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Detection of Cyberbulling on Social Media

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Abstract
Classification features were derived from the content of each tweet, including grammatical dependencies between words to recognize "othering" phrases, incitement to respond with antagonistic action, and claims of well-founded or justified discrimination against social groups. The results of the classifier were optimal using a combination of probabilistic, rule- based, and spatial-based classifiers with a voted ensemble meta-classifier. We demonstrate how the results of the classifier can be robustly utilized in a statistical model used to forecast the likely spread of cyber hate in a sample of Twitter data. The applications to policy and decision making are discussed. We propose a collaborative multi-domain sentiment classification approach to train sentiment classifiers for multiple domains simultaneously. In our approach, the sentiment information in different domains is shared to train more accurate and robust sentiment classifiers for each domain when labeled data is scarce. Specifically, we decompose the sentiment classifier of each domain into two components, a global one and a domain-specific one. The global model can capture general sentiment knowledge and is shared by various domains. The domain-specific model can capture the specific sentiment expressions in each domain. In addition, we extract Trimodal (Naive Bayes IBK, SVM) sentiment knowledge from both labeled and unlabeled samples in each domain and use it to enhance the learning of Trimodal (Naive Bayes IBK, SVM) sentiment classifiers. Besides, we incorporate the similarities between domains into our approach as regularization over the Trimodal (Naive Bayes IBK, SVM) sentiment classifiers to encourage the sharing of sentiment information between similar domains. Two kinds of domain similarity measures are explored, one based on textual content and the other one based on sentiment expressions. Moreover, we introduce two efficient algorithms to solve the model of our approach. Experimental results on benchmark datasets show that our approach can effectively improve the performance of multi-domain sentiment classification and significantly outperform baseline methods

Keywords: *cyber bully detection, Harsh words detection , Twitter Abuse detection*

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I. INTRODUCTION

Data mining is a process of searching large data to discover patterns for simple analysis. Data mining is a technology to help companies focus on their data warehouse. So, it is called Knowledge Discovery in Data (KDD)[12]. KDD decisions are allowed by data mining tools for businesses. Data mining tools can answer business questions that traditionally were time consuming to resolve. the data mining process steps. Hate crimes are communicative acts, often provoked by events that incite retribution in the targeted group, toward the group that share similar characteristics to the perpetrators (King & Sutton, 2013). Collecting and analyzing temporal data allows decision makers to study the escalation, duration, diffusion, and de-escalation of hate crimes following "trigger" events. However, decision makers are often limited in the information that can be obtained in the immediate aftermath of such events. When data can be obtained, they are often of low granularity, subject to missing information (hate crimes are largely unreported to the police), and invariably retrospective. However, the recent widespread adoption of social media offers a new opportunity to address these data problems. The continued growth of online social networks and microblogging Web services, such as Twitter, enable a locomotive, extensive and near real-time data source through which the analysis of hateful and antagonistic responses to "trigger" events can be undertaken. Such data affords researchers with the possibility to measure the online social mood and emotion following large-scale, disruptive, and emotive events such terrorist attacks in near real-time

II. LITERATURE SURVEY

Bo Pang, has proposed an important part of our information- gathering behavior has always been to find out what other people think. With the growing availability and popularity of opinion-rich resources such as online review sites and personal blogs, new opportunities and challenges arise as people now can, and do,

actively use information technologies to seek out and understand the opinions of others. The sudden eruption of activity in the area of opinion mining and sentiment analysis, which deals with the computational treatment of opinion, sentiment, and subjectivity in text, has thus occurred at least in part as a direct response to the surge of interest in new systems that deal directly with opinions as a first-class object. This survey covers techniques and approaches that promise to directly enable opinion-oriented information seeking systems. Our focus is on methods that seek to address the new challenges raised by sentiment aware applications, as compared to those that are already present in more traditional fact-based analysis. We include material on summarization of evaluative text and on broader issues regarding privacy, manipulation, and economic impact that the development of opinion-oriented information-access services give rise to. To facilitate future work, a discussion of available resources, benchmark datasets, and evaluation campaigns is also provided.

Johan Bollen, has proposed We perform a sentiment analysis of all tweets published on the microblogging platform Twitter in the second half of 2008. We use a psychometric instrument to extract six mood states (tension, depression, anger, vigor, fatigue, confusion) from the aggregated Twitter content and compute a six-dimensional mood vector for each day in the timeline. We compare our results to a record of popular events gathered from media and sources. We find that events in the social, political, cultural and economic sphere do have a significant, immediate and highly specific effect on the various dimensions of public mood. We speculate that large scale analyses of mood can provide a solid platform to model collective emotive trends in terms of their predictive value with regards to existing social as well as economic indicators. Microblogging is an increasingly popular form of communication on the web. It allows users to broadcast brief text updates to the public or to a selected group of contacts. Microblog posts, commonly known as tweets, are extremely short in comparison to regular blog posts, being at most 140 characters in length. The launch of Twitter is responsible for the popularization of this simple, yet vastly popular form of communication on the web. Users of these online communities use microblogging to broadcast different types of information. A recent analysis of the Twitter network revealed a variegated mosaic of uses (Java), including a) daily chatter, e.g., posting what one is currently doing, b) conversations, i.e., directing tweets to specific users in their community of followers, c) information sharing, e.g., posting links to web pages, and d) news reporting, e.g., commentary on news and current affairs. Despite the diversity of uses emerging from such a simple communication channel, it has been noted that tweets normally tend to fall in one of two different content camps: users that microblog about themselves and those that use microblogging primarily to share information (Moor Naaman). In both cases, tweets can convey information about the mood state of their authors. In the former case, mood expressions are evident by an explicit "sharing of subjectivity" (Crawford), e.g. "I am feeling sad". In other cases, even when a user is not specifically microblogging about their personal emotive status, the message can reflect their mood, e.g., "Colin Powell's endorsement of Obama: amazing. :)". As such, tweets may be regarded as microscopic instantiations of mood. It follows that the collection of all tweets published over a given time period can unveil changes in the state of public mood at a larger scale. An increasing number of empirical analyses of sentiment and mood are based on textual collections of data generated on microblogging and social sites. Examples are mood surveys of communication on Myspace (Thelwell, Wilkinson, and Uppal), and Twitter (Thelwell et al). Some of these analyses are focused on specific events, such as the study focused on micro bloggers' response to the death of Michael Jackson (Kim et al) or a political election in Germany (Tumasjan et al.), while others analyze broader social and economic trends, such as the relationship between Twitter mood and both stock market fluctuations (Bollen, Mao, and Zeng) and consumer confidence and political opinion (O'Connor et al). The results generated via the analysis of such collective mood aggregators are compelling and indicate that accurate public mood indicators can be extracted from online materials. Using publicly available online data to perform sentiment analyses significantly reduces the costs, efforts and time needed to administer large-scale public surveys and questionnaires. These data and results present great opportunities for psychologists and social scientists.

Brendan O'Connor, has proposed We connect measures of public opinion measured from polls with sentiment measured from text. We analyze several surveys on consumer confidence and political opinion over the 2008 to 2009 period, and find they correlate to sentiment word frequencies in contemporaneous Twitter messages. While our results vary across datasets, in several cases the correlations are as high as 80%, and capture important large- scale trends. The results highlight the potential of text streams as a substitute and supplement for traditional polling. If we want to know, say, the extent to which the U.S. population likes or dislikes Barack Obama, an obvious thing to do is to ask a random sample of people (i.e., poll). Survey and polling methodology, extensively developed through the 20th century (Krosnick, Judd, and Wittenbrink), gives numerous tools and techniques to accomplish representative public opinion measurement. With the dramatic rise of text-based social media, millions of people broadcast their thoughts and opinions on a great variety of topics. Can we analyze publicly available data to infer population attitudes in the same manner that public opinion pollsters query a population? If so, then mining public opinion from freely available text content could be a faster and less expensive alternative to traditional polls. (A standard telephone poll of one thousand respondents

easily costs tens of thousands of dollars to run.) Such analysis would also permit us to consider a greater variety of polling questions, limited only by the scope of topics and opinions people broadcast. Extracting the public opinion from social media text provides a challenging and rich context to explore computational models of natural language, motivating new research in computational linguistics. In this work, we connect measures of public opinion derived from polls with sentiment measured from analysis of text from the popular microblogging site Twitter. We explicitly link measurement of textual sentiment in microblog messages through time, comparing to contemporaneous polling data. In this preliminary work, summary statistics derived from extremely simple text analysis techniques are demonstrated to correlate with polling data on consumer confidence and political opinion, and can also predict future movements in the polls. We find that temporal smoothing is a critically important issue to support a successful model.

III. EXISTING METHOD

In dosLDA, documents are projected into a low dimensional topic space by assigning each word with a latent topic. It employs an extra generative process on the topic proportion of each document and models the whole corpus via a hierarchical Bayesian framework.The BoW representation disregards the linguistic structures between the words. Consumer expectations are not predicted clearly. Less accurate prediction on opinion analysis. User review-based word alignment is cumbersome. High latency to analyze the datasets. A BoW approach uses words within a corpus as predictive features and ignores word sequence as well as any syntactic or semantic content. This approach can lead to misclassification due to word use in different contexts and, if words are used as a primary feature for classification, it has been shown that combining sequential words into ngrams (list of words occurring in sequence from 1–n) improves classifier performance by incorporating some degree of context into the features (Pendar, 2007). However, an n-gram approach can suffer from the problem of high levels Burnap/Williams: Machine Classification of Cyber Cyper pooling 225 of distance between related words—for example, if related words appear near the start and near the end of a sentence (Chen, Zhou, Zhu, & Xu, 2012). Dadvar, Triesch Nigg, and de Jong (2013) used profane words in a social media account username, references to profanities and bullying-sensitive topics, and first and second person pronouns to classify antagonistic behavior on YouTube. Dinakar, Jones, Havasi, Lieberman, and Picard (2012) also focused on the identification of cyberbullying using a BoW approach, but also incorporated lists of profane words, parts-of-speech and words with negative connotations as machine learning features. Furthermore, they included a common-sense reasoning approach to classification by using a database that encoded particular knowledge about bullying situations (e.g., associating wearing dresses with males).

IV. PROPOSED SYSTEM

We regard extracting opinion targets/words as a co-ranking process. We assume that all nouns/noun phrases in sentences are opinion target candidates, and all adjectives/verbs are regarded as potential opinion words, which are widely adopted by previous method. The given data is possibly of any modality such as texts or images, while it can be treated as a collection of documents. SUBJECT wise and TOPIC wise Opinion analysis is also possible. We formulate opinion relation identification as a word alignment process. We employ the word-based alignment model to perform monolingual word alignment, which has been widely used in many tasks such as collocation extraction and tag suggestion. Consequently, Cyper pooling is used more and more, to the point where it has become a serious problem invading these open spaces. Cyper pooling refers to the use of aggressive, violent or offensive language, targeting a specific group of people sharing a common property, whether this property is their gender (i.e., sexism), their ethnic group or race (i.e., racism) or their believes and religion. While most of the online social networks and microblogging websites forbid the use of Cyper pooling, the size of these networks and websites makes it almost impossible to control all of their content. Therefore, arises the necessity to detect such speech automatically and filter any content that presents hateful language or language inciting hatred. In this paper, we propose an approach to detect hate expressions on Twitter. Our approach is based on unigrams and patterns that are automatically collected from the training set. These patterns and unigrams are later used, among others, as features to train a machine learning algorithm. Our experiments on a test set composed of 2010 tweets show that our approach reaches an accuracy equal to 87.4% on detecting whether a tweet is offensive or not (binary classification), and an accuracy equal to 78.4% on detecting whether a tweet is hateful, offensive, or clean (ternary classification).

Tri-Model learning (Naïve Bayes,IBK SVM) is an ensemble method that starts out with a base classifier that is prepared on the training data. A second classifier is then created behind it to focus on the instances in the training data that the first classifier got wrong. The process continues to add classifiers until a limit is reached in the number of models or accuracy. Tri-Model (Naive Bayes,IBK,SVM) Learning accommodates for both objective and subjective identification on any modalities High classification result. word alignment model for opinion relation identification high accuracy. The overall performance improved because

of the use of partial supervision. Less time to progress the result by using large dataset. Improved accuracy guaranteed. A better decision support system could increase business.

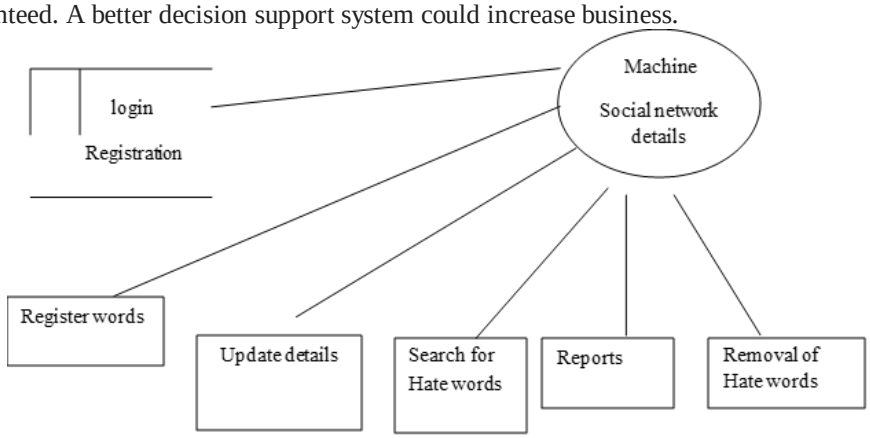

Fig 4.1 User Registration

V. KEY RESULTS

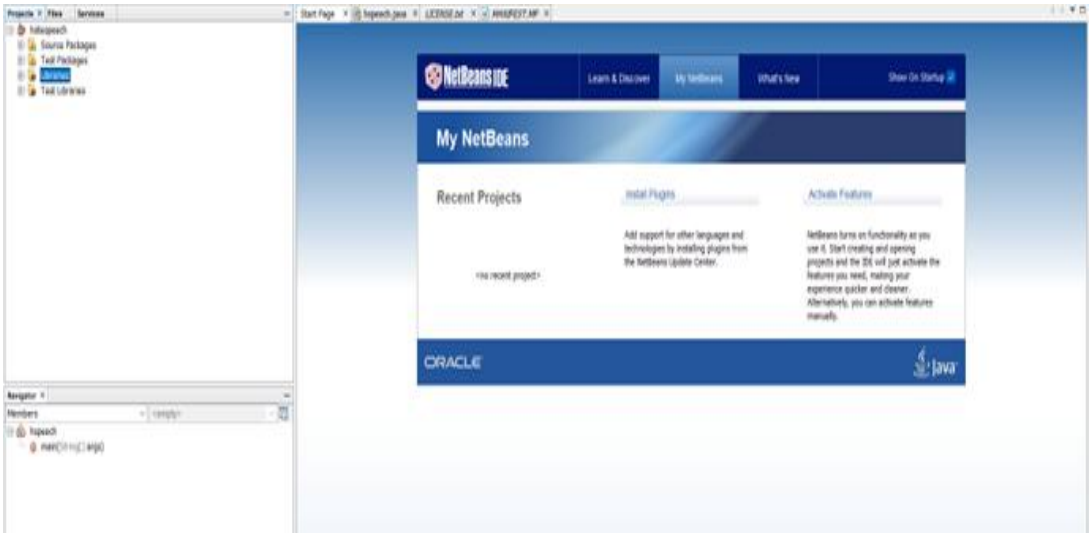

Fig 4.2 Homepage

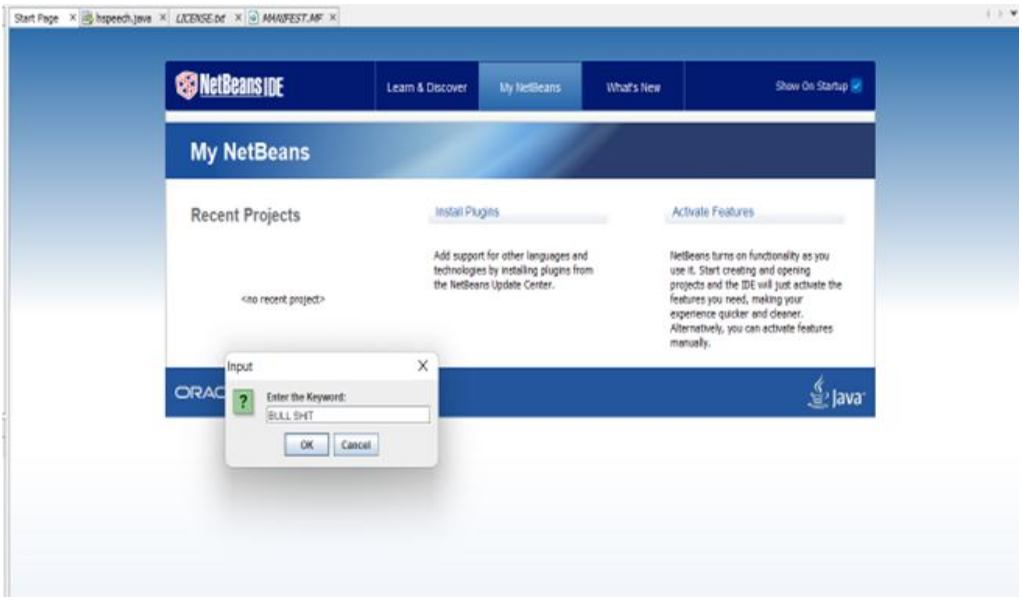

Fig 4.3 Search for Keywords

Fig 4.4 Showing Filtered Words

VI. FUTURE ENHANCEMENTS

Online harassment or cyberbullying behaviors have become a severe issue that damages the life of people on a large scale. The anti-harassment policy and standards supplied by social platforms and power to flag and block or report the bully are useful steps towards safer online community, but they are not enough. Popular social media platforms such as Twitter, Facebook, and Instagram or others receive an enormous number of such flagged content every day; hence, scrutinizing immense reported content and users is very time-consuming and not practical and effective. In such cases, it will be significantly helpful to design automated, data-driven methods for evaluating and detecting such harmful behaviors in social media. Successful cyberbullying detection would enable early identification of damaging and threatening scenarios and control such incidents from happening. Future study could enhance automated cyberbullying detection by combining textual data with video and images to build a machine learning model to detect cyberbullying behavior and its severity, which could be step towards automated systems for analyzing contemporary social online behaviors from written text and visual content that can negatively affect mental health. The detection algorithm could analyze the bully's posts and then align it to preselected level of severity thus gives early awareness about extent of cyberbullying detection.

VII. CONCLUSION

In this work, we proposed a new method to detect Cyper pooling in Twitter. Our proposed approach automatically detects Cyper pooling patterns and most common unigrams and uses these along with sentimental and semantic features to classify tweets into hateful, offensive and clean. Our proposed approach reaches an accuracy equal to 87.4% for the binary classification of tweets into offensive and non-offensive, and an accuracy equal to 78.4% for the ternary classification of tweets into, hateful, offensive and clean. In future work, we will try to build a richer dictionary of Cyper pooling patterns that can be used, along with a unigram dictionary, to detect hateful and offensive online texts. We will make a quantitive study of the presence of Cyper pooling among the different genders, age groups and regions, etc.

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