Deep Learning Model for Classifying Drug Abuse Risk Behavior in Tweets

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***Abstract*—Social media such as Twitter can provide urgently needed drug abuse intelligence to support the campaign of fighting against the national drug abuse crisis. We employed a targeted tweet collection approach and a two-staged annotation strategy that combines conventional annotation with crowdsourced annotation to produce annotated training dataset. In this demo, we share deep learning models trained in a boosting manner using the data from the two-staged annotation method and unlabeled data collection to detect drug abuse risk behavior in tweets.**

Keywords- drug abuse detection, social media, deep learning, Twitter

I. INTRODUCTION

A Public Health Emergency has been declared [1] with the rising trend of drug abuse in the US in recent years. The most recent National Survey on Drug Use and Health (NSDUH) [2] reported that an estimated 10.6% of the total population aged 12 and above misused illicit drugs within one month prior to the interview in 2016. In the same year, the Centers for Disease Control and Prevention (CDC) [3] reported 42,249 deaths due to opioid drugs, which outnumbered the deaths by motor vehicle accidents, suicides and homicides. On top of that, heroin alone caused more deaths than firearms did in 2015 and the number is rising.

In 2017, the Department of Health and Human Services (HHS) announced a new “Opioid Strategy” [5], where “strengthening public health surveillance” was among its five priorities. In contrast with surveillance methods based on clinical records from hospitals and traditional surveys, social media monitoring can provide more real-time surveillance capabilities to improve public health awareness. Twitter has been shown to be an excellent data source in many health-related projects [6-8]. The goal of our ongoing research is to develop an automated machine learning system to detect tweets related to drug abuse risk behavior in near real-time. However, it is a challenging task to detect and classify tweets mentioning drug abuse risk behaviors due to: (1) Sparsity of drug abuse-related tweets among the 500 million daily tweets; (2) The short and ungrammatical nature of tweets; and (3) Limited availability of annotated tweet data for training machine learning models.

This paper addresses these challenging issues and achieves three objectives: **(1)** Build a system that can effectively collect drug abuse-related tweets at a large-scale; **(2)** Design an annotation strategy (drug abuse vs. non-drug abuse) that enables creating datasets at a much lower cost than traditional methods; and **(3)** Develop a deep learning model that can accurately classify tweets into drug abuse risk behavior-positive or negative tweets to support drug abuse monitoring.

II. METHODS

We first collected over 3 million raw tweets using the Twitter Streaming API during January 2017. To keep a balance between coverage and quality of the collected tweets, we used three types of keywords as filters: (1) Prescription and illicit drug names, e.g. marijuana, oxycontin, heroin, LSD, etc.; (2) Slang drug terms, e.g. barbs, crack, blunt, etc.; and (3) Drug abuse-related activities, behaviors, and syndromes, e.g. high, stoned, dizziness, etc. Over 800 keywords were used.

A set of 1,794 human-annotated tweets, jointly annotated by two professors and three students, were used as seed dataset. The seed dataset was used to train an SVM classifier, which was then applied to unlabeled tweets to derive 4,985 positively predicted tweets. These 4,985 tweets were reviewed and annotated through Amazon Mechanical Turk.

For classification, raw tweets were first tokenized and stemmed, then each word was vectorized into 300-dimension vectors using the pre-trained “GoogleNews” Word2vec model. Then, a Convolutional Neural Network (CNN) model [9] model was trained with our boosting training scheme that repeatedly classifies unlabeled tweets and selects high-confidence labels to extend the human-labeled training dataset. It was found that this improves the validation performance.

III. EXPERIMENTAL RESULTS

Our strategy produced a balanced and reliable dataset with 3,102 positive and 3,677 negative tweets in total. We tested and compared our boosted deep learning models with boosted traditional and state-of-the-art machine learning approaches.

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Our model achieved 86.53% accuracy, 88.6% recall, and an 86.63% F1-score using Monte Carlo Cross Validation.

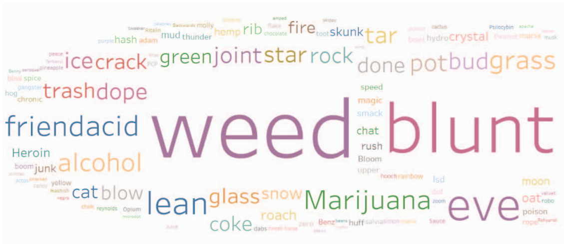

Figure 1. Top mentioned potential drug names in positive tweets.

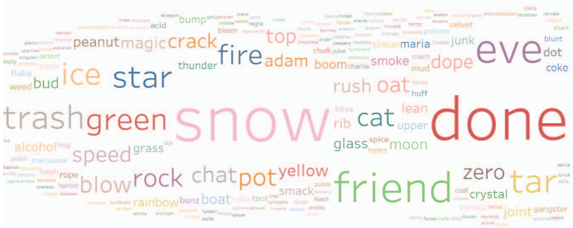

Figure 2. Top mentioned potential drug names in negative tweets.

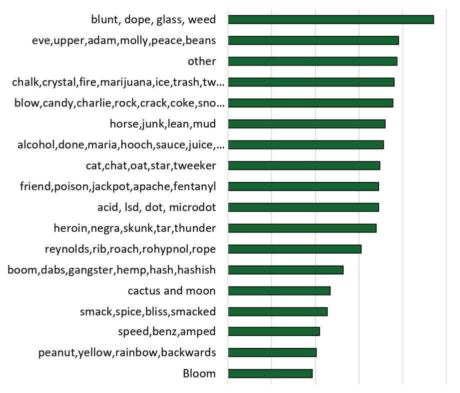

Figure 3 Count of potential drug names and slang terms, grouped by drug categories, in over 100,000 drug abuse-positive tweets.

Figures 1 and 2 show the top mentioned potential drug names and slang terms in drug abuse-positive and negative tweets, respectively. The word distributions are vastly different between the two classes. When we further group synonymous slang terms into drug categories and show them in log-scale (Figure 3), we can see that our approach detects many types of drugs and their slang terms. In fact, Twitter users use slang terms more often than the "clinical" names. For example: heroin: 134 (skunk: 180; thunder: 57; junk: 147; etc.); cocaine: 129 (coke: 782; candy: 334; snow: 409; etc.) Comparing with related works, our method allowed us to identify terms in a much wider scope and is more comprehensive. We are further analyzing the patterns that the drug names and slang words are used in, to enrich a drug abuse ontology, and even discover new and evolving "slanguages" for drug terms.

Figure 4 shows the geographical distribution of over 100,000 positive tweets from January 2017 across the US. The areas with biggest drug abuse indications are: R1: Mid-Atlantic and New England; R2: Great Lakes; R3: Pacific; R4: Florida; R5: Southwest Atlantic; R6: West South-Central; as well as metropolitan areas in R7: Mountain region and R8: North Central region. This map aligns well with the drug threat map in National Drug Threat Assessment 2017 [4].

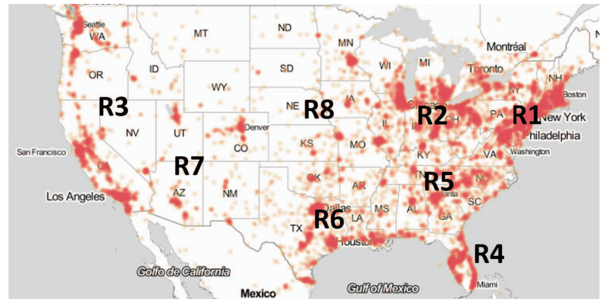

Figure 4. Geo-distribution of over 100,000 drug abuse-positive tweets in the United States.

IV. Conclusion

We have presented three key components of a drug abuse tweet surveillance system: a large-scale data collection and annotation component, our boosting deep learning model that detects drug abuse tweets, and the geospatial and semantic analytics component. Our deep learning classification model achieved the state-of-the-art performance with a two-staged tweet annotation method for labeling more tweets at a lower cost without sacrificing quality. The semantic analysis of identified positive drug abuse behaviors uncovers many drug terms to be used for ontology refinement, and our geospatial analysis allows hotspot identification.

The Amazon Mechanical Turk labeled dataset is available at: *https://github.com/hu7han73/DrugAbuseLabeledTweets.*

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