Facebook User Reactions Towards Marijuana Content

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***Abstract*—We have developed content and sentiment analysis of marijuana-related posts on Facebook based upon users' emotional reactions, including *LOVE*, *HAHA*, *WOW*, *SAD*, and *ANGRY* as well as the number of *LIKE*s and comments posts received. In particular, we extracted posts and resultant reactions from the High Times Magazine page (*https://www.facebook.com/HIGHTIMESMag*) - a longstanding monthly publication known for advocating for the legalization of cannabis. A sentiment analysis tool was built using Google Cloud Prediction API to estimate the sentiment of each post from the text contained therein. The sentiment scores calculated by our tool achieved an accuracy of greater than 90% compared with sentiments heuristically generated based upon user reactions to the posts. Our research also provides insight into Facebook users' activities towards marijuana that may potentially benefit public health surveillance applications.**

I. Introduction

Together with the fast pace of individual state legalization of recreational marijuana, the number of Americans with access to marijuana has increased accordingly, leading to a high prevalence rate of marijuana use, abuse, and dependence. A report by the National Survey on Drug Use and Health (NSDUH) [1] predicted about 22.2 million Americans aged 12 years or older had consumed cannabis in the past month in the U.S. There are approximately 2.4 million persons aged ≥ 12 years that had smoked marijuana for the first time during the preceding 12 months, and nearly 6,600 people start to use marijuana each day [2]. While the trend in substance consumption increases, the risk perception considerably subsides. In particular, the NSDUH data shows that the prevalence in the past month of marijuana exposure among persons aged 12–17 years rose from 6.7% in 2006 to 7.1% in 2013. On the other hand, the percentage who recognized prominent risk from smoking marijuana once a month decreased from 34.6% in 2006 to 24.2% in 2013 [2]. That said, marijuana poses considerable danger to the health and safety of the users themselves, their families, and their communities. Monitoring the actual marijuana demographics use and concerns would be very helpful for health care professionals and authorities to develop appropriate public health interventions.

The prevailing approaches for monitoring marijuana use as well as other addictive substances such as tobacco or alcohol chiefly rely on traditional telephone or face-to-face interviews or gathering data from clinic departments. For example, NSDUH has carried out health risk behavior surveillance nationwide, including illicit drug use and the result is published only once a year [3]. Obviously, this method is time-consuming, labor-intensive, and expensive and typically has a few months of reporting lag and a small coverage of the population. Furthermore, this approach may not be able to detect the actual level of addictive substance usage, as the interviewees may hide the true information. Therefore, it is important to develop an effective and accurate monitoring system to detect marijuana use across the country.

Recently, with the rise in popularity and scale of social media such as Twitter, Facebook, Instagram, and Snapchat, public health monitoring based on health-related data from the social media in real-time is very appealing. Due to the massive, instant, and crowd-sourced nature of social media content, this emerging approach has advantages that potentially surpass the drawbacks of the existing system, such as automated operation, large geographic coverage, large demographic coverage, near real-time data collection, and low cost. As a move towards an automated monitoring system for marijuana use based on social media, we have investigated Facebook user reactions towards marijuana-related posts on a Facebook page - High Times Magazine. With nearly 6 million followers, the page is one of the largest marijuana-advocating online communities on social media. We constructed a sentiment model via the Google Cloud Prediction API to evaluate the sentiment of the page's followers towards the marijuana content on this page. We also devised content analysis for more than $14,625$ posts, leading to several results, including the behavior of the followers.

II. Related Works

Social media platforms recently have quickly become important sources for researchers to track and monitor public health issues. For example, social media data has been successfully mined and leveraged to empower near real-time influenza epidemic surveillance. Google Flu Trends uses query logs to trace the daily rate of influenza in the U.S. several days faster than the CDC reports it [4]. Also, researchers in [5] extracted influenza-related tweets on Twitter and employed machine learning techniques to classify actual messages regarding flu patients. Social media-based tracking methods are also proposed to capture other chronic diseases such as cancer, asthma, toothaches, etc. The authors in [6] examined social media information to gain insights into obesity and diabetes statistics by building a model that maps demographic variables to food names mentioned on Twitter. The system achieved a

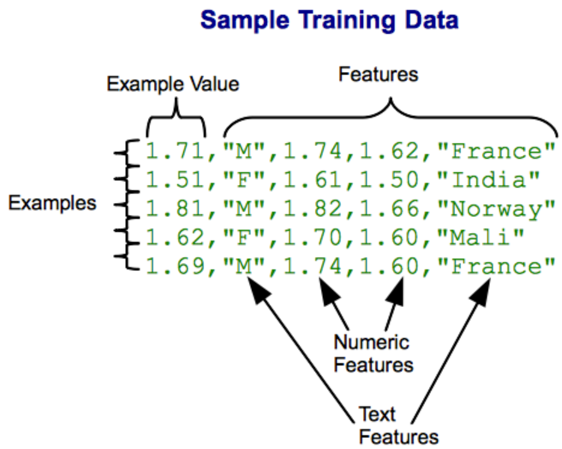

Fig. 1. Data format to estimate the sentiment of tweets using Google Cloud Prediction API [14].

Pearson correlation of 0.77 with the existing statistics across 50 states in the U.S. Another common phenomenon, cardiac arrest, is also monitored from Twitter. Researchers collected tweets published from April–May 2011 with keywords "cardiac arrest", "CPR", "AED", "resuscitation", "heart arrest", "sudden death", and "defib" to discover the public knowledge about this disease [7].

More recently, many researchers have demonstrated the potential for tracking addictive substance use including alcohol, tobacco, and marijuana in the population via social networks. A. Nguyen et al. [8][9] used the term "420 friendly" via rental listings on Craigslist and marijuana-related tweets on Twitter to reveal the marijuana perception. Myslín et al. [10] analyzed the content of Twitter posts to detect tobacco-relevant tweets and sentiment towards the new and emerging products like hookah and electronic cigarettes. Several machine learning classifiers were used to detect tobacco-related/not-related tweets as well as positive versus negative sentiment. Another application of social networks includes detecting the activity of quit smoking social network accounts. The authors in [11] collected Twitter users who tweeted the keywords "quit or stop smoking" or "smoking cessation" to detect the evidence of smoking cessation. In addition to tobacco, the researchers found the potential of high exposure of Internet users, especially, children and adolescents to alcohol marketing posts on the social media [12][13]. The studies suggest that new regulations are needed to impose further restrictions on marketing campaigns regarding addict substances.

III. Methodology

High Times is a monthly magazine founded in 1974 in New York. The publication's objectives are to promote the legalization of cannabis for recreational use and to provide marijuana-related information to readers. Since its establishment, High Times has been actively involved in marijuana-using countercultures. Recently, the magazine became a monthly publication with a growing circulation audited by ABC reaching 500,000 copies an issue; rivaling Rolling Stone and National Lampoon. Following the legalization of marijuana in several West Coast states, its Facebook page membership has increased rapidly to almost 6 million followers. Thus the posts and comments from High Times Magazine page are sufficient to characterize the behavior of its followers who are potentially marijuana consumers.

We developed a Python tool to collect the posts and comments from High Times Magazine from Jan 2016 to Dec 2016. The collected data is stored in a MongoDB database and the data is processed to extract valuable patterns. In total, we collected 14,625 posts, including their metadata, such as post ID, number, and types of reactions and comments with associated user IDs, etc. In other words, from each post, we know how many people react to each post and their associated reaction, their comments to the post, and the timestamp of each comment. The rich information allows us to discover knowledge about user behaviors towards marijuana-related content.

We employed Google Cloud Prediction API [14] for predicting user sentiment towards each post. Google Cloud Prediction API allows a RESTful API for developers to construct machine learning models for prediction. The system works based on a cloud, providing capabilities for various analytic features such as customer spam detection, sentiment analysis, recommendation systems, and more. The steps for predicting the sentiments include: (1) Label data, (2) Prepare data, (3) Update data to Google Cloud Storage; (4) Train a model with the Google Prediction API; (5) Make predictions with the Google Prediction API in your application, and (6) Update your model with new data. The most important step is labeling and preparing the data in which we have to select the right features and save them as a training file. For instance, the prepared data format can be formatted as in Figure 1 to predict a person's height, based on their gender, parents' height, and nationalities. In our research, input features are the summary content of posts (not the full text of an article) and the type of post (e.g. article), and our aim is to predict the overall user sentiment to that post based upon the post's text and general sentiment.

IV. Results and Discussions

At the beginning of 2016, Facebook introduced additional "Reactions" that allow users to express their emotions toward a post, rather than just the classic *LIKE*. The five new emotional reactions are *LOVE*, *HAHA*, *WOW*, *SAD*, and *ANGRY*. Besides the ability to express more complex emotions through these reactions, we believe these visceral reactions are particularly important to investigate because choosing these reactions requires additional effort on the part of the user. Specifically, for a user to express *LOVE*, they must hover over the *LIKE* button for at least one second before the option for *LOVE* appears. Subsequently, users must expend additional effort to select this option. This is, in contrast, to simply "liking" a post, where the user only clicks the *LIKE* button and can move on to another task. Our work is to evaluate those emotional reactions to consider two research questions: (1) Given marijuana-related content posted on the High Times Magazine page, can we use machine learning to predict the users' sentiment towards

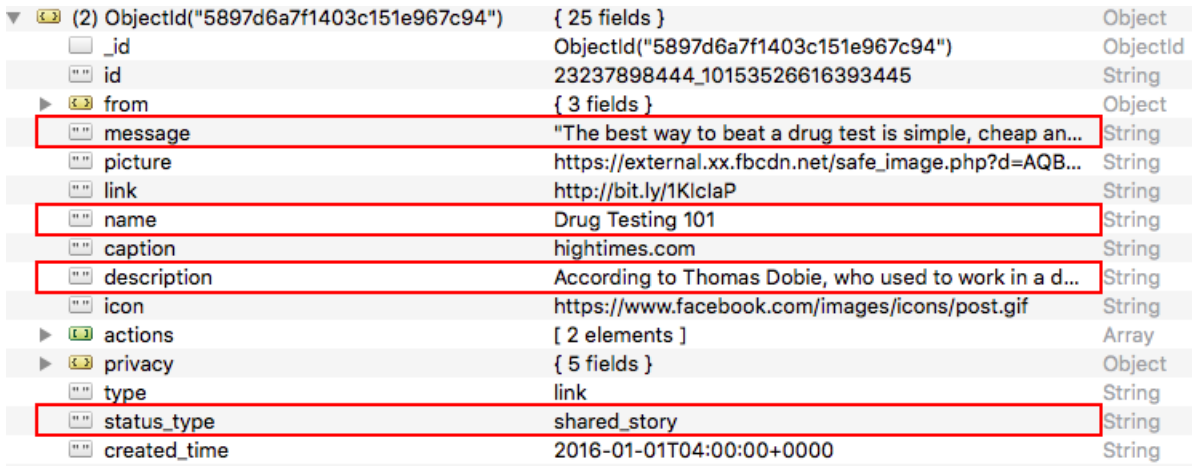

Fig. 2. Features for training sentiment prediction model. Four features including $message$, $name$, $description$, and $status\_type$ were selected as highlighted in the figure.

that content? and (2) What are the characteristics of users' behaviors over time with respect to marijuana-related content. We first address the first questions by using Google Cloud Prediction API to evaluate the emotional reactions *LOVE*, *HAHA*, *WOW*, *SAD*, and *ANGRY*. For our purposes, we define that *emotional reactions* are all reactions excluding *LIKE* and *general reactions* are all reactions including *LIKE*.

A. Sentiment Analysis

1) Followers' Sentiment: To build the prediction model, we need to select the appropriate features and provide a class label (positive or negative sentiment) to the post. Specifically, the four features we use are message, name, description, and status. The message is manually inserted by the page owner (High Times Magazine); name is the title of the article that the owner wants to share from the High Times website; the description is thumb content of the article; and the status of message can be *"shared_story"* or *"image"*. For example, Figure 2 shows those four features among the metadata of the post. Particularly, the message: *"The best way to beat a drug test is simple, cheap and easy."* is text inserted by the page owner, the name: *"Drug Testing 101"*, the description: *"According to Thomas Dobie, who used to work in a drug testing lab, you'd have to be an idiot to fail a drug test for cocaine. Cocaine, honestly, if you do it infrequently - maybe on a Friday night when you go out with your friends"* is the thumb text from the link in the magazine. This message's status is *"shared_story"*.

We classify the emotional reactions into two types: positive and negative. Positive reactions include *LOVE*, *HAHA*, and *WOW*, which generally indicate a positive response of users to a post. On the other hand, negative reactions are *ANGRY* and *SAD*, which generally represent a negative attitude toward a post. Based on these two types of reactions, we label marijuana-related posts within High Times Magazine as positive, negative, or neutral using the following schema:

- Positive: The number of positive reactions, *LOVE*, *HAHA*, and *WOW*, is greater than that of negative reactions, *ANGRY* and *SAD*.
- Negative: The number of positive reactions, *LOVE*, *HAHA*, and *WOW*, is less than that of negative reactions, *ANGRY* and *SAD*.
- Neutral: The number of positive reactions, *LOVE*, *HAHA*, and *WOW*, is equal to that of negative reactions, *ANGRY* and *SAD*.

In other words, the ratio of the number of emotional reactions: $\phi = \frac{n_{LOVE}+n_{HAHA}+n_{WOW}}{n_{ANGRY}+n_{SAD}}$, where n_{LOVE} is the number of *LOVE*s reactions and so on, can sufficiently determine user sentiment. If phi is greater than 1, the post is positive; if phi is less than 1, the post is negative, and if phi is equal to 1, the post is neutral. We organized our training data as in the format $\phi, message, name, description, status\_type$ that are corresponding to label, feature 1, feature 2, feature 3, and feature 4, respectively. About 55% of the data (8,000 records) are used to train the model and the remaining content is used to validate the model.

TABLE I
CONFUSION MATRIX OF THE UNTRAINED GOOGLE PREDICTION API

	predicted positive	**predicted negative**
actual positive	4,746	1,204
actual negative	366	310

TABLE II
CONFUSION MATRIX OF THE TRAINED GOOGLE PREDICTION API

	predicted positive	**predicted negative**
actual positive	5,734	216
actual negative	296	380

2) Effect of Training: We validated our Google Prediction API training model using the remaining 6,626 data records. To quantify the improvement in prediction accuracy before and after training the Google Prediction API, we also used the same data in an untrained model. Table I and II reflect the confusion matrices of the untrained and trained models, respectively.

With respect to our analysis, an actual positive occurs when the number of positive reactions towards a post is greater than or equal to the number of negative reactions towards that post. There are relatively few cases where these two quantities are equal, so we chose to assign them to the positive

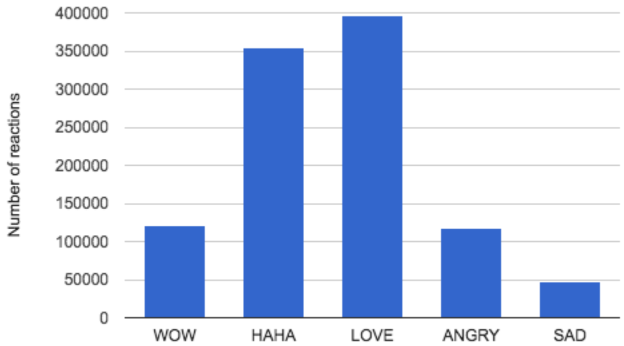

Fig. 3. Reaction counts: number of positive emotional reactions (*WOW*, *HAHA*, and *LOVE*) is much greater than the number of negative ones (*ANGRY* and *SAD*) .

class. Conversely, an actual negative is defined as a post with more negative user reactions than positive. Predicted positive and negative apply to whether the Google Prediction API classifies a post's sentiment as positive/neutral and negative, respectively.

Prior to training, the Google Prediction API accurately reflects user reactions 76.3% of the time, while the accuracy after training reaches 92.3%, an improvement of 21.6%. Looking at the positive predictive (PPV) and negative predictive (NPV) values for the untrained and trained models, both models show high respectively PPVs of 92.8% and 95.1%. However, the NPV for the untrained model is only 20.5% and increases more than 3-fold to 63.8% after training. It should be noted that approximately 10% of the posts have a negative sentiment. With a less sentimentally skewed collection of articles, we expect improvements in accuracy to be much higher than reflected in this data set.

B. Content and Users' Activity Analysis

1) User's activities: We calculated several statistics from the collected data to evaluate user behavior and provide the big pictures of user activities towards marijuana content. Figure 3 presents the *emotional reaction* distributions of High Times article respondents. The number of *LOVE* reactions is greater than the number of any other reactions. In addition, the total number of all three positive responses, *HAHA*, *WOW*, and *LOVE* is over 5.3 times greater than the sum of negative responses, *ANGRY* and *SAD*. Because the publication mainly advocates marijuana consumption, this distribution would indicate that the post respondents generally advocate marijuana use and legalization.

Table III shows in detail, user activities, including the number of *LIKE*s and comments. Specifically, for $14,625$ posts about marijuana, there are $11,789,077$ *LIKE*s, $121,032$ *WOW*s, $354,270$ *HAHA*s, $395,716$ *LOVE*s, $118,056$ *ANGRY*s, $46,955$ *SAD*s and $614,808$ comments. As expected, the number of *LIKE*s overwhelms the number of all other reactions, accounting for 87.7% of user activities. We suspect this is due to *LIKE* having a long history since Facebook became popular. Users are very familiar with the like action that is accomplished with one mouse click on computers or a single touch on a mobile device. This is in contrast to the other available reactions that require additional user action like hovering the mouse over the *LIKE* button so that the other reaction icons appear. It is also worth noting that users must then select one, and only one, of the six reactions. Additionally, users can comment multiple times, but may only provide a single reaction type. Given the simplicity of "liking" a post and the additional effort users must expend to provide one or more comments, the number of *LIKE*s is 19 times more than that of comments.

TABLE III
ACTION COUNTS

Actions	Counts	Percentage
LIKE	11,789,077	87.71%
WOW	121,032	0.90%
HAHA	354,270	2.64%
LOVE	395,716	2.94%
ANGRY	118,056	0.88%
SAD	46,955	0.35%
COMMENT	614,808	4.57%

2) Best-fitting lines for user counts vs reaction counts: It is worthwhile to examine the density of the users who give a certain number of emotional reactions over the long term because ones engaging with marijuana content online are likely to use marijuana in real life. To conveniently formulate the relationship between the user counts versus the emotional reactions, we present the reaction counts according to logarithmic bins. Particularly, we used $1, 2-4, 5-8, 9-16, 17-32, 33-64, 65-128, 129-256, 257-512,$ and $513-1024$ bins. Figure 4 presents the number of users versus the range of emotional reaction counts in bin units with a linear vertical axis (Figure 4(a)) and log-scale vertical axis (Figure 4(b)). Specifically, the figures show that the number of followers having only one comment is about $200,000$ while the user counts for subsequent bins are reduced exponentially. The best-fitting line for the comment graph in the log-scale figure is $y = -0.543 * x + 5.956$, $r^2 = 0.995$ in which x is the reaction counts (in bin units) and y is the number of users in log10 scale. In other words, the number in linear scale is $y = 10^{-0.543*x+5.956}$. Clearly, the number of users with two, three, or more comments reduces exponentially. The number of users giving more than 512 comments is just two. In the same way, we can formulate the best-fitting lines for other emotional reactions: *LOVE*: $y = -0.461 * x + 5.493, r^2 = 0.996$, *SAD*: $y = -0.573*x+4.823, r^2 = 0.994$, *WOW*: $y = -0.607*x+5.874, r^=0.995$ *HAHA*: $y = -0.541 * x + 5.203, r^2 = 0.993$, and *ANGRY*: $y = -0.555 * x + 5.262, r^2 = 0.984$.

3) Most active followers: Figure 5 illustrates the top ten active members that gave the highest number of *LIKE*s and a larger number of comments than any others. From it, we see a high frequency of activity for those users. From 08/2016 to 11/2016, the top ten users produced more than 1,000 likes each month, as in Figure 5(a). During this period, several states in the U.S. were voting on marijuana legalization for recreational reasons, resulting in 4 more states, namely, California, Nevada, Maine, and Massachusetts, that passed the law. The favorable regulations on marijuana production and consumption led to

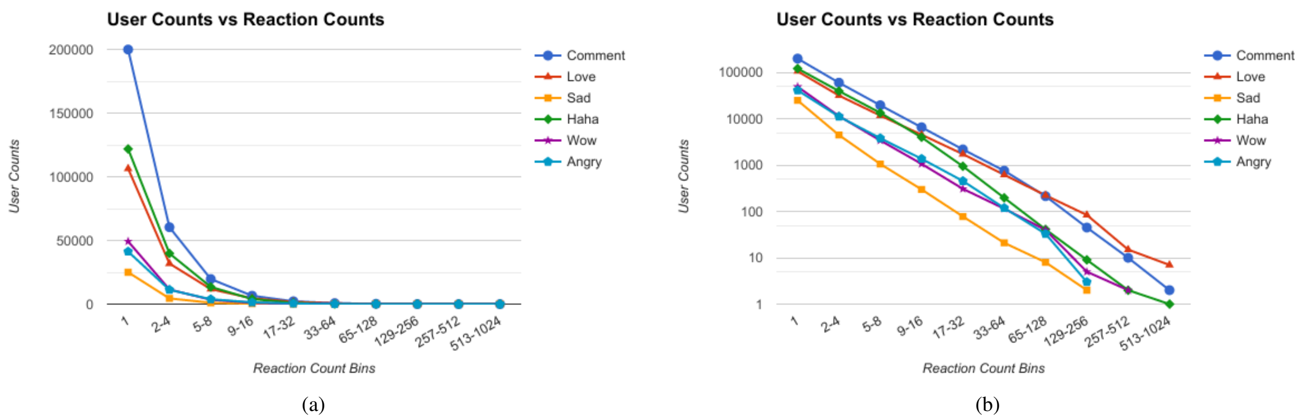

Fig. 4. User counts versus emotional reaction counts in linear vertical scale and log vertical scale.

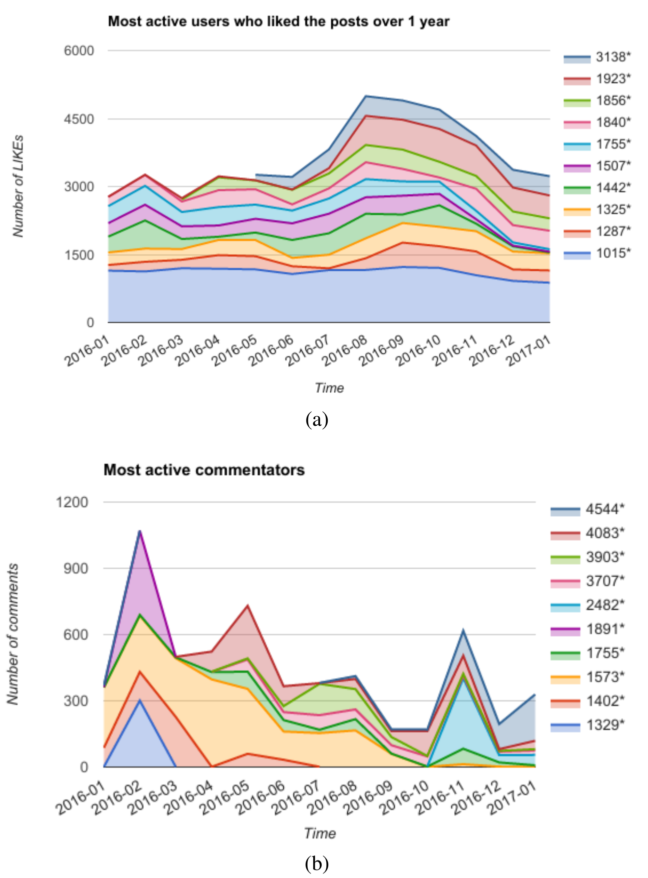

Fig. 5. Most active users: (a) Top ten active users who like the posts and (b) Top 10 active users who gave comments over 1 year period (User IDs are trimmed for the sake of privacy).

the large number of *LIKE*s, i.e., more than 4,000 each month. We note that the user with ID 1015* is the most active of all, with nearly one thousand *LIKE*s each month. Figure 5(b) shows the top ten users with commenting activities from Jan 2016 to Jan 2017 reaching hundreds of comments per month. Because commenting actions requires more user effort, there are not any users with more comments for the whole considered period than liking actions.

4) Samples of posts with the most number of followers' responses: We considered the posts with the highest number of user responses *LIKE*s, *LOVE*s, and *ANGRY*s. As shown in the Appendix, those posts that advocate marijuana use and legalization get the highest number of *LIKE*s or *LOVE*s. For example, post *"Germany Will Legalize Medical Marijuana in 2017"* from May 2016 was liked by $21,121$ followers or post *"It's Official! Pennsylvania Will Become 24th State to Legalize Medical Marijuana"* was loved by 951 followers. In many scenarios, the number of *LIKE*s is proportional to that of *LOVE*s. Therefore, there are several overlapped posts in Table IV and V. Furthermore, posts about ending the use of marijuana for recreational purposes or mentioning law enforcement cracking down on illegal marijuana production and consumption received the highest number of *ANGRY*s (Table VI). These reactions are understandable since High Times promotes marijuana use and many followers are likely to use recreational marijuana.

V. Conclusion

This work presents a new research trend by mining posted content on Facebook to discover the users' perception of the emerging addictive substance, marijuana, via their activities towards marijuana content on the High Times Facebook page. The mining technique for emotional reactions and commenting actions on that page were used to evaluate the sentiments and users' behavior. Our data indicates the most users in this online community advocate marijuana consumption and legalization. We built a sentiment analysis model that can predict the sentiment of a post with an accuracy of over 90% when compared with actual user sentiment. The study also exhibits some interesting patterns, including the frequencies of emotional reaction types, likes, and comments. Our research shows the widespread viewing of marijuana content on social media and its popularity to a large number of online users. This phenomenon suggests that a new generation of online and automated monitoring systems leveraging the availability of related social media data can be developed to empower health care professionals and authorities.

Acknowledgments

The collected data is used solely for research purposes. We neither re-list nor resell the data to third parties.

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APPENDIX

TABLE I
POSTS WITH THE MOST NUMBER OF REACTION *LIKE*S

Time	Posts	Sentiment	*LIKE* counts
2016-05-04	Germany Will Legalize Medical Marijuana in 2017.	0.7910043	21121
2016-05-23	About Time! Congress Finally Approves Medical Marijuana for Veterans.	0.8985692	20139
2016-04-14	It's Official! Pennsylvania Will Become 24th State to Legalize Medical Marijuana.	0.8049126	18531
2016-04-15	Just In - U.S. Senate Votes to Give Veterans Access to Medical Marijuana.	0.4200057	17890
2016-11-17	All Purple Errythang. Featuring the Prometheus Titan from Pyp Tek. See what's up at PypTek.com	0.8734275	16836
2016-07-12	#ICYMI Gras! Germany Will Legalize Medical Marijuana in 2017.	0.7830224	13384
2016-03-25	Los Angeles Considering Using Marijuana Taxes to Help Homeless.	0.3321877	12698
2016-05-10	Big News! Orlando Is the Latest Florida City to Decriminalize Marijuana Possession	0.7812765	9943
2016-04-18	Gov. Wolf Signed This Weekend! Pennsylvania Becomes 24th Medical Marijuana State.	0.6322331	9574
2016-06-30	#TBT Instant Classic. Police Accidentally Get an Entire Neighborhood High with Marijuana Bonfire.	0.7066627	9279

TABLE II
POSTS WITH THE MOST NUMBER OF REACTION *LOVE*S

Time	Posts	Sentiment	*LOVE* counts
2016-11-17	All Purple Errythang. Featuring the Prometheus Titan from Pyp Tek. See what's up at PypTek.com	0.8734275	1889
2016-11-08	Live weed election results from the roof of High Times headquarters in Los Angeles.	0.5184424	1328
2016-05-23	About Time! Congress Finally Approves Medical Marijuana for Veterans.	0.8985692	1268
2016-11-09	Live cannabis election results and another victory joint on the biggest night in weed history!	0.823861	1152
2016-04-15	Just In - U.S. Senate Votes to Give Veterans Access to Medical Marijuana.	0.4200057	960
2016-04-14	It's Official! Pennsylvania Will Become 24th State to Legalize Medical Marijuana.	0.8049126	951
2016-05-04	Germany Will Legalize Medical Marijuana in 2017.	0.7910043	868
2016-03-25	Los Angeles Considering Using Marijuana Taxes to Help Homeless.	0.3321877	773
2016-11-08	Celebrating biggest Election Day in weed history at High Times Headquarters!	0.7283296	767
2016-11-09	Florida passes Medical Marijuana by a landslide. Here's what it covers.	0.7100577	700

TABLE III
POSTS WITH THE MOST NUMBER OF REACTION *ANGRY*S

Time	Posts	Sentiment	*ANGRY* counts
2016-12-16	This week, the DEA took yet another swipe at marijuana..	0.4938319	3423
2016-09-04	A ban on the sale of guns to marijuana and other drug users is reasonable because the use of such...	0.4104775	1245
2016-06-29	Despite All The Support.. Congress Blocks Medical Marijuana for Veterans.	0.5505621	958
2016-05-16	#NEW - Congressional Forces Vote Against Studying Medical Marijuana as Alternative to Painkillers...	0.5330661	860
2016-11-18	What year is it!? A man is being HANGED for marijuana possession today.	0.7036561	549
2016-03-02	US Supreme Court Ruling Could End Legal Marijuana Sales	0.4500553	492
2016-08-11	After all the recent hype! DEA denies petitions to reschedule cannabis...	0.09124758	489
2016-08-11	Presenting - the Hateful Eight. These are the biggest anti-marijuana crusaders right now. Reading abou...	0.9461759	471
2016-06-17	NEW: Scientists Edge Closer to a Marijuana Breathalyzer.	0.7393151	468
2016-03-18	#RadicalRant: Teenage Girl Dies in Her Father's Arms, Killed by Marijuana Prohibition	0.1201716	449
2016-07-03	Despite All the Support, Congress Blocks Medical Marijuana for Veterans.	0.7094786	442