode = myWall) or in all the OSN walls (mode = SN); whereas $\#bMessages$ is the number of messages among those in $\#tMessages$ that have been blocked;
 - window is the time interval of creation of those messages that have to be considered for RF computation; minBanned = (min, mode, window), where min is the minimum number of times in the time interval specified in window that OSN users identified by creatorSpec have to be inserted into the BL due to BL rules specified by author wall (mode = myWall) or all OSN users (mode = SN) in order to fulfil the constraint.
- 4) T indicates the time period the users identified by creatorSpec and creatorBehavior have to be banned from author wall.

Example 2. The BL rule:

(Prabhu; (Age < 17); (0:5; myWall; 2 week); 2 days) inserts into the BL associated with Prabhu's wall those young users (i.e., with age less than 17) that in the last week have a relative frequency of blocked messages on Remo's wall greater than or equal to 0:5. Furthermore, the rule states that these banned users have to stay in the BL for two days. If Remo adds the following component (4,SN, 2 week) to the BL rule, he enlarges the set of banned users by inserting also the users that in the last week have been inserted at least four times into any OSN BL.

6. Results and Discussion

The analysis of related work has highlighted the lack of a publicly available benchmark for comparing different approaches to content based classification of OSN short texts. To cope with this lack, we have built a dataset D of messages. 1266 messages from publicly accessible groups have been selected and extracted by means of an automated procedure that removes undesired spam messages and, for each message, stores the message body and the name of the group from which it originates. The messages come from the group's web page section, where any registered user can post a new message or reply to messages already posted by other users. The set of classes considered in our experiments is $\Omega = \{\text{Neutral; Violence; Vulgar; Offensive; Hate; Sex}\}$, where $\Omega - \{\text{Neutral}\}$ are the second level classes. The percentage of elements in D that belongs to the Neutral class is 31%. In order to deal with intrinsic ambiguity in assigning messages to classes, we conceive that a given message belongs to more than one class. Each message has been labeled by a group of five experts and the class membership values $y_j \in \{0,1\}^\Omega$ for a given message m_j were computed by a majority voting procedure. After the ground truth collection phase, the messages have been selected to balance

as much as possible second-level class occurrences. The group of experts has been chosen in an attempt to ensure high heterogeneity concerning sex, age, employment, education and religion. In order to create a consensus concerning the meaning of the Neutral class and general criteria in assigning multi-class membership we invited experts to participate to a dedicated tuning session. We are aware of the fact that the extreme diversity of OSNs content and the continuing evolution of communication styles create the need of using several datasets as a reference benchmark. We hope that our dataset will pave the way for a quantitative and more precise analysis of OSN short text classification methods.

Table 1: Results of the Proposed Model in Term of Precision (P), Recall (R) and F-Measure (F1) Values for Each Class

Metric	First level		Second Level				
	Neutral	Non-Neutral	Violence	Vulgar	Offensive	Hate	Sex
P	81%	77%	82%	62%	82%	65%	88%
R	93%	50%	46%	49%	67%	39%	91%
F1	87%	61%	59%	55%	74%	49%	89%

In order to provide an overall assessment of how effectively the system applies a FR, we look at Table 1. This table allows us to estimate the Precision and Recall of our FRs, since values reported in Table 1 have been computed for FRs with content specification component set to (C; 0:5), where $C \geq 2$. Let us suppose that the system applies a given rule on a certain message. As such, Precision reported in Table 1 is the probability that the decision taken on the considered message (that is, blocking it or not) is actually the correct one. In contrast, Recall has to be interpreted as the probability that, given a rule that must be applied over a certain message, the rule is really enforced. Let us now discuss, with some examples, the results presented in Table 1, which reports Precision and Recall values. The second column of Table 1 represents the Precision and the Recall value computed for FRs with (Neutral; 0:5) content constraint. In contrast, the fifth column stores the Precision and the Recall value computed for FRs with (Vulgar; 0:5) constraint. Results achieved by the content-based specification component, on the first level classification, can be considered good enough and reasonably aligned with those obtained by well-known information filtering techniques. Results obtained for the content-based specification component on the second level are slightly less brilliant than those obtained for the first, but we should interpret this in view of the intrinsic difficulties in assigning to a messages a semantically most specific category.

7. Conclusions

In this work, we have presented an unwanted text message filtering from OSN user walls. The system uses a ML soft classifier to enforce customizable content-based FRs. Furthermore, the flexibility of the system in terms of filtering options is boosted through the management of BLs.

The first task is the extraction and/or selection of contextual features that have been shown to have a high discriminative power. The second task contains the learning phase. As the underlying domain is dynamically changing, the collection

of pre-classified data may not be representative in the longer term.

The use of machine learning text classification technique makes classification more automatic and more efficient. The present batch learning strategy, based on the preliminary collection of the entire set of labeled data from experts, permitted an accurate experimental evaluation but needs to be developed to include new operational requirements. Our plan is to solve this problem by investigating the use of on-line learning paradigms able to include label feedbacks from users in future work. The proposed system may have problems similar to those encountered in the specification of OSN privacy settings.

Our plan is to investigate the development of a GUI and a set of related tools to make easier BL and FR specification, for usability of an application.

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