

Twitter Bullying Detection

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ABSTRACT

Data mining of Social networks is a new but interesting field within Data Mining. We leverage the power of sentiment analysis to detect bullying instances in Twitter. We are interested in understanding bullying in social networks, especially in Twitter. To best of our understanding, there is no previous work on using sentiment analysis to detect bullying instances. Our training data set consists of Twitter messages containing commonly used terms of abuse, which are considered noisy labels. These data are publicly available and can be easily retrieved by directly accessing the Twitter streaming API. For the classification of Twitter messages, also known as tweets, we use the Naïve Bayes classifier. It's accuracy was close to 70% when trained with "commonly terms of abuse" data. The main contribution of this paper is the idea of using sentiment analysis to detect bullying instances.

General Terms

Data Mining, Classification, Clustering

Keywords

Twitter, Sentiment Analysis

1. INTRODUCTION

The Social networks are a powerful medium that can be used for positive as well as negative purposes. Recent data suggest that bullying and suicides go hand in hand [4,7], e.g., the more kids get bullied the higher these kids in risk of committing suicide. In the context of social networks, we will focus on Cyber-bullying. This form of bullying has many adverse effects, such as frequent nightmares, sad moods that last more than a day, etc.

For this project, we are interested in understanding bullying in social networks, particularly in Twitter. So, in addition to performing data mining tasks to classifying bullying instances, via opinion mining/sentiment analysis techniques, we are also interested in visualizing how these instances evolve and/or behave. We use graph visualizations, both dynamic and static, [18] to illustrate clustering of bullies over time. We believe that such mechanism makes sense when dealing with multivariable, frequently changing data. Such is the case of a bullying swarm from public tweets in Twitter.

One of the core elements of our project is sentiment analysis. In order to do that, we need to train a classifier. Typically, to do that, you need hand-labeled training data, which is not efficient due to the large amounts of data, from different topics, in Twitter. To optimize this, we use distant supervision, similarly to [1]. However, instead of using emoticons, we use a set of commonly

used terms of abuse. With the help of a tool that we built, the Twitter Streaming API, and text processing and analysis tools, we were able to speed up the process of labeling data. Lastly, the trained classifier was validated against test data consisting of tweets collected over a given time period (e.g., 4 weeks).

1.1 Motivation for our work

There was a time when bullying was identified just as the strong kids picking on the weak kids. Typically, bullies would overpower their victims by using their size and strength as intimidation, and the victims would feel helpless to defend themselves against their attacks.

Recently, bullying has been recognized as a major public health problem in the Western World. It has become more than just a physical attack; bullies now assault their victims over the Internet by sending or posting text or images in different media, such as instant messengers, chat rooms, websites, and blogs. Their intention is clearly to hurt or embarrass another person. This is called "cyber-bullying."

Nowadays, cyber bullying has become an increasing public concern considering recent cases associated with suicides [2]. As the Cyber-bullying research center [7] and other sources [2] say, bullying behavior in youth is associated with depression, suicidal ideation, and suicide attempts. These associations have been found not only in elementary school, middle school, and high school students, but also in cyber space. In light of these studies and the suicide cases reported in mass media [7], we proposed, as our ISM 245 project, a software infrastructure for inferring and visualizing bullying instances in Twitter.

1.2 Goal

We aim to apply Data Mining techniques to social issues that are common in our community. More specifically, our main goal is to detect bullying instances in social networks and increase their visibility so that social institutions could do something about it; e.g., counseling for victims and bullies, detention of most reckless bullies.

1.3 Concept

Data mining of Social networks is a new but interesting field within Data Mining. For our project we have selected Twitter as the source of our data for several reasons. First, there is a public timeline (public tweets) from where we could extract data. Second, via Twitter API, these data are much easier to access than the data in other social networks like Facebook. Third, we have

found many available APIs for interacting with Twitter. Consequently, we don't have to re-invent the wheel when it comes to both accessing Twitter's data and focusing on the data mining part.

2. RELATED WORK

We have found there have been many papers written on sentiment analysis a diverse set of contexts, e.g., blogs. Pang and Lee [11] give a detailed survey of sentiment analysis. Researchers have also analyzed the impact of machine learning techniques in the domain of micro-blogs [1]. Within the context of bullying detection, we could not find any paper that would leverage the power of sentiment analysis in micro-blogging (e.g., Twitter) to detect and visualize bullying instances.

In the paper [1], the authors present the results of machine learning algorithms for classifying the sentiment of Twitter messages. They classify tweets either as positive or negative with respect to specific emoticons found in the Twitter messages.

In [13], the authors present their observations of the micro-blogging phenomena by studying the topological and geographical properties of Twitter's social network. We find that people use micro-blogging to talk about their daily activities and to seek or share information. They also analyze the user intentions associated at a community level and show how users with similar intentions connect with each other.

In [11] "Opinion Mining and Sentiment Analysis" – the authors presents a survey covering 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.

In paper [10], the authors consider the problem of detecting spammers on Twitter. They first collected a large dataset of Twitter that includes more than 54 million users, 1.9 billion links, and almost 1.8 billion tweets. Compared to this our dataset consisted of 1.8 million tweets. Using tweets related to three famous trending topics from 2009, they construct a large labeled collection of users, manually classified into spammers and non-spammers. The authors then identified a number of characteristics related to tweet content and user social behavior, which could potentially be used to detect spammers on twitter.

In paper [14], the authors study how micro-blogging can be used for sentiment analysis purposes. They show how to use Twitter as a corpus for sentiment analysis and opinion mining. They use a dataset formed of collected messages from Twitter.

In [15], the authors apply several common machine learning techniques to the problem of tweet sentiment analysis, including various forms of a Naive Bayes and a Maximum Entropy Model. They did various optimizations as well based on error analysis and intuitions that are specific to the unique rhetoric and language of Twitter.

In [16], the authors illustrate a sentiment analysis approach to

extract sentiments associated with negative or positive polarity of specific subjects in a document, instead of classifying the whole document as positive or negative. The essential issues in sentiment analysis are to identify how sentiments are expressed in texts and whether the expressions indicate positive (favorable) or negative (unfavorable) opinions toward the subject.

Paper [17] delivers a new Twitter content classification framework based on sixteen existing Twitter studies and a grounded theory analysis of a personal Twitter history. It expands the existing understanding of Twitter as a multifunction tool for personal, profession and commercial communications with a split level classification scheme that offers broad categorization and specific sub categories for deeper insight into the real world application of the service.

Overall, sentiment analysis and text classification are well studied fields. They are becoming a quite popular area of research and social media analysis these days, especially in the domain of user reviews and tweets. Work has been done in using emoticons as labels for positive and negative sentiment [1]. We based our project on this sort of labeling. However, instead of using emoticons we are using the commonly used terms of abuse as the labels. i.e., for negative sentiment we use "Gay," "Homo," and "Dike." For positive sentiment we use the term "Queer."

3. PROBLEM STATEMENT

We are interested in building a software application for detecting bullying instances in Twitter. We are focusing on bullying detection for social reasons, which range from "reducing the number of suicides caused by bullying," to "making micro-blogging a no bullying zone."

Our software application would be capable of accurately classifying Twitter messages as negative or positive with respect to some commonly used terms (using distant supervision). According to [2], for the current generation of young people the words "Gay," "Bitch," and "Slag" are the most commonly used terms of abuse in schools. However, only "Gay" and "Bitch" have a high negative polarity. Considering 'Gay' is the most popular term of abuse [2], we directed the focus of our bullying analysis to those cases involving *gender bullying*. Consequently, we searched for other derogative terms similar to the word "Gay" that could help us in our bullying analysis. We chose the terms "Homo," and "Dike" for their high negative polarity, and "Queer" for their high positive polarity. The polarity of these terms is shown below.

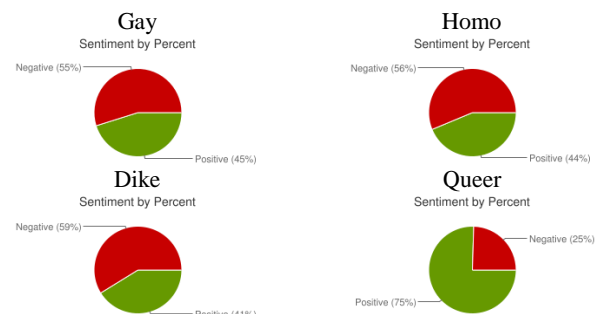


Figure 1, Polarity of words "Gay," "Dike," "Homo," and "Queer"

3.1 Hypotheses

Our hypotheses are that we can accurately classify sentiment (especially negative sentiment) in Twitter messages by using machine learning techniques, and that we could infered bullying instances by tracking the users, and users' followers, that are "trash talking" other users.

3.2 Defining Bullying

To assist our research, we have identified the users, and their followers, which are "trash talking" other users as "bullies" and the users being "trash talked" as "victims." The idea of tracking those users, and their followers, which are "trash talking" other people is based on our assumption that bullies like to work in groups. They like to overpower people by means of intimidation to feel stronger and bigger and they feel is more effective if they are in a bigger group since they would be able to dominate more people. Consequently, they would feel stronger if there are a larger number of individuals like them.

Trying to detect bullying instances via text mining on Twitter messages is a complex task given the characteristics of these messages. The following sub-section lists some of these characteristics.

3.3 Characteristics of Tweets

As pointed out in [1], we are aware of the many unique attributes of Twitter messages, which impose many challenges to our research with respect to the analysis of potential bullying instances. Some of these unique attributes are, to name a few:

1. Length. A maximum length of 140 characters per Twitter message. From our training set, the average length of a tweet was 16 words and the average length of a sentence was 88 characters.
2. Available data. We could easily collect huge amounts of data with ease. This is attributed to the fact that we are relying on public tweets and Twitter provides an API for collecting tweets.
3. Language Model. The use of misspellings, emoticons or other ASCII symbols, and slangs is highly frequent in tweets. So trying to decode them into something we could classify will be quite the challenge.
4. Domain. Tweet messages cover a variety of topics. That is, they are not tailored to a specific topic.

4. RESEARCH METHODOLOGY

Given our definition of bully, we show some examples of what it could be a bullying instance; i.e., those that could have either a negative (with potential bullying sentiment). To compare it with the neutral and positive polarity, we show some examples of tweets with neutral, or positive sentiment (See Table 1).

Table 1. Tweets with potential bullying sentiment

Polarity	Value
Negative	Hey @souljaboytellem U R GAY U R GAY U R GAY U R GAY (#souljaboytellem live >

	http://ustre.am/2UhS)
Neutral	RT @becca_darling gay gay gay i need to see this immediately http://bit.ly/4uInA . PrrrrYAYGAY
Positive	2003 episode of Queer As Folk. Wow 2003 was a good gay year. I kind of wish I got into the series. Gay life has evolved since... sort of.

We know there are times when it is unclear whether there is some sentiment in a tweet. It is even unclear if a tweet could be flagged as a bullying instance. For these cases, we use a simple litmus test: If a tweet contains the any of the terms of abuse (those with high negative feeling) listed above, then it belongs to the negative class. If the tweet could appear as a sentence in Wikipedia, then it belongs to the neutral class. Finally, if the tweet contains the word "Queer," then it belongs to the positive class. Since we are focusing on detecting bullying instances, we use positive or negative tweets for our experiment. Why positive ones? This is because we want to differentiate between a tweet with positive sentiment and another with negative sentiment. In future work, we will handle the case of neutral tweets in our classification scheme.

Those tweets classified as negative tweets will be considered as potential bullying instances. To confirm their "bullying" polarity, we used Amazon's Mechanical Turk. Once this polarity has been confirmed, we would process them so that we could extract some relevant information, such as the username of the person who posted the negative tweet (potential bully) and the username of the person mentioned in the tweet. This information would be used to monitor potential bullies, as well as their followers, with respect to their targeted victim. In other words, we the social graph of the initial bully would be inspected to see if his/her followers were also "trash talking" the victim initially mentioned by initial bully. If they were, then they would be flagged as potential bullies and would be monitored. The outcome of the monitoring process will be several social graphs; one per tracked bully. Only those users mentioning the victim will be included in the social graph. We will the Graph Exchange XML Format to persist the social graphs. Figure 2 shows the social graphs of two potential bullies. We used an open source graph visualization framework called Gephi¹ to visualize these two social graphs.

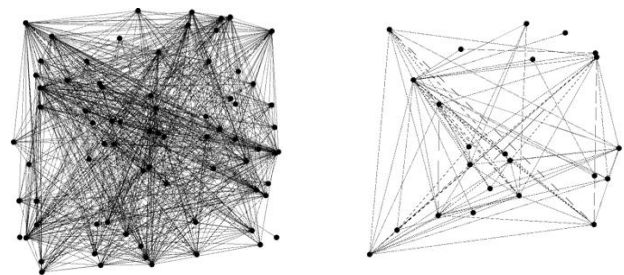


Figure 2, Two social graphs of potential bullies.

Each one of the users found in the social graph is virtually connected to the victim; i.e., each user in that graph is "trash talking" the victim. The overall connections between a bully and a victim (s) will be persisted in another graph, which we call "Bullying graph." The purpose of this graph is to visualize all detected bullying instances, find clusters of bullies, and show

¹ <http://gephi.org>

hidden connections between victims (two victims being bullied by the same bully) over a period of time.

5. APPROACH

Sentiment analysis is a special case of text mining generally focused on identifying opinion polarity, and while it's often not very accurate, it can still be useful as the basis for detecting bullying instances in Twitter. Since our main goal is to detect bullying instances, we will focus only on the negative tweets.

Our approach was to collect data from different sources. Then, we would filter them to about 5000+ tweets. The reason for this was simply to have a more controllable data set for our experiments. Some of the sources of our data include, a data set of over 18 millions tweets provided by Prof. Zhang, over 2 million tweets (about 4 weeks of data) collected directly from Twitter.

We built a framework on top of LingPipe² tool kit for classifying Twitter messages (tweets). Our framework uses LingPipe's Naive Bayes machine learning classifier as baseline, using Boolean word feature extraction. We also build a Tweets Extractor component that will retrieve tweets periodically. Our framework treats both the classifier and feature extractor as one component. This way we could easily extract and classify as more tweets are streaming in. These components will be described in more detailed as we go over the steps taken to perform our sentiment analysis work.

The following steps describes the approach we followed to perform sentiment analysis.

5.1 Data Collection and Pre-processing.

In this step, we accessed Twitter's public timeline looking for tweets containing the words of our interest. Even though there were existing data sets of Twitter sentiment messages [1], we decided to collect our own and aggregate them to the existing ones provided by [1] and to those provided by Prof. Zhang. We removed all facts that didn't express opinions like news and objective phrases from collected data. Then, we extracted the keywords from the text that may lead to correct classification. Keywords about the original data were stored as a feature vector; i.e., $F = (f_1, f_2, \dots, f_n)$. Each coordinate of a feature vector represents one word, also called a feature, of the original text. The value for each feature may be a binary value, indicating the presence or absence of the feature, an integer that may further express the intensity of the feature in the original text. It is important to have a good selection of features since it strongly influences the subsequent learning in the machine learning process. Unfortunately, this task for finding best features does not exist. Therefore, we relied on the use of our commonly used terms of abuse previously mentioned in this paper.

Our approach included the use of Bag-of-Words model where every word is feature name with a value of True. This is a popular model used in Information Retrieval. It takes individual words, called unigrams, in a sentence as features, assuming their conditional independence. In other words, the whole sentence is represented by an unordered collection of words. Each feature in the vector represents the existence of one word. The challenge of using this model is to decide what the most appropriate choice of

words are to become features. For simplicity, we chose the schema described in section 3.2.

To give a simple example, which considers this model, let's use the following tweet: 'Ha! Just saw my gay bro on glee' may be represented by the following model.

$F = \{ 'Ha!': 1, 'Just': 1, 'saw': 1, 'my': 1, 'gay': 1, 'bro': 1, 'on': 1, 'glee': 1, 'lindo': 1 \}$

This model can definitely be improved by removing some words that bring a little to the sentiment analysis of a sentence, such as pronouns, articles, and prepositions. These words are known as "List of stop words."

We built a Tweets Extractor component. This component was built on top of the Twitter4J open source³ library and the Twitter Streaming API⁴. This component will periodically crawl Twitter's public timeline in search for tweets containing the words of our interest.

5.2 Classification

This step focuses on finding the subjectivity and polarity of the tweets. To accomplish this we rely on the use of classification algorithms. These algorithms are efficient techniques for sentiment classification tasks. They could predict the label of a given input. However, they require a training set consisting of labeled examples before they could classify new tweets. For our project we are using the simplest one but nonetheless one with great efficiency in classification problems: Naive Bayes technique.

In simple terms, the Naive Bayes classifier or model, based on the Bayes' theorem⁵, assumes that the presence or absence of a particular feature of a class is unrelated to the presence or the absence of any other feature. In our case, each word in a tweet is considered a unique variable in the Naive Bayes model. The goal is to determine the probability of that word and whether it belongs to certain class: positive or negative.

In our problem domain, we will use the Naive Bayes classifier to classify collected tweets either with negative or positive sentiment. To do this, it is required to train our classifier by creating a training data set. For training data, we collected messages that contained the words "Gay," "Homo," "Dike," and "Queer" by using our in-house Tweets extractor. The test data was collected at random by streaming in public tweets from Twitter's public timeline that did or did not have our four words of interest. We manually labeled 460 tweets; i.e., a set of 300 negative tweets and 160 positive tweets. Along with those 460 tweets, 500 tweets were labeled by using Amazon's Mechanical Turk. The following table represents the used classification labels that were presented as a survey to workers in Amazon's Mechanical Turk service.

³ <http://twitter4j.org>

⁴ http://dev.twitter.com/pages/streaming_api_methods

² <http://alias-i.com/lingpipe/index.html>

⁵ http://en.wikipedia.org/wiki/Bayes%27_theorem

Table 2. Mechanical Turk Classification Labels

Opinion Polarity	Value
Negative with Bullying Intentions	B
Negative without Bullying Intentions	A
Positive or good content	P
Neutral or does not fit in above 3	N

We used Amazon Mechanical Turk for additional sentiment analysis of tweet data (i.e., to confirm whether collected tweets were properly labeled, and whether they were really bullying instances). We created a Human Intelligence Task (HIT) with the task of classifying each tweet in one out of the four categories shown in Table 2.

It is also important to remove all facts that don't express opinions like news and objective phrases. For the sake of simplicity, a small sample of the preliminary results will be shown below (Table 3).

Table 3. Some Mechanical Turk's Preliminary Results

Polarity Value	Value
B	your gay your gay your gay YOU A MUFKKIN FAGG get off my back cuz I didn't do shitt!! -_- hella irritated damn.
A	phone located. h8 being cut off from single method of communication to man friend. gay gay gay
N	Ask the Monkey! Gay M&Ms, gay cartoon voices & gay icons videogames. + what WAS going to happen Pushing Daisies? http://tinyurl.com/nlztj8
P	Gay pride gay pride gay pride

We present our results and the evaluation of them in the following section.

6. Evaluation

6.1 Set-up for Experiments

Even though there were existing data sets of Twitter sentiment messages [1], we decided to collect our own and aggregate them to the existing ones provided by Prof. Zhang and those publically available⁶. We use both Twitter4J [8] and the Twitter Streaming API⁷.

⁶ <https://sites.google.com/site/twittersentimenthelp/for-researchers>

⁷ <http://apiwiki.twitter.com/>

We configured our built Tweet Extractor to only retrieve tweets in English, within California, and contained the four words of our interest.

For the training data, the Twitter Extractor will periodically query the Twitter API. To avoid being blocked due to exceeding the limit access quota enforced by Twitter, our extractor would query the Twitter API for about 20 minutes, and then it would wait for 10 minutes before sending a new query request to the Twitter API. We collected 4 weeks worth of training data. We mostly ran our extractor at night for about 2 hrs.

The total number of collected tweets exceeded the 15 million tweets. However, in order to have a more controlled experiment, we randomly picked 5 thousand tweets; Approximately, $\frac{3}{4}$ were positive, and $\frac{1}{4}$ were negative tweets.

The test data automatically collected, using our Tweet Extractor. However, instead of using our words of interest, we use no query terms. Therefore, the extractor was collecting whatever was available in the Twitter's public timeline. Different to the 2 hrs a night collection of tweets, we ran the extractor for 3 hrs during the day. Not all the test data had any of the four words of interest.

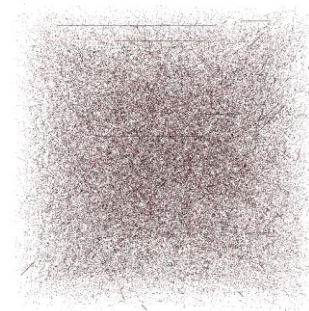
6.2 Results

As part of the evaluation of our results, we explored the use of Amazon's Mechanical Turk (Crowd sourcing) to classify unlabeled data, and to verify and validate newly labeled data. The use of Crowd sourcing along with that of machine learning algorithms helped us with the building of an infrastructure that could detect bullying instances in Twitter's public timeline. Table 4 summarizes the results of some of our experiments.

Table 4. Some Mechanical Turk's Preliminary Results

Training: 500 tweets			
	Positive	Negative	Accuracy
Naïve Bayes	65.7%	72.9%	67.3%
Amazon's MTurk	65.2%	74.0%	67.1%

Despite the surfeit of data collected, the Twitter system would identify, target, and delete spammer (potential bullies) faster than we could fully inspect their social graphs. The resulting missing clusters of information would render a chaotic bullying graph; prohibiting any further analysis. Interestingly enough, one can interpret this observation as a sign of Twitter's success in implementing a powerful spam filter technology. Figure 3 shows one of resulting bullying graphs.

**Figure 3, Bullying Graph**

7. CONCLUSIONS

We were able to leverage the power of sentiment analysis to detect bullying instances in Twitter. We build a framework that uses the Twitter streaming API to collect our data; both training and test data. We successfully use and extend the Naïve Bayes classifier found in the LinPipe. The classifier was close to 70% accurate. Even though we did not get the ideal results, we still think that bullying detection is possible. However, it may require a more sophisticated infrastructure that could constantly run for a long time without getting our accesses blocked by Twitter. It is a hard task to perform due to how good Twitter is with identifying potential bullies (flagged as spammers). i.e., they remove them before we can fully track them. The mind of a bully is more complicated than we thought.

8. LEARNINGS

Bullying detection is a hard task to perform due to how good Twitter is with identifying potential bullies (flagged as spammers). i.e., they remove them before we can fully track them. The mind of a bully is more complicated than we thought. Sometimes they attack victims without specifically naming them.

We learnt the practical applications of some of the theories that we had learnt in the class, text mining, clustering, dimensionality reduction and classification. The most valuable lesson was to apply the theoretical concepts we learnt in the class to something very current and practical. We learnt various new tools and technologies and improved our command on others. To name a few, we learnt LingPipe, Gephi, Amazon Mechanical Turk. These new technologies may be very useful for job and career point of view. We also learned how to do feature extraction, sentiment analysis with distant supervision, and use machine learning algorithms.

9. FUTURE WORK

As future work, we plan on developing a free iPhone or Android application, so that parents could become more aware of bullying in social networks. We can have a future version integrate with law enforcement and FBI to track and solve serious cases of bullying particularly those which result in suicide or death.

We plan to work during the summer and submit the improved report in a Data Mining conference after some enhancements and more data generation.

10. ACKNOWLEDGMENTS

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