
Detection and Characterization of Illegal Marketing and Promotion of Prescription Drugs on Twitter

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Abstract

Illicit online pharmacies allow the purchase of prescription drugs online without a prescription. Such pharmacies leverage social media platforms such as Twitter as a promotion and marketing tool with the intent of reaching out to a larger, potentially younger demographics of the population. Given the serious negative health effects that arise from abusing such drugs, it is important to identify the relevant content on social media and exterminate their presence as quickly as possible. In response, we collected all the tweets that contained the names of certain preselected controlled substances over a period of 5 months. We found that an unsupervised topic modeling based methodology is able to identify tweets that promote and market controlled substances with high precision. We also study the meta-data characteristics of such tweets and the users who post them and find that they have several distinguishing characteristics that sets them apart. We were able to train supervised methods and achieve high performance in detecting such content and the users who post them.

1 Introduction

Prescription drug abuse is the use of a prescription medication in a way not intended by the prescribing healthcare professional. Prescription drug abuse is a national epidemic, and is the cause for the largest percentage of deaths from drug overdose. Prior studies have established that illicit online pharmacies (IOPs) represent an understudied venue for illegal access of prescription drugs via the internet[6]. IOPs often provide access to controlled substances without a valid prescription. Recent studies have also shown that IOPs utilize social networking platforms such as Twitter to promote and market their products [4, 5]. Hence, the already challenging issue of addressing and minimizing the prevalence of prescription drug abuse is exacerbated due to the utilization of social media by IOPs [7]. This is because social media provides IOPs a gateway to directly market their product to the masses. While progress in federal and state-based efforts have begun to address traditional forms of drug diversion linked to non-medical use of prescription drugs (such as through the implementation of state Prescription Drug Monitoring Programs), information on emerging digital environments that enable the non-medical use of prescription drug access and abuse behavior, such as through IOPs that use social media are inadequate.

As part of an effort to better understand the national epidemic of prescription drug abuse and all its associated risk factors, it is important to understand the ecosystem of IOPs and how they utilize social media in the illegal promotion and marketing of prescription drugs; specifically identify the relevant content on social media and the external URLs it may point to, identify the characteristics of such content and the users who post it etc to inform the design and development of methodologies that can identify such marketing content as soon as they emerge to prevent further exposure to this

codeine	high man deaths australia market	weed ask slow dreams sex	best free pills online buy	percocet	laughter medicine laughing agree best	dose strippers lean cup poured	offer online super best price
oxycontin	order online quantity discount prescription	fda children approves 11 young	approval pediatric abuse police fake	oxycodone	canada drug potential monopoly give	buy online free pills cheap	wife doctor airport prescriptions west
vicodin	online buy high quality price	liquid dragon flavored unicorns delicious	teeth wisdon pulled pain surgery	hydrocodone	drug accidental died toxicity tyler	pain feel good makes sleep	online pharmacy buy order canada

Table 1: This table shows a sample of three example themes from 6 of the drugs (fentanyl did not yield relevant topics). The top five words for each topic are displayed. The themes marked in bold were annotated as relevant, and the rest were marked irrelevant.

public safety and patient safety hazzard. The eventual goal of such a study is to build realtime surveillance systems to detect rogue content about promoting IOPs as it constantly emerges and evolves on popular social media platforms.

In order to achieve these goals, we mine all the messages containing a predefined list of prescription drugs from the popular microblogging service Twitter. We found that a topic modeling based methodology could efficiently narrow down on a subset of tweets that promote IOPs. Furthermore, we study the similarities and differences between the *rogue* tweets (and users) and regular tweets (and users) both quantitatively and qualitatively and find that they differ remarkably in many ways. This is substantiated through a series of statistical significance tests, time-series analysis, and by training machine classifiers whose performance yield high scores on several metrics (accuracy, precision, recall, f1-score).

2 Data Collection

We collected messages published on the popular microblogging platform Twitter over a period of approximately 5 months; from June to November 2015. Twitter provides a public API that enables the collection of messages posted by its users via its online platform [9]. We used a data collection methodology involving cloud-based computing services offered by Amazon Web Servies (AWS) and virtual computers via Amazon EC2 `t2.micro` instances set to filter and collect tweet objects containing specific keywords of controlled substances.

Keywords included the brandnames and international non-proprietary (e.g. generic) names (INN names) of commonly abused prescription analgesic opioid drugs. The INN names of prescription opioid drugs used in this study includes Percocet, Codeine, Oxycodone, OxyContin, Hydrocodone, Vicodin and Fentanyl. These keywords were used in conjunction with the Twitter Streaming API in order to track tweets that contained these keywords. In order to ensure the collection of the full volume of data containing these keywords, care was taken so that the limit rates imposed by Twitter were not reached¹. This generated a total of 620,477 tweets that were collected between the period of June and November 2015.

3 Detecting Illegal Marketing on Twitter

In order to identify rogue content from our dataset, we begin by summarizing the content using unsupervised topic models. Topics models like LDA implicitly learn the word co-occurrence patterns from the document level word generations [1]. Hence, they suffer immensely in the presence of sparsity (on an average, tweets are 5 words/document). We use the Biterm Topic Model instead,

¹A detailed description of the data collection methodology has been published in a previous study, and will be cited for camera ready.

where the biterm denotes an unordered pair of terms in a short context (“apple store”, “C program”), and the topics are learnt from the biterns aggregated over the entire corpus [2]. In our experiments, we set the number of topics based on the rule of thumb that $k \approx Sparsity(\mathbf{X})^{-1}$, where \mathbf{X} is that data matrix of documents-by-terms and manually annotated each of the topics based on the top-10 words from the topic (the number of topics were set to 20 for the experiments). This annotation was carried out in an open ended manner where the annotators (a data science expert, and an expert in public health policy) were asked to mark the themes as relevant based on their judgement of whether the theme could possibly contain tweets relevant to the marketing and promotions of IOP. The themes were to be marked as relevant, irrelevant or in need of further investigation. Table 1 provides summary of results from this phase. The inter-annotator agreement was 1. This suggests that there are clear indications in the lexical groupings of the topics that indicate whether or not they are pertinent to the illicit marketing, promotion and sales of prescription drugs. In order to further calibrate this methodology, once a set of relevant or *rogue* topics were identified, those tweets whose topic decompositions contained a rogue topic as its most dominant component were isolated. This subset of tweets were again manually annotated as rogue if the contents of the tweets suggested the marketing and promotion of IOPs. In most cases, more than 90% of the tweets in the *rogue* topics indeed were annotated to be rogue.

DRUG NAMES		CODEINE		PERCOCET		OXYCONTIN	
feature names	rogue	non-rogue	rogue	non-rogue	rogue	non-rogue	
retweeted_status	0	0.4131	0.0571	0.4688	0.0036	0.2764	
retweet_count	0.3234	409.16	0.4321	244.13	0.0036	7.2593	
favorite_count	0	386.82	0	198.88	0	5.1835	
in_reply_status_id	0	0.0658	0	0.0578	0	0.0773	
possibly_sensitive	0	0.102	0	0.023	0	0.0158	
entities_urls	1	0.1724	1	0.1764	0.9927	0.7331	
entities_symbols	0	0.0009	0	0.0048	0	0.0007	
entities_hashtags	0	0.1647	0	0.1800	0	0.3242	
user_verified	0	0.0022	0	0.0025	0	0.0227	
user_friends_count	12.39	1123.05	10.08	1281.12	15.03	1731	
user_follower_count	28.39	2666.85	31.025	3411.784	31.97	7669	
user_statuses_count	166995	38823.55	155576	41665	159218	41679	
user_favorites_count	0	5436.99	0	6054	0.0109	4700	

DRUG NAMES		OXYCODONE		HYDROCODONE		VICODIN	
feature names	rogue	non-rogue	rogue	non-rogue	rogue	non-rogue	
retweeted_status	0	0.3075	0.0992	0.1339	0.0147	0.2062	
retweet_count	0	16.248	0.2977	1.6805	0.0147	6.7211	
favorite_count	0	8.7775	0	2.5229	0	12.0797	
in_reply_status_id	0	0.0703	0	0.1623	0	0.2034	
possibly_sensitive	0	0.0107	0	0.0112	0	0.0134	
entities_urls	0.9999	0.7109	0.8777	0.2692	1	0.0769	
entities_symbols	0	0.0021	0	0.0001	0	0.0011	
entities_hashtags	0.0145	0.4165	0.0114	0.1953	0.0221	0.1528	
user_verified	0	0.0346	0	0.0084	0	0.0045	
user_friends_count	9.828	1511.60	37.4427	1028.98	12.2022	1342.68	
user_follower_count	25.518	11600.15	110.52	3326.318	46.48	3066.871	
user_statuses_count	158638	50960.00	129878	38677	160245	31104.78	
user_favorites_count	0.2956	3939.64	36.42	7172.15	0.3492	13508.133	

Table 2: This table lists the mean values of several Twitter based features for the rogue set of tweets and the regular set for all the drugs.

Next, we wish to characterize tweets with content related to the promotion and marketing of IOPs, and users who engage with IOP related content. The goal for such an analysis is to understand the unique markers of rogue tweets and users so that intelligent systems can be trained and deployed to detect their presence and emergence in the social media arena. As part of this effort, we analyze various twitter based features of the tweets and the users, and quantitatively (through statistical tests) and qualitatively lay out their similarities and differences. Then, we train a machine classifier to learn the differences between the features and test its performance on unseen test data. Table 2 shows the mean value for each group of data across drugs for all the features². We divide the features into five semantic groupings; each representing a specific aspect of user behavior or the characteristics of tweets.

The *User Engagement Features* such as `favorite_count` and `in_reply_to_status_id` (whether the tweet is a reply to an existing tweet). are consistently 0 for the rogue set of tweets across all drugs. This suggests that rogue tweets do not invite active engagement from general users. The `retweeted_status` and `retweet_count` indicate whether the tweet under consideration is a retweet, and the number of times the original tweet has been retweeted (at the time of data collection).

²We omit fentanyl since very few rogue tweets were identified.

metric	oxycodone	oxycontin	hydrocodone	vicodin	percocet	codeine
accuracy	0.9457	0.9451	0.8449	0.9658	0.9565	0.9342
average precision	0.9621	0.9582	0.8930	0.9749	0.9740	0.9673
f1-score	0.9451	0.9455	0.8342	0.9656	0.9551	0.9443
precision	0.9573	0.9414	0.8949	0.9692	0.9837	0.9842
recall	0.9337	0.9500	0.7822	0.9634	0.9285	0.9023
zero-one-loss	0.0542	0.0548	0.1551	0.0314	0.0434	0.0232

Table 3: This illustrates the classification results for different drugs using logistic regression.

We observe that these two features are either 0 or remarkably low for the rogue set of tweets across all drugs. For those drugs for which the `retweeted_status` and `retweet_count` were non-zero, we further investigated the cause for the retweets. We found that some of the retweets were propagated by the author of the original tweet itself. Collectively, all the user engagement features seem to suggest that users in general choose not to engage with content that might seem suspicious.

The *Tweet Based Features* are those that describe the content of the tweet. This includes `entities_urls`, `entities_hashtags`, `entities_symbols` and `possibly_sensitive`. The `entities_urls` feature indicates whether or not a tweet contains a url embedded in it. From Table 2, we observe that this feature is consistently 1 or very close to 1 across all the drugs. This suggests that one of the sole strategies in the marketing and promotion of IOPs is to direct the users out of the Twitter domain and into the landing page of the IOPs.

The *User Network Features* are those that indicate the size of a user’s network on Twitter like `user_followers_count` and the `user_friends_count`). From Table 2, we observe that both these features have much smaller values in the rogue set than the non-rogue set. On an average, the `user_friends_count` for the regular set is approximately 107x higher than the rogue set; and the `user_followers_count` is approximately 188x higher in the regular set than the non-rogue set. This suggests that the users propagating and perpetuating the rogue tweets are fairly isolated in the network. This may be explained by the relative short life of many IOPs, which are often removed or become inactive due to a number of factors including enforcement activities [8].

The *User Profile Features* numerically describe the profile of a user and includes `user_statuses_count`, `user_favorites_count` and `user_verified`. We note that the `user_statuses_count` (the total number of status messages published so far by the user) for the rogue set is on an average approximately 5x as much as that of the regular set (this number is in the order of 100000s for the rogue set, and in the order of 10000s for the regular set). We also analyzed the data of creation of the user accounts. More than 70% of the accounts in the rogue set were created in or after 2014. We also note that there are no verified users in the rogue set of tweets because the `users_verified` feature is consistently 0 across all drugs. This indicates that the influential nodes on Twitter do not engage with

We now proceed to train a machine classifier to be able to automatically classify a tweet as being *rogue* or not based on the features engineering above. The data is randomly split into 70% training and 30% test splits. The results were repeated and averaged over 10 different runs. The results from logistic regression are summarized in Table 3 [3]. We observe good performance consistently across all drugs. This provides sufficient evidence to promise success of real world systems that can be deployed in order to detect such anomalous behavior.

4 Discussion and Conclusion

In this work, we developed a methodology to isolate tweets which promote and market illicit online pharmacies. We also identified and studied the unique markers of such content and the users who generate it, and demonstrated that these unique markers could help identify the rogue tweets from unseen data. A simple machine classifier trained on numerical features was used to predict rogue tweets on unseen data. However, the scenario of marketing and promotion for IOPs are perhaps constantly evolving. The perpetrators of such messages might adopt newer strategies of promotion and reaching out to the users. Hence, there is a need for more sophisticated online learning techniques where intelligent systems can automatically learn the nuances and adapt accordingly.

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