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Analysis of Women Safety in Indian Cities Using Machine Learning on Tweets

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ABSTRACT

At this time, women are subjected to a significant amount of violence, such as harassment, in several locations throughout various cities. This behavior begins with stalking and then progresses to abusive harassment, which is also referred to as abusive assault. Given the special reference to the participation of many social media websites or applications like Twitter, Facebook, and Instagram platforms, the primary focus of this article is on the function of social media and how it can be utilized to promote the safety of women in India. Specifically, we examine the role that social media can play in promoting the safety of women in India. This article also focuses on building duties among ordinary people in different sections of Indian cities so that the safety of women in their immediate surroundings may be maintained. The text messages, audio data, video data, photos, smiling expressions, and hash tags that make up a Tweet are all contained inside the Twitter program. This tweet content may be used to read among the people, therefore educating them to take harsh measures in response to abusive tweets directed at women and allowing for the punishment of such persons in the event that harassment is committed. Hashtag-enabled platforms like Twitter and Instagram may be put to use to rapidly disseminate information across the whole planet and give women the confidence to openly discuss their thoughts and emotions without fear of repercussions. By doing this, we are able to determine their state of mind when they go out to work, travel on public transit, or are surrounded by unknown males, as well as whether or not they have a sense that they are safe in these situations.

KEY WORDS: Women, Safety, Sexual Harassment, Hash tag, Sentimental Analysis

1. INTRODUCTION

Twitter has become the ideal social network for microblogging in our contemporary period, with over one hundred million members who create over five hundred million messages known as "Tweets" every single day. Due to the fact that Twitter attracts such a large audience, its users feel compelled to share their opinions and viewpoints on each and every problem and subject that can be found on the internet; consequently, Twitter functions as a source of information for all of the various institutions, businesses, and organizations. In the tweets area of the Twitter platform, users will exchange their thoughts and points of view with one another. Because there is a character limit of just 140 on this tweet, users are required to condense their communications as much as possible by making use of slang, abbreviations, shot forms, emoticons, and so on. In addition to this, a lot of individuals communicate their points of view by using polysemy and sarcasm as well. As a result, the language used on Twitter might be classified as unstructured. The feeling that was intended to be conveyed by the message may be gleaned from the tweet. The process known as sentimental analysis is used in order to accomplish this extraction. The findings of a sentimental analysis can be put to use in a wide variety of contexts, including determining people's attitudes toward a particular brand or the introduction of a new product; analyzing public sentiments regarding government policies; determining people's perspectives on women; and so on. A significant amount of research has been conducted on the information that was collected from Twitter in order to carry out categorization of tweets and examine the results. In this article, we also discuss several studies on machine learning and research on how to execute sentimental analysis utilizing that domain on Twitter data. Both of these topics are covered in the introduction. The algorithmic and model-based approaches to machine learning are the exclusive focus of this work. Some forms of violence and harassment, such as staring at women and making remarks, are commonplace even in urban settings, despite the fact that these behaviors, which are offensive and should not be tolerated, may be considered forms of violence and harassment. Numerous studies that have been carried out in India demonstrate that women have complained of being subjected to sexual harassment and other activities such as those mentioned above. Studies of this kind have also shown that the majority of women in populous metropolitan places such as Delhi, Pune, Chennai, and Mumbai have the feeling that they are in danger whenever they are surrounded by people they do not know. People in India are given the opportunity to openly share their ideas and opinions on Indian politics and society on various social media platforms. In a similar manner, women who have been the victims of any kind of violence or sexual harassment may talk about their experiences, and this can bring together a group of individuals who are not responsible for the wrongdoing and help them take action. From the analysis of tweets text collection obtained by Twitter, it includes names of people who have harassed women as well as names of women or innocent people who have stood against such violent acts or unethical behavior of men and thus made it uncomfortable for them to walk freely in public. Additionally, it includes names of people who have stood against such violent acts or unethical behavior of men.

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Processing the machine learning algorithms and models will include using the data set consisting of the tweet as the input. The tweet data will be smoothed down using this method, which will also remove any numbers that are zero. A technique is designed in order to evaluate the twitter data and eliminate redundant information from the data set. Laplace's theory and Porter's theory are used in the development of the approach. Social media platforms such as Twitter, Facebook, and Instagram have garnered a significant number of users in recent years. People's feelings regarding society, politics, women, and other topics are communicated via the use of text messages, emoticons, and hash tags on platforms like these. There are a few different approaches to sentiment analysis, some of which may be categorized as machine learning-based or lexicon-based learning.

2. LITERATURE SURVEY

It is quite popular for people to voice their opinions on social media platforms and on microblogging websites such as Twitter in this day and age. A significant number of individuals are turning to social media in order to voice their opinions on everything that is going well or poorly in our society as well as everything that is occurring in day-to-day life. On social media, among the numerous topics that are discussed and about which people voice their opinions, one of those topics is woman safety. The vast majority of individuals speak about good things and point out the specific change that is required in our society. This change is what is needed to drive the negativity out of our neighborhood and make women feel secure again. There will be X men and Y women all around the nation who will tweet once or twice a day concerning the safety of women, and the data collected from these tweets may be utilized as a dataset. When using this dataset, it is very usual practice to apply an analytical algorithm to the data that has been taken from social media and classify it according to whether or not it has positive or negative characteristics.

A classifier that can determine the contextual polarity of subjective phrases found inside a sentence is presented by us. Because our method uses lexical scoring that is drawn from the Dictionary of Affect in Language (DAL) and expanded via WordNet, we are able to automatically score the great majority of the words in our input and so eliminate the need for human labeling of the words. In order to account for the influence of the setting, we supplement lexical score using n-gram analysis. We begin by combining DAL scores with syntactic elements, and then we proceed to extract ngrams of constituents from each and every phrase. The polarity of all syntactic parts inside the sentence is also taken into consideration as a property of the phrase. Both an easier baseline composed of lexical n-grams and a more challenging baseline consisting of a majority class demonstrate considerable improvement when compared to our findings. The process of determining whether a piece of written communication contains positive, negative, or neutral views is the subject of much study in the field of sentiment analysis. The job formerly known as document-level analysis has been elevated to the level of phrase and phrasal analysis. The former is appropriate for categorizing news articles (for example, editorials vs reporting) into positive and negative categories, while the latter is necessary for question-answering and recommendation systems. For instance, a recommendation system has to be able to suggest restaurants (or movies, books, etc.) depending on a range of criteria, such as the quality of the cuisine, the level of service, or the atmosphere. It's possible for a single review phrase to have both good and negative thoughts, depending on which aspects of a restaurant are being discussed. Take for example the following statement (1), in which the author expresses conflicting feelings on the cuisine and the service of a restaurant. Because of this, it is essential to do sentiment analysis on a phrase-by-phrase basis while working on projects such as this one.

(1) Although The Taj offers excellent cuisine, I was disappointed by the quality of their service. Subjective phrases in a sentence are the bearers of feelings in which an experiencer communicates an attitude, most often towards a target. These subjective expressions, depending on the context of the sentence in which they occur, may reflect either a neutral or a polar attitude toward the topic at hand. The content and structure of the sentence are the primary factors that define context. For instance, the subjective phrase that is emphasized in the following statement (2) may seem to have a bad connotation, but when seen in the broader context of the sentence, it has a good connotation.

(1) The thief managed to get inside the business, but his plans were foiled when the police arrived just in time. Our mission is to determine the polarity of a sentence's context based on the subjective words included inside it. Using a prior polarity lexicon of words to first set priors on target phrases and then making use of the syntactic and semantic information in and around the sentence to make the final prediction is one method that has been used historically to

approach this problem. This is known as the "traditional approach." We also employ a lexicon to establish priors, similar to how previous methods did; however, we investigate novel applications of a Dictionary of Affect in Language (DAL) (Whissel, 1989) that has been expanded using WordNet (Fellbaum, 1998). In order to take into account the significance of context, we supplement this method using n-gram analysis. Similar to what was done by Wilson et al. (2005), we provide a method for classifying polarities according to whether they are neutral, positive, negative, or both. Our method is innovative because it makes advantage of the following characteristics: • Lexical scores established using DAL and expanded with WordNet: The Hirschberg Dictionary of Affect has seen widespread usage as a tool to assist with the understanding of feeling conveyed in speech. 1 We determine the polarity of sentences based on Wiebe's work (Wiebe et al., 2005); the polarity of all of the instances shown here is derived from annotations in the MPQA corpus. It is abundantly clear that the overall cultural norms influence the polarity assignments that were selected for this corpus. 24 et al., 2005). It includes a series of quantitative ratings that have been given along axes that measure pleasantness, activity, and concreteness. The term "scoring system" will be used throughout the rest of this study to refer to the approach that we provide for assigning numerical priors to words by making use of these three axes. This system has a good coverage of the sentences that need to be classified and does not need any kind of user involvement when it comes to labeling terms with previous polarity.

N-gram Analysis: making use of the polarity that is automatically inferred from grammatical components We use lexical affect scores for each of the phrase's words to determine the polarity of each syntactic item in the input phrase, and we then extract n-grams based on these constituents. Patterns that are provided by N-grams of syntactic elements that have been labeled with polarity help increase the accuracy of polarity prediction for subjective phrases. • Polarity of Surrounding Elements: We make use of the calculated polarity of syntactic constituents that are located around the phrase that we are attempting to categorize. These characteristics contribute to a more accurate depiction of the influence that the context has on the polarity of the subjective term. We demonstrate that the categorization of subjective phrases using our method achieves a higher level of accuracy when compared to two different baselines, one of which is a majority class baseline and the other is a more challenging baseline consisting of lexical n-gram characteristics. We also provide an analysis of how the various component DAL scores contribute to our results through the introduction of a "norm" that combines the component scores, separating polar words that are less subjective (for example, Christmas and murder) from neutral words that are more subjective. In this way, we are able to determine how the various component DAL scores affect our findings (e.g., most, lack). In the second section, a review of prior work is presented, with a particular emphasis on phrasal level sentiment analysis.

An Analysis of the Literature The work of sentiment analysis has progressed from analysis at the document level (for example, "Turney., 2002"; "Pang and Lee, 2004") to analysis at the sentence level (for example, "Hu and Liu., 2004"; "Kim and Hovy., 2004"; "Yu and Hatzivassiloglou., 2003") in recent years. These researchers began by using a prior polarity lexicon in order to establish priors on terms. When identifying sentiment at the sentence level, different sorts of cues, such as an average of word polarities or models for learning sentence sentiment, are also utilized. Examples of these types of clues include: Nasukawa and Yi (2003) are credited as being the pioneers of research on contextual phrasal level sentiment analysis. To determine sentiment, they used manually constructed patterns. Their method exhibited a high degree of accuracy, but a poor recall rate. Additionally, Wilson et al. (2005) investigate contextual phrasal level sentiment analysis, although they use an approach to machine learning that is more similar to the one we offer. Both of these researchers adhere to the conventional methodology and begin by establishing priors for individual words by making use of a prior polarity lexicon. The research conducted by Wilson et al. (2005) makes use of a vocabulary that contains over 8000 subjectivity cues. This lexicon was compiled from three different sources: (Riloff and Wiebe, 2003); (Hatzivassiloglou and McKeown, 1997) and The

General Inquirer2. Words that were not automatically assigned a good or negative connotation were assigned by hand. Words were obtained from GI, DAL, and WordNet for the study conducted by Yi et al. (2003). Only those words from DAL were considered in the analysis that had a pleasantness score that was at least one standard deviation from the mean. In addition, some researchers (Kamps and Marx, 2002) manually tag words with their previous polarity. Nasukawa is one among these researchers. We, on the other hand, utilize quantitative scores, which enables us to apply them in the calculation of scores for the complete phrase, in contrast to all of these other studies, who use categorical tags for preceding lexical polarity. Even if phrasal level analysis is the goal of Wilson et al. (2005)'s method, the authors admit that it "just provides each hint occurrence its own label" [p. 350]. Their gold standard operates at the clue level as well and provides a value to each hint depending on how often it occurs in various formulations (e.g., if a clue appears in a mixture of negative and neutral expressions, its class is negative). They make notice of the fact that they do not establish the bounds of subjective expression; hence, they categorize things at the word level. This method is considerably unlike to the one that we use, which is to calculate the polarity of the whole sentence. The corpus of 535 papers was mined for a total of 17,243 subjective phrases, each of which was annotated to indicate the polarity of its context (11,114 sentences). There are two types of subjective phrases: "direct subjective" and "expressive subjective." "Direct subjective" statements are significantly simpler to categorize since they do not hide the fact that the speaker is referring to their own private state (Quirk et al., 1985). Phrases that are considered to be "expressive subjective" provide indirect or oblique references to the speaker's internal feelings and are thus more difficult to categorize. We isolated about one third of the sentences as direct subjective with non-neutral expressive intensity, whereas the other phrases were all expressive subjective. There were 2779 expressions that were favorable, 6471 expressions that were negative, and 7993 phrases that were neutral. The manually annotated tag that is applied to phrases in the corpus is considered our "Gold Standard." 4 DAL DAL is an emotional meaning analyzer for the English language that was constructed in the form of a dictionary. The examples that were used to compile the dictionary came from a wide variety of sources, including interviews, descriptions of teenagers' and college students' emotional experiences, and essays written by the latter group. As a result, the 8742-word dictionary is comprehensive and free from the influence of any one specific source. On a scale ranging from 1 (low) to 3 (high), each word is rated according to its pleasantness, also known as assessment, activeness, and imagery.

The lowest possible score is 1, and the highest possible score is 3. (high). Polarity may be measured by how pleasant something is. Affection, for instance, is assigned a pleasantness score of 2.77 in Table 1, which is closer to 3.0 and is hence a term that has a lot of positive connotation. In a similar vein, activeness is a measurement of the activation or arousal level of a word, as is evident from the activeness scores of both slug and energetic that are included in the table. The third score is called the imagery score, and it determines how easily a word conjures up an image in one's mind. Affect, for instance, is difficult to visualize, and as a result, it has a score that is closer to one. In contrast, flower is a highly definite concept, and as a result, it has an imagery score of three. Because the dictionary assigns distinct weights to the many inflectional versions of a word, such as affect and affection, morphological parsing and the mistakes that might follow from it are eliminated. This is one of the most significant aspects of the dictionary. In addition, Cowie et al. (2001) demonstrated that the three scores are not connected with one another; this indicates that each of the three ratings provides information that is complimentary to the others.

3. PROPOSED SYSTEM

Women have the right to the city, which indicates that they are free to travel anywhere they want, whenever they want, regardless of whether it is to an Educational Institute or any other location that women wish to attend. On the other hand, women have the impression that they are not secure in public locations like shopping malls and malls in general while they are on their way to their place of employment because of the many unknown factors. These ladies are constantly being harassed and shamed for their bodies. The primary reason why females are harassed is either their lack of safety or the absence of any tangible repercussions in their lives. There have been situations in which girls have been harassed by their neighbors while they were walking to school, or there have been situations in which there has been a lack of safety, which has resulted in a feeling of fear in the minds of small girls. These girls continue to suffer for the rest of their lives as a result of that one instance that occurred in their lives, in which they were forced to do something that was unacceptable, or they were harassed abusively by one of their own neighbors or some other unknown person. The most progressive cities look at the issue of women's safety from the point of view of women's rights to participate fully in city life without fear of being harmed or harassed. It is the responsibility of society to imprecise the requirement for the protection of women, and it must also acknowledge that women and girls have the same right as men do to live in a safe environment in the city. This is in contrast to the normal practice of society, which is to place restrictions on women. Figure 1 presents the proposed system architecture

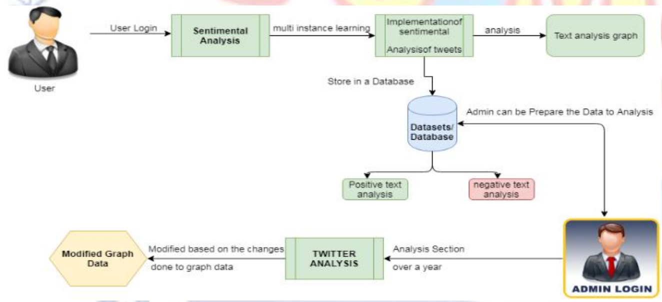

Figure 1: Proposed System Architecture

Every user's data, including credentials, new tweets, retweets, and a score for each tweet, will be saved in the database for the administrator to monitor and utilize for analytical purposes. The user data are subjected to the sentiment analysis in order to monitor and validate whether or not any tweets include derogatory language against women. This analysis is carried out by the administration on each and every user's tweets to ensure the protection of the ladies. The tweets of users who have their data preserved in the database will be subjected to sentimental analysis at some point. The administrator may now begin preparing the data in order to carry out the analysis. The tweets that each user of the program creates will be referred to as the first input for the sentiment analysis, and as a result, they will be the dataset. This will be the case since the tweets will be the initial input. In addition to this, a graph depicting the text analysis may also be shown. The filters are going to be saved in the database by Admin. Filters are essentially a list of terms that will be looked for in the context of a tweet in order to determine whether or not it is abusive. There are two different kinds of filters that may be used: positive keyword filters and negative keyword filters. Words that are harsh to women or that show disdain for them in any way might be considered positive keywords. The words that are considered normal and do not mistreat women in any way are considered negative terms.

The database has the capability of storing an unlimited amount of both positive and negative terms. When the administrator decides to put the emotional analysis into action, each and every term in the database will be compared with each and every word that the user includes in their tweets. The tweet will be labeled as positive sentimental analysis if it contains even one of the positive keywords, and tweets that fit this category are harmful to women. In the event that a negative term is discovered inside the tweet, the analysis will be categorized as a negative sentimental analysis, which is not harmful to women. As a result, by the time we reach this point, we will have produced two distinct forms of sentimental analysis dependent on the filter in the database. A list of all the tweets in the application that are harmful to women will be included in the section of the analysis titled "positive sentimental analysis." In a similar manner, while doing a negative sentimental analysis, a list that is clean and does not include abusive tweets will be generated. In addition to the context of the tweet, facts about the user will also be presented at each of the analysis lists.

4. RESULTS

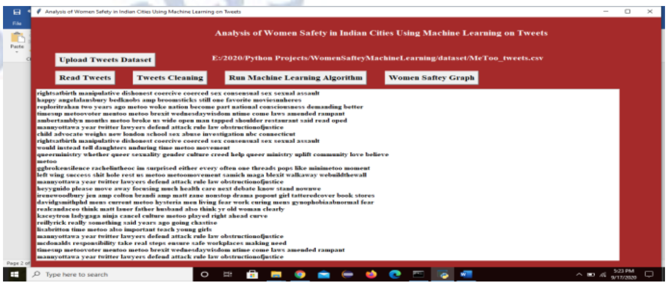

Figure2: Analysis of Women Safety Tweets

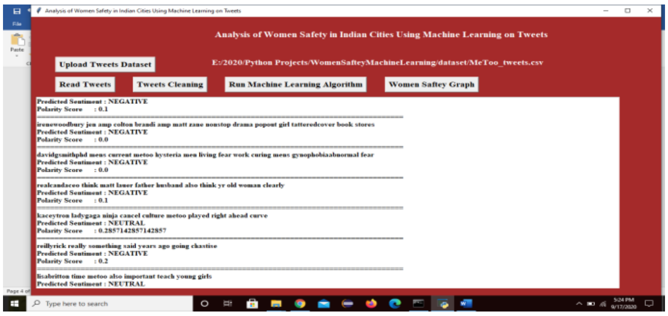

Figure 3 : Scores of Women Safety Tweets

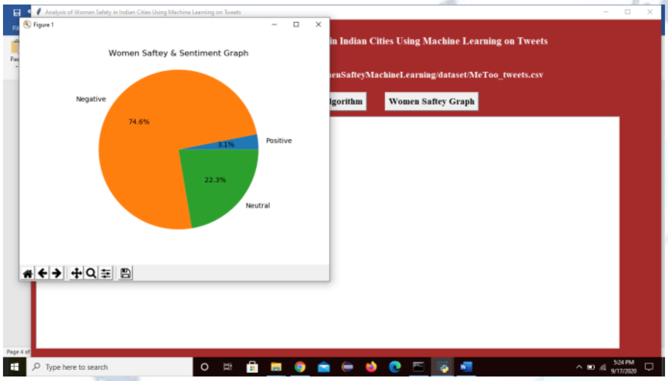

Figure 4: Women Safety and Sentiment Graph

4. CONCLUSION

Throughout the entirety of the research paper, we have talked about a variety of machine learning algorithms that have the potential to assist us in organizing and analyzing the massive amount of data obtained from Twitter, which consists of millions of tweets and text messages that are shared on a daily basis. When it comes to the analysis of vast amounts of data, these machine learning methods are quite successful and helpful. This includes the SPC algorithm and linear algebraic Factor Model techniques, both of which aid to further classify the data into relevant groupings. Support vector machines are yet another kind of machine learning algorithm that is highly popular in the process of extracting useful information from Twitter and getting an idea about the current situation regarding the safety of women in urban areas in India.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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