

Identifying High-Impact Opioid Products and Key Sellers in Dark Net Marketplaces: An Interpretable Text Analytics Approach

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Abstract— As the Internet based applications become more and more ubiquitous, drug retailing on Dark Net Marketplaces (DNMs) has raised public health and law enforcement concerns due to its highly accessible and anonymous nature. To combat illegal drug transaction among DNMs, authorities often require agents to impersonate DNM customers in order to identify key actors within the community. This process can be costly in time and resource. Research in DNMs have been conducted to provide better understanding of DNM characteristics and drug sellers' behavior. Built upon the existing work, researchers can further leverage predictive analytics techniques to take proactive measures and reduce the associated costs. To this end, we propose a systematic analytical approach to identify key opioid sellers in DNMs. Utilizing machine learning and text analysis, this research provides prediction of high-impact opioid products in two major DNMs. Through linking the high-impact products and their sellers, we then identify the key opioid sellers among the communities. This work intends to help law enforcement authorities to formulate strategies by providing specific targets within the DNMs and reduce the time and resources required for prosecuting and eliminating the criminals from the market.

Keywords— Dark Net Marketplace (DNM); high-impact opioid product prediction; key seller identification; machine learning

I. INTRODUCTION

As the Internet based applications become more prevalent and bring convenience to the society, Dark Net Marketplaces (DNMs), web-based trading platforms for illegal transactions, also grow as a byproduct. DNMs utilize anonymizing technology, e.g., the Onion Router (Tor) and cryptocurrency, to offer untraceable transaction services to their users [1][2]. Any DNM user can post or purchase on DNM, resulting in a wide variety of illegal products and services. Among all product types, drugs are the most common products on DNMs. Figure 1 shows an example of opioid product listing on a major and currently active DNM, Dream Market.

Drug retailing on DNM has raised public health and law enforcement concern for its highly accessible nature [3]. Serving as illegal underground communities, DNMs are a great source of drug-related information. Users on DNMs can easily gain information about reputation of drug dealers and popular product choices [4][5]. Among various types of drug, opioid has

been identified as the second largest drug category, with a growing trend in DNMs [6]. Some types of opioid such as fentanyl have extreme negative effects on human body and can lead to serious damage or death if overdosed [7]. In order to combat illegal transactions in DNMs, authorities, such as FBI, require agents to impersonate customers in DNMs to identify key actors within the communities [8]. However, this demands enormous effort and time to formulate strategies to arrest key opioid sellers in DNMs [9]. Thus, research on DNMs has been conducted to provide law enforcement with analytical insights.

Most DNM studies often focus on drug policy and criminology study [4][10]. Such research conducts anonymous surveys on the DNM communities and analyzes the user behaviors with a more qualitative manner. Some work utilizes techniques and tools to automate the DNM data collection process and build analytics on the collected data. This body of research aims to provide an overview of DNM community and reveal high-level insights such as user retention [11], drug distribution networks [12], and seller behaviors [13]. While existing research emphasizes on high-level findings and general properties of DNMs, it does not offer more specific applications such as identifying key opioid sellers that can generate operational insights on allocating the resources in law enforcement. Moreover, past research indicates the need for further exploration on drug selling activities on DNMs [12].

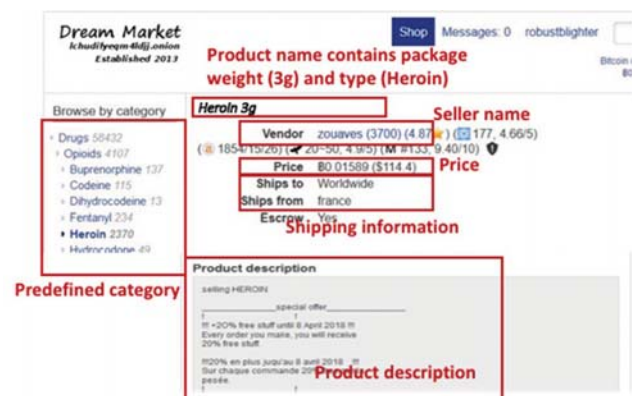


Figure 1. An example of an opioid product listing in Dream Market

Hence, this research is motivated to help reduce the time and resources for law enforcement in identifying specific targets who are worth investigation. To achieve this goal, we propose a systematic process leveraging Machine Learning (ML) techniques and text analytics of product listings offered on DNMs. Through this process we aim to predict the high-impact opioid product listings and identify their associated key opioid sellers in DNMs.

II. LITERATURE REVIEW

To gain the background knowledge of existing DNM research and understand relevant techniques and methodologies, we review the following three areas of literature: 1) DNM characteristics and sellers' behavior, 2) common predictive analytics techniques, and 3) text analytics of product descriptions.

A. DNM Characteristics and Sellers' Behavior

Existing studies have developed automated web crawlers and parsers to retrieve relevant information from DNMs [12] [14]. As a web-based transaction platform, DNMs contain information about two key components: products and sellers. However, the granularity of the information for each of these components varies for each DNM. As the majority of the DNMs do not display the quantity sold for any specific product, researchers resort to estimating the total sold quantity of each item by the number of the user reviews for that product [13]. DNMs also follow general economic rules. Extant research reveals the relationship between demand and trades. That is, most of the drug trades on DNMs take place at where the demands exist, and it largely refers to the United States [14].

Some studies focusing on drug trafficking aim to identify the characteristics of drug distribution networks. Most sellers on DNMs focus only on one market and had only one unique identifier (e.g., ID or PGP). Also, sellers are typically specialized in selling certain drug types. Doing so helps them to create their own drug distribution network and build up their reputations. With stable distribution network and good reputation, sellers are able to secure their businesses while retaining the customers at the same time [12]. Given the results from past DNM research, it appears the U.S. is currently the biggest market of DNMs drug transaction. Within this market, drug sellers on DNMs tend to construct their distribution network and establish reputation. Such findings justify the needs of further exploration of drug sellers' behavior on DNMs. Researchers identify the wholesale activity for opioid on the DNMs. With significant discounts, sellers are able to make an inventory closeout to reduce the amount of drug product in hand [13]. 90% of the drug products on DNMs are sold within five months, and 70% of the sellers on DNMs become inactive after five months [11]. The ones who remain active might be due to the success of their businesses.

As existing works provide a general overview of drug selling activities on DNMs, most of the analysis are in a more descriptive manner, generating insights that are more reactive for the authorities. To provide proactive insights, quantitative

and automated predictive analytics techniques can be leveraged.

B. Predictive Analytics Techniques for Security Applications

Predictive analytics has been widely used to forecast the value of a variable of interest in security applications [15]. ML has emerged as one of the most efficient techniques in predictive analytics [16][17]. ML model's 'flexibility' and 'interpretability' are two general criteria for determining the best model that suits the application [16]. Flexibility refers to the amount of possible variations a model can create; it usually correlates with model's 'accuracy.' Interpretability represents the degree of how well the model can be logically explained. A higher flexibility often leads to a lower interpretability of a model [16]. In security applications, a "good" model often needs to have a high interpretability as well as a high accuracy. Figure 2 summarizes popular ML models in terms of flexibility and interpretability.

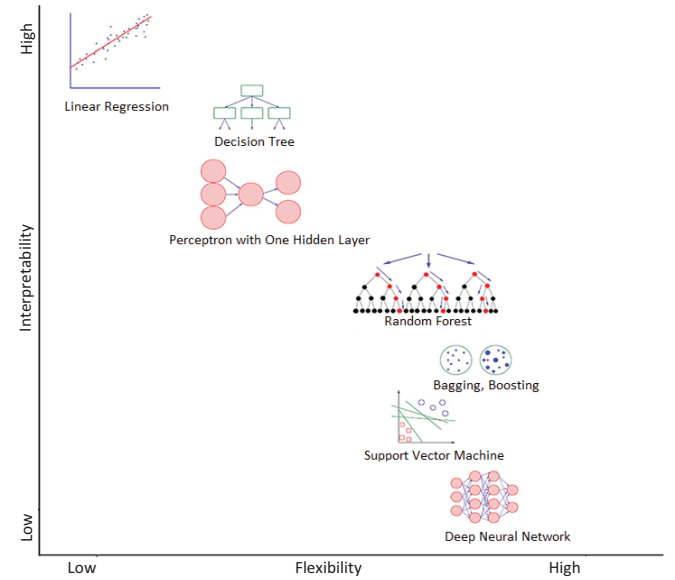


Figure 2. Relationship of model interpretability and flexibility for selected ML models (Adapted from [16] with minor changes).

The risk of 'overfitting' is another property that needs to be considered when choosing a ML model in security applications. A model with higher flexibility tends to suffer more from overfitting, especially when the data volume is not large enough [16]. Powerful ML models that have been widely used in security include Support Vector Machine (SVM), Neural Network (NN), and Decision Tree (DT). Past research utilizes SVM to categorize products on DNM, providing a better granularity of product information [18]. NN has been used in security-related research such as key actor identification [19]. DT has been leveraged to successfully classify user generated content in security-related applications [20]. To inform our model selection, we assess these common models based on the three mentioned criteria: interpretability, flexibility, and overfitting.

Despite the common usage of SVM as a predictive model in text and sentiment classification [21][22][23], it is often

associated with a low interpretability, and may overfit the training set if complex feature transformations are applied [17]. Neural Network, the basis of deep learning algorithms, is another powerful ML model. NN is capable of capturing complicated patterns, leading to excellent performance if the right hyperparameters are given [17]. Nevertheless, due to its complex network topology, NN may easily overfit the training data, and has such a low interpretability that is often referred as a “black box”. Decision Tree, on the other hand, has moderate interpretability and flexibility. DT uses a tree-like structure containing nodes and leaves, making the prediction in a step-by-step manner. However, DT also overfits the training data when too many nodes are given. Moreover, due to moderate flexibility, DT does not provide the best performance. To address these issues, variants of DT that use aggregation can be leveraged. These variants often refer to Random Forest (RF) and Gradient Boosted Machine (GBM) [17]. RF and GBM are suitable for different occasions, largely depending on the performance of a plain DT. With the random property, RF is more suitable to be applied when the plain DT is a strong classifier [17] [24]. In contrast, when the plain DT is a weak classifier, GBM is often more desirable [17][25].

In this research, in order to provide law enforcement authorities with proactive insights, a model with high interpretability and moderate flexibility can be more useful than a model with high flexibility but low interpretability, as the knowledge of the decision process can help the authorities gain intuition towards high-impact product and seller identification.

C. Text Analytics of Product Listings

Besides ML models, textual features also provide important insights in predictive analytics. Past studies have shown the effect of textual information on the conversion rate (i.e., the percentage of visitors who buy a product) of online shopping sites [26]. As a form of online shopping services, DNMs contain tremendous amount of textual information in the form of product listings descriptions. To generate such textual features in a systematic process, Latent Semantic Analysis (LSA) has been shown to be successful in retrieving relevant information from text. The core notion of LSA is to reduce text documents into several orthogonal linear combinations of feature values. The feature values are commonly calculated as the term frequency (in bag-of-word) or term frequency-inverse document frequency (tf-idf) scores. The latter generally outperforms the former due to the normalization of document frequency [27][28].

III. RESEARCH GAPS AND QUESTIONS

Past research explores the general DNM characteristics and drug sellers’ behavior, establishing the foundation of DNM research. However, it mostly treats all types of drug as a whole, and did not focus on specific types, such as opioid. Also, it is more reactive and do not leverage predictive analytics to identify high-impact products or key sellers to provide proactive insights. Based on these gaps, the following research questions are proposed:

- How to predict high-impact opioid products in a systematic manner?
- How to identify key opioid sellers based on the prediction results?

IV. RESEARCH DESIGN

Our study is designed with four major components, namely Data Collection, Opioid Listing Filtering, Feature Extraction, and Modeling and Analysis. Figure 3 illustrates our research design.

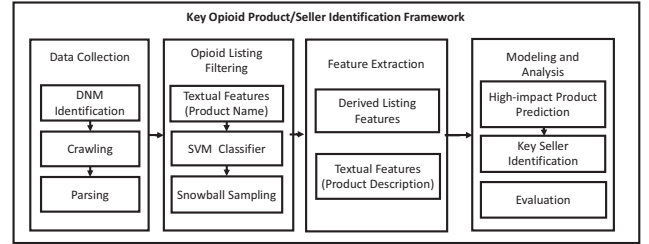


Figure 3. Research design

A. Data Collection

The data collection component aims to gather DNM data and includes three main steps. First, DNMs are identified from a publicly available up-to-date directory of DNMs, DeepDotWeb [29]. We selected AlphaBay and Dream Market as the two largest DNMs in this online directory. AlphaBay was ceased in 2017 and is known as the largest DNM by far. After identifying relevant marketplaces, several anonymous crawlers were developed to collect the raw html files including product listings and review pages. Lastly, parsers were developed to retrieve relevant information such as price from the html files and store them into database in a structured format. Additionally, to expand our research testbed, we combined our dataset with the AlphaBay DNM collection provided in [30]. After proper pre-processing, we obtain 18,890 opioid products as our research testbed (Table I). To create a gold-standard dataset, we utilize the Potency Score as an indicator. Potency Score reflects the clinical potency of a product. In our preliminary analysis, the lower 90% of the opioid products contribute less than one percent of the actual impact, while the remaining 10% have an impact of more than 99%. Thus, we selected the 90% quantile as the threshold to differentiate if an opioid product is highly impactful. For training and testing purposes, holdout validation was conducted by randomly selecting 90% of our testbed for training and 10% for testing for both impact groups.

TABLE I. RESEARCH TESTBED

DNM	Total # of listings	# of opioid listings	Collection Year
AlphaBay	114,223	14,498 (12%)	2016-2017
Dream Market	116,723	4,392 (4%)	2016-2018
Total	230,946	18,890 (8%)	2016-2018

B. Opioid Listing Filtering

Since DNMs also contain products that are not related to opioid, an automated process is required to distinguish the

opioid-related products. Through an opioid product keyword list obtained from medical resources including National Institute of Drug Abuse [31] and American Addiction Centers [32], an initial product list of opioid types was compiled. After the initial identification, tf-idf and LSA are leveraged to create a set of features from the product name. Then, an SVM classifier is trained to label other potential opioid products. Lastly, we examined the outcome, and expanded the keywords list according to the results. The whole process is iterated for multiple times until the keyword list stop expanding during this snowball-sampling procedure, identifying 18,890 opioid products out of a total of 230,046 listings as result.

C. Feature Extraction

To transform the data into suitable format for the described ML models, feature extraction processes were conducted on the unstructured text, namely product name and product description. As depicted in Figure 1, product name contains information of package weight and opioid type; writing styles of product description also vary for products. Some sellers embed promotion information in the description in uppercase words. Figure 4 shows an example that reveals the same type of opioid products with different descriptions and sold quantities.

Product Name	Description	Quantity sold
STRONG China White Fentanyl, 5x potency	Introducing our new super potent Fentanyl/Mannitol mix. 5% fentanyl 50mg per gram. -- The mix is created using a wet solution, the mannitol is dissolved into a clear liquid and under reflux process and reduced pressure. ... Uppercase Product Promotion	2
100mg Fentanyl HCL 99% purity	Completely pure unadulterated fentanyl HCL. Please make sure you have clearly researched this chemical before using. Comes in fine white powder. THIS IS ACTUAL HIGH PURITY FENTANYL, NO ANALOGUES!! SALE ON UNTIL FURTHER NOTICE. ...	146

Figure 4. Example of two fentanyl products with different description styles

To capture such textual information, the following feature extraction process was employed. Firstly, a parser leveraging Regular Expression (Regex) matching is developed to retrieve the unit package ‘weight’ and ‘opioid type’ from product name. Secondly, we calculate the proportion of ‘uppercase words’ and the ‘word counts’ for each product name and description, representing the ‘emphasis’ and ‘length’ of each product name and description. Lastly, to represent the context of the product description, tf-idf and LSA are again leveraged to obtain 50 numeric features from each product description. Table II summarizes the extracted features.

TABLE II. SUMMARY OF EXTRACTED FEATURES

Features	Description
Product Name	Name of the product shown on the listing page.
Description	Description of the product shown on the listing page.
Price	Price of the product.
Days on stock	How many days the product has been on stock.
Quantity Sold	Transaction amount for a product.
Trust level	Seller’s reputation, provided by buyers.
Seller level	How long since the seller join AlphaBay.
Type	The opioid type of the product
Weight	The weight of the product package in grams.
Length	Word counts in product name/description.
Emphasis	Proportion of uppercase words in product description.

LSA features

50 numeric values mapped from the description context (50 Orthogonal vectors obtained from LSA and tf-idf).

D. Modeling and Analysis

After the data is properly processed through the first three steps, the last step is to conduct analysis to predict high-impact opioid products and identify key sellers. As discussed previously, a clinical potency metric called Potency Score is introduced to reflect the impact of products. To this end, we identified three indicators of impact based on discussions with medical professionals in the field. Accordingly, the Potency Score (PS) is defined as the product of *quantity sold*, *package weight*, and its *potency ratio* (relative to the potency of morphine [33]). The Potency Score of product k , is given as follows:

$$PS_k = (Q_k \times W_k \times P_k)$$

Whereas the subscript k denotes the k -th opioid product listing, Q , W , and P refer to the quantity sold, unit package weight, and unit potency ratio relative to the same weight of morphine, respectively. After calculating the Potency Scores, the products with top 10 percent Potency Scores are chosen as candidates of high-impact opioid products, resulting in a 90 percent majority baseline for the following modeling and evaluation.

In order to predict high-impact products, ML models are leveraged. Since maintaining high interpretability helps law enforcement authorities better understand the decision process, DT is selected as the model’s family. In our preliminary analysis, the plain DT generates a prediction with 91 percent accuracy, which is barely better than the 90 percent majority baseline and therefore is recognized as a weak learner. Thus, as noted in the literature review section, GBM aggregation is utilized to improve the model performance. Given the mentioned properties of GBMs, we selected the Extreme Gradient Boosting Tree (XGBoost), a computationally efficient implementation of GBM aggregation to implement the model [34]. To evaluate our prediction results, precision, recall, and f-score are used as the most common measures of classification performance [2]. SVM and NN are also used as benchmarks.

Based on the prediction results, the high-impact opioid products are linked to sellers in order to identify key sellers. With the trained high-impact product prediction model (HIP-Model), we can obtain the classification results for the desired opioid listing dataset. By aggregating the results, a list of potential key sellers is generated. Figure 5 illustrates the key seller identification procedure.

Algorithm 1: Key Seller Identification

Input: Opioid Listing, each row represented as X_i
Output: Key seller list
begin
 foreach X_i **in** Opioid Listing **do**
 $y_i \leftarrow$ Class result indicated by the trained HIP-Model(X_i)
 if $y_i = 1$ **then**
 Append X_i to the High-impact Product List, represented as P_j
 foreach P_j **in** High-impact Product List **do**
 $S_j \leftarrow$ SellerName retrieved from P_j
 Append S_j to the Key Seller List
return Key Seller List

Figure 5. Key seller identification procedure

V. RESULTS AND DISCUSSION

Table III summarizes the prediction performances for XGBoost model in AlphaBay and Dream Market. To assess the significance of the results, paired t-tests with 31 resampled training and testing sets were conducted. XGBoost generally outperforms other models with or without LSA linguistic features. However, LSA linguistic features may not necessarily improve the performance. Since LSA is a relatively simple approach, more sophisticated computational linguistic or natural language processing methods may need to be applied to capture contextual information in future research.

TABLE III. EXPERIMENT RESULTS

Model	Results for AlphaBay (%)			
	Accuracy	Precision	Recall	F-score
XGBoost	93.8%***	75.0%***	55.6%***	63.9%***
XGBoost + LSA	94.6%	79.6%	63.0%	70.3%
SVM	84.6%***	25.9%***	30.6%***	28.1%***
SVM + LSA	84.2%***	39.9%***	27.6%***	32.6%***
NN	88.7%***	66.7%***	59.8%***	63.1%***
NN + LSA	88.8%***	70.4%***	62.5%***	66.2%***
Model	Results for Dream Market (%)			
	Accuracy	Precision	Recall	F-score
XGBoost	95.1%	87.2%	69.4%	77.3%
XGBoost + LSA	94.47%***	75.9%***	67.4%**	71.4%***
SVM	89.0%***	54.5%***	49.0%***	51.6%***
SVM + LSA	82.1%***	44.2%***	39.2%***	41.6%***
NN	93.3%***	59.3%***	56.9%***	58.1%***
NN + LSA	93.9%***	60.9%***	57.8%***	59.3%***

*** $p \leq 0.001$, ** $p \leq 0.05$

Among our testing set of 1,266 listings, 101 of them are predicted as high-impact products. Through linking products and sellers, 51 sellers are associated with these products. 19 sellers out of the 51 hold more than one product predicted as high-impact, and therefore are recognized as existing key sellers. Table IV summarizes the top 5 sellers identified in our testing set. As shown in the table, morphine, fentanyl, and heroin are among the top high-impact products associated with key sellers. Moreover, our results show that U.S., Canada, U.K., Netherlands, and China are the countries associated with the top

50 sellers in DNMs, while China is being the only country from Asia in this list.

TABLE IV. TOP 5 OPIOID SELLERS WITHIN TESTING SET

Seller Name	Country	# of Products	Focused Category	Sales Volume
h**w	Canada	13	morphine	\$166,390
h*****3	U.S.	11	fentanyl	\$39,513
T*****y	Netherlands	10	heroin	\$25,345
p*****l	Canada	5	fentanyl	\$25,680
B*****s	China	5	fentanyl	\$5,277

To show the interpretability of our model via an illustrative example, we demonstrate the obtained model for a key seller suggested by our method. In Figure 6, we visualize the XGBoost decision process for the corresponding product. The green path refers to a step-by-step decision process for a product in our model. Each node of the model divides the products into two subgroups based on a learned criterion. If the product has a property that meets the criterion, it goes to the left path of the node, and vice versa. In this example, the model first examines weight of the opioid package. Since the product weighs 226.8 grams (i.e., greater than 22.25 grams), it is a candidate for being high impact. Next, the model examines the duration that this product has been on the stock. Since the product has only been on stock for 50 days (i.e., less than 320 days), it remains to be a candidate for being a high-impact product. Next, the model examines the time the seller has been active in the DNM represented by a positive integer denoted by ‘seller level.’ Passing along the left path after checking the seller level, the model examines if this product is NOT a type of codeine (‘Codeine = 0’). Since the product type is codeine, it traverses to the right path and its weight is checked again. At the end, the product is classified as a high-impact product.

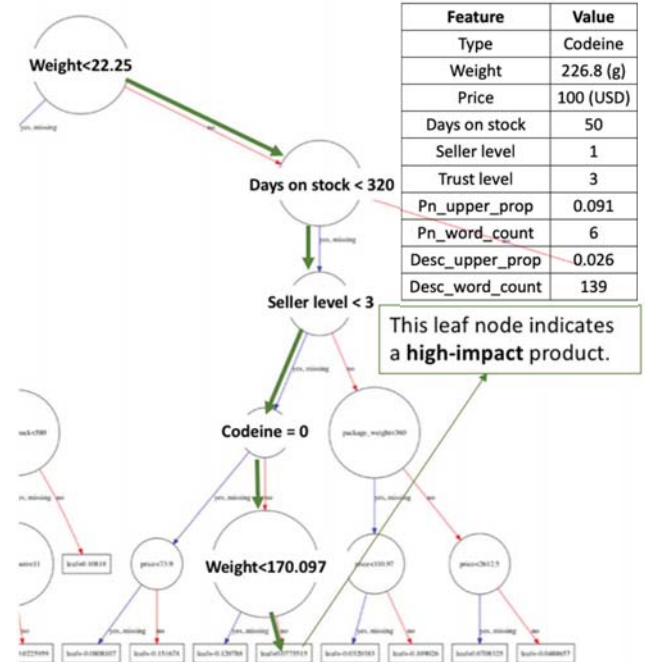


Figure 6. Decision process of a high-impact opioid product

The plausible interpretation behind the above-mentioned decision is as follows: (1) high impact opioid products are often sold in larger quantities and weights; (2) high-impact opioid products often do not stay on stock for a long time; (3) the high-impact products are often sold by sellers with a high level of activity in the market. Offering such insights can be extremely useful in guiding the future law enforcement's strategies.

VI. CONCLUSION AND FUTURE WORK

Along with the rise of legal online platforms, Dark Net Marketplaces also prosper as platforms hosting illegal transactions involving mostly drugs. As a result, drug retailing on DNMs has raised public health and law enforcement concern for its highly accessible nature. In this study, an interpretable analytical process was proposed to predict high-impact opioid products based on their clinical potency, leading to identifying key opioid sellers within the DNMs. Our experiments on two major DNMs show that Extreme Gradient Boosting Tree contributes to achieving the balance between interpretability and performance. Our method surpasses other machine learning models in terms of predictive performance. Also, the decision tree-based model allows for more interpretability through visualizing the decision-making process and provides proactive insights for law enforcement authorities to allocate their resources for prosecuting key opioid sellers. Using the proposed method, we were able to identify existing and potential key sellers among the DNMs. More sophisticated computational linguistic and natural language processing methods are needed in future research to enhance the performance.

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