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DENOISING ENCODER WITH SEMANTICS AND EXCLUSION FOR SPOTTING CYBERBULLY

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Abstract— The rapid growth of social networking is supplementing the progression of cyberbullying activities. Most of the individuals involved in these activities belong to the younger generations, especially teenagers, who are at more risk of suicidal attempts. Cyberbullying is the process of using the Internet, cell phones, or other devices to send or post text or images intended to hurt or embarrass another person. Through machine learning techniques, we can detect language patterns used by bullies and their victims, and develop rules to automatically detect cyberbullying content. Here, we introduce a new machine learning method to deal with this problem. Our method named Semantic-Enhanced Marginalized Stacked Denoising Auto-Encoder (smSDA) is developed via a semantic extension of the popular deep learning model. The smSDA method detects the hidden attributes of the bullying information. Our approach experiments on two public cyberbullying corpora i.e. twitter and MySpace. The outcome of our proposed method is better than the other text representation learning methods.

Introduction

Recent research has shown that most teens experience cyberbullying during their online activities, including mobile phone use and also while participating in gaming or social networking sites over the Internet. The effects of online bullying become serious (suicide attempts) when victims fail to overcome the emotional stress caused by abusive, threatening, degrading, and aggressive messages. The influence of cyberbullying is displeased by the fact that children are reluctant to share their predicament with adults (parents/teachers), because of fear of losing their mobile phones and Internet access privileges. Reporting it to law enforcement agencies, Internet service providers, and others are identifying predators and their victims. In this study, we find predators and victims by identifying the most active users in the form of predators and the most active victims. A user can be a predator or a victim based on the number of bullying messages he or she publishes or receives in the Internet community. It also includes the number of bullying messages that a user publishes and receives also on the number of users in his / her network since the user-published publication can be read by all users in the network. The user will be the most active predator if published many bullying and receiving messages published by many users.

The user is the most active victim if he/she receives many bullying messages from many other active predators. To find the most predators and active victims, users must be arranged in the network. Thus, finding the most predators and active victims is the ordering process. We use a ranking algorithm to detect the most active predators and victims. The proposed approach builds a matrix to detect bullying and represent the associated graph. Although cyberbullying is a common problem in Internet communities, abusive material is not categorized or categorized in any way, making the investigation of cyberbullying is a challenge. For our experiment, we collect three different data sets from Web 2.0. Through our methodology, we show the results of improved bullying detection using the choice of semantic and balanced features. Our work is a unique technique that deals with cyber as an identification graph using the ranking algorithm and the calculated cyberbullying matrix, bullying predators, and victims. First, we suggest a new statistical detection method based on. The weighted TF-IDF scheme has features similar to bullying. It also efficiently identifies the underlying bullying features to improve performance. Second, we provide a graph model for the detection of the most active predators and victims in social networks. In addition to identifying predators and victims, this graph model can be used to classify users in terms of online victimization levels, based on their involvement in cyberbullying activities. Thirdly, our experience has shown that the proposed approach is effective and effective. The accuracy of the methods of detection of text-based electronic bullying is still limited. Our main goal is to explore the value of social information in the discovery of electronic bullying higher than the signals available in the textual content of messages. We believe that because bullying is a social problem. Using a set of Twitter messages, our approach identifies social and textual features and creates a complex model for detecting cyberbullying. The results obtained indicate that social signals are useful in detecting cyberbullying and that using multiple channels of information (text as well as social features) leads to higher detection performance.

3. LITERATURE REVIEW

3.1 Representation Learning: A Review and New Perspectives.

The success of machine learning algorithms generally depends on data representation, and we hypothesize that is because different representations can entangle and hide more or less the different explanatory factors of variation behind the data. Although specific domain knowledge can be used to help design representations, learning with generic priors can also be used, and the quest for AI is motivating the design of more powerful representation-learning algorithms implementing such priors. This paper reviews recent work in the area of unsupervised feature learning and deep learning, covering advances in probabilistic models, auto-encoders, manifold learning, and deep networks. This motivates longer-term unanswered questions about the appropriate objectives for learning good representations, for computing representations (i.e., inference), and the geometrical connections between representation learning, density estimation, and manifold learning.

3.2 Users of the world, unite! The challenges and opportunities of Social Media.

The concept of Social Media is top of the agenda for many business executives today. Decision makers, as well as consultants, try to identify ways in which firms can make profitable use of applications such as Wikipedia, YouTube, Facebook, and Twitter. Yet despite this interest, there seems to be very limited understanding of what the term ''Social Media'' exactly means; this article intends to provide some clarification. We begin by describing the concept of Social Media, and discuss how it differs from related concepts such as Web 2.0 and User Generated Content. Based on this definition, we then provide a classification of Social Media which groups applications currently subsumed under the generalized term into more specific categories by collaborative projects, blogs, content communities, social networking sites, virtual game worlds, and virtual social worlds.

3.3 Bullying in the digital age: a critical review and meta-analysis of cyberbullying research among youth.

Although the Internet has transformed the way our world operates, it has also served as a venue for cyberbullying, a serious form of misbehavior among youth. With many of today's youth experiencing acts of cyberbullying, a growing body of literature has begun to document the prevalence, predictors, and outcomes of this behavior, but the literature is highly fragmented and lacks theoretical focus. The general aggression model is proposed as a useful theoretical framework from which to understand this phenomenon. Additionally, results from a meta-analytic review are presented to highlight the size of the relationships between cyberbullying and traditional bullying, as well as relationships between cyberbullying and other meaningful behavioral and psychological variables. Mixed-effects meta-analysis results indicate that among the strongest associations with cyberbullying perpetration were normative beliefs about aggression and moral disengagement, and the strongest associations with cyberbullying victimization were stress and suicidal ideation. Several methodological and sample characteristics served as moderators of these relationships. Limitations of the meta-analysis include issues dealing with causality or directionality of these associations as well as generalizability for those meta-analytic estimates that are based on smaller sets of studies ($k < 5$). Finally, the present results uncover important areas for future research. We provide a relevant agenda, including the need for understanding the incremental impact of cyberbullying (over and above traditional bullying) on key behavioral and psychological outcomes

3.4 Peer relations in the anxiety-depression link: test of a mediation model.

The association between anxiety and depression symptoms is mediated by peer relations difficulties among a sample of adolescent ages 14-17 years. Adolescents completed measures of anxiety symptoms, depression symptoms, peer group experiences (i.e., peer acceptance and victimization from peers), and friendship quality (i.e., positive qualities and conflict). As hypothesized, Time 1 anxiety symptoms

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predicted Time 2 (T2) depression symptoms and this the association was mediated by T2 low perceived peer acceptance and T2 victimization from peers, both of which emerged as unique mediators when they were considered simultaneously in the model. Contrary to expectations, qualities of adolescents' best friendships at T2 did not emerge as mediators and were largely unrelated to symptoms of anxiety and depression. Implications of the findings include the importance of addressing peer relations difficulties, especially peer acceptance and victimization, in the treatment of anxiety and the prevention of depression among anxious youth.

3.5 Modeling the Detection of Textual Cyberbullying.

The scourge of cyberbullying has assumed alarming proportions with an ever-increasing number of adolescents admitting to having a deal with it either as a victim or as a bystander. Anonymity and the lack of meaningful supervision in the electronic medium are two factors that have exacerbated this social menace. Comments or posts involving sensitive topics that are personal to an individual are more likely to be internalized by a victim, often resulting in tragic outcomes. We decompose the overall detection problem into the detection of sensitive topics, lending itself into text classification sub-problems. We find that binary classifiers for individual labels outperform multiclass classifiers. Our findings show that the detection of textual cyberbullying can be tackled by building individual topic-sensitive classifiers.

4. PROPOSED METHOD

4.1 Cyberbullying Detection:

- In this module we propose the Semantic-enhanced Marginalized Stacked Denoising Auto-encoder (smSDA). We describe how to leverage it for cyberbullying detection. smSDA provides robust and discriminative representations The learned numerical representations can then be fed into our system.
- In the new space, due to the captured feature correlation and semantic information, even trained in a small size of training corpus, can achieve a good performance on testing documents.
- Based on word embedding, bullying features can be extracted automatically. Also, the possible limitation of expert knowledge can be alleviated by the use of word embedding

4.2 Semantic-Enhanced Marginalized Denoising Auto-Encoder:

❖ Automatic extraction of bullying words based on word embedding is proposed so that the involved human labor can be reduced. During the training of smSDA, we attempt to reconstruct bullying features from other normal words by discovering the latent structure, i.e. correlation, between bullying and normal words. The intuition behind this idea is that some bullying messages do not contain bullying words.

- The correlation information discovered by smSDA helps to reconstruct bullying features from normal words, and this in turn facilitates the detection of bullying messages without containing bullying words. For example, there is a strong correlation between bullying word kill and the normal word you since they often occur together.

- If bullying messages do not contain such obvious bullying features, such as kill is often misspelled as kill, the correlation may help to reconstruct the bullying features from normal ones so that the bullying message can be detected. It should be noted that introducing dropout noise has the effects of enlarging the size of the dataset, including training data size, which helps alleviate the data sparsity problem.

4.3 OSN System Construction

- In the first module, we develop the Online Social Networking (OSN) system module. We build up the system with the feature of Online Social Networking. Where this module is used for new user registrations and after registrations the users can log in with their authentication.
- Where after the existing users can send messages privately and publicly, options are built. Users can also share posts with others. The user can able to search the other user-profiles and public posts. In this module, users can also accept and send friend requests.
- With all the basic feature of Online Social Networking System modules is build up in the initial module, to prove and evaluate our system features.

4.4 Construction of Bullying Feature Set:

- Bullying features play an important role and should be chosen properly. In the following, the steps for constructing the bullying feature set Zb is given, in which the first layer and the other layers are addressed separately.
- For the first layer, expert knowledge, and word embeddings are used. For the other layers, discriminative feature selection is conducted.
- In this module firstly, we build a list of words with negative effects, including swear words and dirty words. Then, we compare the word list with the BoW features of our corpus, and regard the intersections as bullying features.
- Finally, the constructed bullying features are used to train the first layer in our proposed smSDA. It includes two parts: one is the original insulting words based on domain knowledge and the other is the extended bullying words via word embedding's.
- Observe attentively over some time.

4.5 Semantic Dropout Noise:

The dropout noise adopted in smSDA is a uniform distribution, where each feature has the same probability to be removed. In cyberbullying detection, most bullying posts contain bullying words such as foul languages. Cyberbullying words can be explored by using a different dropout noise that features corresponding to bullying words that have a larger probability of corruption than other features. The imposed a large probability of bullying. This kind of drop-out noise can be denoted as semantic dropout noise because semantic information is used to design a dropout structure. The correlation between features can enable other normal words to predict bullying labels. The proposed smSDA can deal with the problem of learning a robust feature representation, which is a high-level concept representation. The correlation explored by this auto encoder structure enables the subsequent classifier to learn the discriminative word and improve the classification performance. Also, the semantic dropout noise exploits the correlation between bullying features and normal features better and hence, facilitates cyberbullying detection.

4.6 System Architecture:

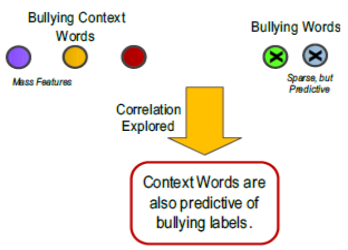

Fig. 4.6 (a): System Architecture

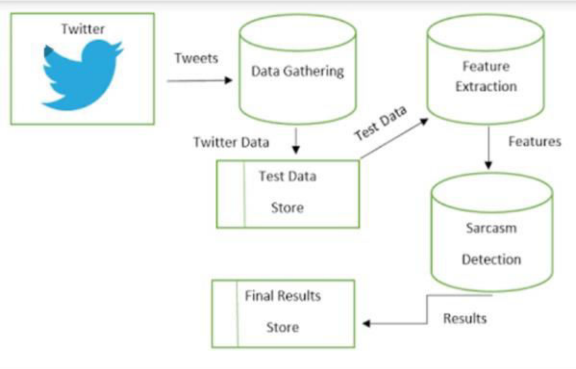

Fig. 4.6(b): System Architecture for Detecting Bullying Words on Social Media

5. Results

We evaluate our proposed semantic enhanced marginalized stacked denoising auto-encoder (smSDA) with two public real-world cyberbullying corpora. We start by describing the adopted corpora and experimental setup. Experimental results are then compared with other baseline methods to test the performance of our approach. At last, we provide a detailed analysis to explain the good performance of our method.

5.1 Descriptions of Datasets:

Two datasets are used here. One is from Twitter and another is from MySpace groups. The details of these two datasets are described below: Twitter Dataset: Twitter is ‘’a real-time information network that connects you to the latest stories, ideas, opinions, and news about what you find interesting. Registered users can read and post tweets, which are defined as the messages posted on Twitter with a maximum length of 140 characters. The Twitter dataset is composed of tweets crawled by the public Twitter stream API through two steps.

In Step 1, keywords starting with ”bull” including ”bully”, ”bullied” and ”bullying” are used as queries in Twitter to preselect some tweets that potentially contain bullying contents. Retweets are removed by excluding tweets containing the acronym ‘’RT‘’.

In Step 2, the selected tweets are manually labeled as bullying trace or non-bullying trace based on the contents of the tweets. It should be pointed out here that labeling is based on bullying traces. A bullying trace is defined as the response of participants to their bullying experience. Bullying traces include not only messages about direct bullying attack, but also messages about reporting a bullying experience, revealing self as a victim. Therefore, bullying traces far exceed the incidents of cyberbullying. Automatic detection of bullying traces is valuable for cyberbullying research. To preprocess the tweets, a tokenizer is applied without any stemming or stop word removal

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operations. In addition, some special characters including user mentions, URLs, and so on are replaced by predefined characters, respectively. The features are composed of unigrams and bigrams that should appear at least twice.

MySpace Dataset: MySpace is another web2.0 social networking website. The registered accounts are allowed to view pictures, read the chat, and check other people's profile information. The MySpace dataset is crawled from MySpace groups. Each group consists of several posts by different users, which can be regarded as a conversation about one topic. Due to the interactive nature behind cyberbullying, each data sample is defined as a window of 10 consecutive posts and the windows are moved one post by one post so that we got multiple windows. J. Bayzick, A. Kontostathis, and L. Edwards, These, three people labeled the data for the existence of bullying content independently. To be objective, an instance is labeled as cyberbullying only if at least 2 out of 3 coders identify bullying content in the windows of posts. The raw text for these data, as XML files, have been kindly provided by Kontostathis. The XML files contain information about the posts, such as post text, post data, and users' information, which is put into 11 packets. Here, we focus on content-based mining, and hence, we only extract and preprocess the post's text. The preprocessing steps of the MySpace raw text include tokenization, deletion of punctuation, and special characters. The unigrams and bigrams features are adopted here. The threshold for negligible low-frequency terms is set to 20, considering one post that occurred in a long conversation will occur in at least ten windows. Since there were no standard splits of training vs. test datasets in our adopted Twitter and MySpace corpora, we need to define the training and testing datasets. As analyzed above that the lack of labeled training corpus hinders the development of automatic cyberbullying detection, the sizes of training corpus are all controlled to be very small in our experiments. For the Twitter dataset, we randomly select 800 instances, which accounts for 12% of the whole corpus, as the training data and the test data samples are used as testing data. To reduce variance, the process is repeated ten times so that we can have ten sub-datasets from Twitter data. For the MySpace dataset, we also randomly pick 400 data samples as the training corpus and use the rest data for testing. The process is repeated ten times to generate ten sub-datasets constructed from MySpace data. Finally, we have twenty sub-datasets, in which ten datasets are from the Twitter corpus and another ten datasets are from MySpace corpus.

5.2 Experimental Results:

It is clear that our approaches outperform the other approaches in these two Twitter and MySpace corpora. The first observation is that semantic BoW model (sBow) performs slightly better than BoW. Based on BoW, sBoW just arbitrarily scale the bullying features. This means that semantic information can boost the performance of cyberbullying detection. For a fair comparison, the bullying features used in our method and sBoW is unified to be the same. Our approaches, especially smSDA, gain a significant performance improvement compared to sBoW. This is because bullying features only account for a small portion of all features used. It is difficult to learn robust features for small training data by intensifying each bullying features amplitude. Our approach aims to find the correlation between normal features and bullying features by reconstructing corrupted data so as to yield robust features. In addition, Bullying Word Matching (BWM), as a simple and intuitive method of using semantic information, gives the worst performance. In BWM, the existence of bullying words is defined as rules for classification. It shows that only an elaborated utilization of such bullying words instead of a simple one can help cyberbullying detection. We also compare our methods with two stat-of-arts text representation learning methods LSA and LDA. These two methods do not produce a good performance on all datasets. This may be because both methods belong to dimensionality reduction techniques, which are performed on the document-word occurrence matrix. Although the two methods try to minimize the reconstruction error as our approach does, the optimization in LSA and LDA are conducted after dimensionality reduction. The reduced dimension is a key parameter to determine the quality of the learned feature space. Here, we fix the dimension of the latent space to 100. Therefore, a deliberate searching for this parameter which may improve the performances of LSA and LDA and the selection of the hyper parameter itself is another tough research topic. Another reason may be that the data samples are small (less than 2000) and the length of each Internet message is short (For Twitter, the maximum length is 140 characters), and thus the constructed document-word occurrence matrix may not represent the true co-occurrence of terms. Deep learning methods including mSDA and smSDA generally outperform other standard approaches. This trend is particularly prominent in the F1 measure because cyberbullying detection problems are class-imbalance. The larger improvements on the F1 score verify the performance of our approach further. Deep learning models have achieved remarkable performance in various scenarios with their own robust feature learning ability. smSDA is able to capture the correlation between input features and combine the correlated features by reconstructing masking feature values from uncorrupted feature values. Further, the stacking structure and the nonlinearity contribute to mSDA's ability for discovering complex factors behind data. Based on mSDA, our proposed smSDA utilizes semantic dropout noise and sparsity constraints on the mapping matrix, in which the efficiency of training can be kept. This extension leads to stable performance improvement on cyberbullying detection and the detailed analysis has been provided in the following section. We compare the performances of mSDA and smSDAu, which adopt biased semantic dropout noise and unbiased semantic dropout noise, respectively. The results have shown that smSDAu performs slightly worse than smSDA. This may be explained by the fact that the unbiased semantic dropout noise cancels the enhancement of bullying features. The off-diagonal elements in the matrix are used to compute mapping weights that are the same, which can not contribute to the reinforcement of bullying features.

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5.3 Output

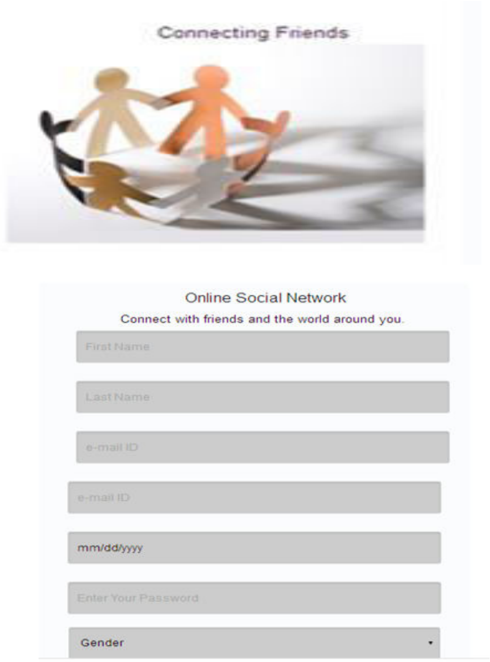

Fig.5.3 (a): Application form for users

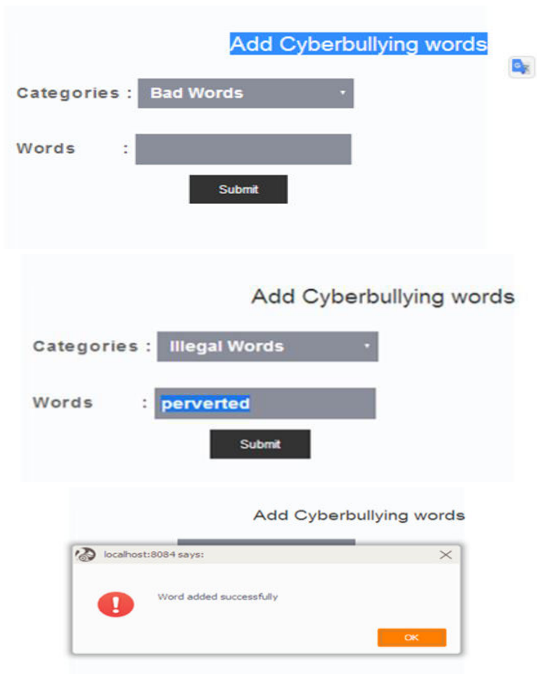

Fig.5.3 (b): Process of adding cyberbullying words

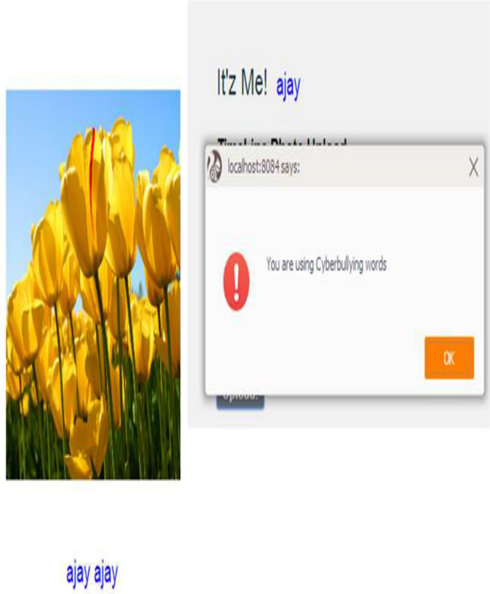

Fig.5.3(c): Detection of cyberbullying words

6. Conclusion

This paper addresses the text-based cyberbullying detection problem, where robust and discriminative representations of messages are critical for an effective detection system. By designing semantic dropout noise and enforcing sparsity, we have developed a semantic-enhanced marginalized denoising autoencoder as a specialized representation learning model for cyberbullying detection. In addition, word embeddings have been used to automatically expand and refine bullying word lists that are initialized by domain knowledge. The performance of our approaches has been experimentally verified through two cyberbullying corpora from social media: Twitter and MySpace.

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