Your Style Your Identity: Leveraging Writing and Photography Styles for Drug Trafficker Identification in Darknet Markets over Attributed Heterogeneous Information Network

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ABSTRACT

Due to its anonymity, there has been a dramatic growth of underground drug markets hosted in the darknet (e.g., Dream Market and Valhalla). To combat drug trafficking (a.k.a. illicit drug trading) in the cyberspace, there is an urgent need for automatic analysis of participants in darknet markets. However, one of the key challenges is that drug traffickers (i.e., vendors) may maintain multiple accounts across different markets or within the same market. To address this issue, in this paper, we propose and develop an intelligent system named uStyle-uID leveraging both writing and photography styles for drug trafficker identification at the first attempt. At the core of uStyle-uID is an attributed heterogeneous information network (AHIN) which elegantly integrates both writing and photography styles along with the text and photo contents, as well as other supporting attributes (i.e., trafficker and drug information) and various kinds of relations. Built on the constructed AHIN, to efficiently measure the relatedness over nodes (i.e., traffickers) in the constructed AHIN, we propose a new network embedding model Vendor2Vec to learn the low-dimensional representations for the nodes in AHIN, which leverages complementary attribute information attached in the nodes to guide the meta-path-based random walk for path instances sampling. After that, we devise a learning model named videntifier to classify if a given pair of traffickers are the same individual. Comprehensive experiments on the data collections from four different darknet markets are conducted to validate the effectiveness of uStyle-uID which integrates our proposed method in drug trafficker identification by comparisons with alternative approaches.

KEYWORDS

Darknet Market; Drug Trafficker Identification; Attributed Heterogeneous Information Network (AHIN); Network Embedding.

1 INTRODUCTION

The market of illicit drugs (e.g., cannabis, cocaine, heroin) is considerably lucrative - i.e., the estimated yearly revenue for the global market reached about $426-$652 billion in 2017 [23]. Driven by such remarkable profits, the crime of drug trafficking (a.k.a. illicit drug trading) has never stopped but co-evolved along with the advance of modern technologies [4, 16, 17, 28, 32, 38, 39]. Darknet, as a hidden part of the Internet, employs advanced encryption techniques to protect the anonymity of its users. The markets hosted in the darknet are built on The Onion Router (TOR) service to hide the IP address, the escrow system, the encrypted communication tools like Pretty Good Privacy (PGP), and the virtually untraceable cryptocurrency (e.g., bitcoin) to facilitate anonymous transactions among participants. Figure 1.(a) illustrates a typical transaction in darknet markets. Due to its anonymity, there has been a dramatic growth of underground drug markets hosted in the darknet (e.g., Silk Road 3 [33], Dream Market [27], Valhalla [37], known as "eBay of drugs" or "Amazon of drugs"). Illegal trading of drugs in these markets has turned into a serious global concern because of its severe consequences on society (e.g., violent crimes) and public health at regional, national and international levels [8].

To combat drug trafficking in the cyberspace, there is an urgent need for analysis of participants in darknet markets, as it could provide valuable insight to the investigation of drug trafficking ecosystem and prediction of future incidents while building pro-active defenses [6]. However, one of the key challenges is that drug traffickers may maintain multiple accounts across different markets or in the same market for the reasons [2, 4, 34] such as ripper (i.e.,
an old account has lost the trust of other members), branding (i.e., a vendor creates an alias to positively review his/her own products or services), and anonymity. Linking different accounts to the same individuals is essential to track their status and better understand the online drug trafficking ecosystem [40]. Given the growing scale of darknet markets and the large number of user accounts, it is simply impossible to manually link suspicious accounts and track their latest status. Therefore, it is highly desirable to develop novel methodologies that can automatically link multiple accounts of the same individuals in darknet markets.

To automate the process, some of existing approaches [2, 5, 20] relied on stylometry analysis which aims at linking different accounts to the same user based on his/her writing styles (e.g., as illustrated in Figure 1.(b) and (c), the vendor likes using specific emoticon in the product description). Since drug traffickers in darknet markets have to prove the possession of illegal drugs by posting their own product photos, their distinct photography styles might be revealed by the posted photos. A recent research [40] proposed to link multiple accounts of the same vendors in different darknet markets based on their distinct photography styles (e.g., the way to display products and camera model as shown in Figure 1.(c)). Though each kind of analysis has shown success in fingerprinting underground market participants, using them respectively may suffer different challenges (e.g., stylometry analysis only is sensitive to the language of content [40], while photography style analysis only may face the challenge of intrinsic ambiguity arising from resale or photo plagiarizing). Can we leverage both writing and photography styles to develop an integrated framework for drug trafficker identification in darknet markets?

In this paper, we propose to leverage both writing and photography styles to develop an intelligent system (named uStyle-uID) to automatically link multiple accounts of the same individuals for drug trafficker identification in darknet markets. In uStyle-uID, given a pair of vendors (denoted by their usernames in the related markets), to determine whether they are the same individual, we not only analyze their posted contents (i.e., including their posted texts and photos), but also consider their writing styles and photography styles as well as other supporting attributes (i.e., vendor and drug information) and various kinds of relations. To depict vendors, drugs, texts, photos and their associated attributes as well as the rich relations among them, we present an attributed heterogeneous information network (AHIN) [26] for modeling. To tackle the challenge of high computation cost and memory constraint of measuring the relatedness over vendors in the constructed AHIN, we propose a new network embedding model named Vendor2Vec to learn low-dimensional attribute-aware embeddings for the nodes in AHIN. The proposed Vendor2Vec model leverages complementary attribute information of each node to guide the meta-path based random walk for path-instance sampling; then a skip-gram model [30] is utilized to learn effective node representations for AHIN. Finally, based on the learned latent representations of the nodes (i.e., vendors) in AHIN, we devise a learning model named vIdentifier to classify whether a given pair of vendors are the same individual.

2 PROPOSED METHOD

The overview of our developed system uStyle-uID for drug trafficker identification in darknet markets is shown in Figure 2. In this section, we will introduce the detailed approaches which are integrated in uStyle-uID for drug trafficker identification.
2.1 Feature Extraction

We propose to characterize vendors in darknet markets in a comprehensive view by extracting various features.

(1) Posted text and writing style extraction. To fingerprint a vendor based on his/her posted texts, we consider both his/her posted text content and writing style. For text content, we apply doc2vec [25] to convert each text of variant size into a fixed length feature vector (empirically, we set the dimension to 100). For writing style [2, 20], we propose to extract multi-scale stylometry features at three different levels as follows: 1) Lexical features: can be further divided into character-based and word-based groups to capture stylistic traits. At this level, we extract (i) number of characters, (ii) number of digits/white spaces/special characters, (iii) number of words, (iv) average word length, and (v) vocabulary richness [36].

2) Syntactic features: capture the writing style from the sentence structure. In this category, we adopt (i) frequency of punctuation, (ii) frequency of function word, (iii) number of sentences beginning with a capital letter, and (iv) frequency of parts-of-speech n-grams (we set $n = 3$ in our case). 3) Structural features: represent the way an author organizes the layout of his/her posted text. We consider (i) total number of paragraphs, (ii) indentation of paragraph, (iii) whether there’s separator between paragraphs, and (iv) number of words/sentences/characters per paragraph. For each posted text, we then concatenate its converted feature vector representing the posted text content and the feature vector describing its writing style as an attribute associated with this posted text.

(2) Posted photo and photography style extraction. To represent the content of a posted photo, we propose to utilize image2vec [15] to convert it into a fixed length feature vector (empirically, we set the dimension to 100). Since drug traffickers in darknet markets have to prove the possession of illegal drugs by posting their own product photos, their distinct photography style might be revealed by the posted photos. We propose to capture the photography style by extracting its low-level and high-level features. 1) Low-level features: refer to the information that can be directly obtained from a photo’s exchangeable image file format (EXIF) data, which include (i) camera make and model, (ii) camera angle, (iii) exposure time, (iv) focal length, and (v) image size. 2) High-level features: are extracted from the photo’s original content. We first convert the photo into its HSV (hue, saturation, value) representation and then extract the following five types of high-level features: (i) colorfulness, (ii) exposure of light, (iii) saturation, (iv) hue count, and (v) contrast. In our current implementation, colorfulness, exposure of light and saturation are calculated using the method in [7]; while hue count and contrast are measured by [24]. For each posted photo by a vendor, we then concatenate its converted feature vector representing the posted photo content and the feature vector describing its photography style as an attribute associated with this posted photo.

(3) Attributed features of vendors and drugs. Besides the above extracted features, vendors’ basic information and drugs they sell also play an important role in resolving their identities. Therefore, we further extract three kinds of features to depict each vendor: username, PGP key and contact information. Note that, for username, we first apply standard string matching techniques to measure the similarity of two usernames, if their similarity is greater than a user-specific threshold, we regard these two usernames as the same (e.g., “MF***Jones” and “MF***J0nes”). For each drug, we further extract its category, escrow information and shipping information (e.g., from where and to where). Then, we apply one-hot encoding [41] to convert the extracted features to a binary feature vector to be an attribute associated with each vendor/drug.

(4) Relation-based Features. In order to characterize the rich relations among vendors, drugs, posted texts and photos, we further extract the following relation-based features: 1) R1: the vendor-sell-drug relation indicates whether a vendor sells a drug; 2) R2: the vendor-write-text relation denotes if a vendor writes a text; 3) R3: the vendor-post-photo relation indicates whether a vendor posts a photo; 4) R4: the text-describe-drug relation denotes whether a text describes a drug; 5) R5: the photo-characterize-drug relation indicates if a photo characterizes a drug.

2.2 AHIN Construction

Though heterogeneous information network (HIN) [35] has shown the success of modeling different types of entities and relations, it has limited capability of modeling additional attributes attached to entities. Thus, to depict vendors, drugs, texts, photos and their associated attributes as well as the rich relationships among them, we propose to use attributed HIN (AHIN) for representation.

Definition 2.1. Attributed heterogeneous information network (AHIN) [26]. Let $T = \{T_1, ..., T_m\}$ be a set of $m$ entity types. For each entity type $T_i$, let $X_i$ be the set of attributes of type $T_i$ and $A_i$ be the set of attributes defined for entities of type $T_i$. An entity $x_j$ of type $T_i$ is associated with an attribute vector $f_j = \{f_{j1}, f_{j2}, ..., f_{j|A_i|}\}$. An AHIN is defined by a graph $G = (V, E, A)$ with an entity type
mapping $\phi: \mathcal{V} \rightarrow T$ and a relation type mapping $\psi: \mathcal{E} \rightarrow \mathcal{R}$, where $\mathcal{V} = \bigcup_{i=1}^{m} \mathcal{X}_i$ denotes the entity set and $\mathcal{E}$ is the relation set, $T$ denotes the entity type set and $\mathcal{R}$ is the relation type set, $\mathcal{A} = \bigcup_{i=1}^{m} \mathcal{A}_i$, and the number of entity types $|T| > 1$ or the number of relation types $|\mathcal{R}| > 1$. The network schema [26] for an AHIN $\mathcal{G}$, denoted by $\mathcal{T}_\mathcal{G} = (T, \mathcal{R})$, is a graph with nodes as entity types from $\mathcal{T}$ and edges as relation types from $\mathcal{R}$.

To solve this problem, we propose a novel attribute-aware AHIN embedding model named Vendor2Vec which consists of attribute-aware meta-path random walk and skip-gram model. Given an AHIN $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$ with schema $\mathcal{T}_\mathcal{G} = (T, \mathcal{R})$, and a meta-path scheme $\mathcal{P}$ in the basic form: $T_1 \rightarrow \cdots \rightarrow T_t \rightarrow T_{t+1} \rightarrow \cdots \rightarrow T_L$, we use attribute-aware meta-path to guide a random walker in AHIN, the transition probability at step $i$ is calculated as:

$$ p(v^{i+1} | v^i, \mathcal{P}) = \begin{cases} \text{sim}(f(v^i), f(v')) & \sum_{v'' \in N_{T_{t+1}}(v')} \text{sim}(f(v'), f_{v''}) \\ 1 & (v^i, v^{i+1}) \in \mathcal{E}, \phi(v^{i+1}) = \phi(v') = T_{t+1} \\ |N_{T_{t+1}}(v^i)| & (v^i, v^{i+1}) \in \mathcal{E}, \phi(v^{i+1}) = T_{t+1}, v' = 0 \\ 0 & \text{otherwise,} \end{cases} $$

where $v'$ denotes the latest entity the walker visited is with the same type of $v^{i+1}$, $\text{sim}(f(v'), f_{v''})$ is the similarity between two entities’ attribute vectors (e.g., it can be calculated by using cosine similarity measure), $\phi$ is the node type mapping function, $N_{T_{t+1}}(v^i)$ denote $T_{t+1}$ type of neighborhood of node $v^i$, $\mathcal{V}$ denotes a node in $N_{T_{t+1}}(v^i)$. Since we have three different meta-paths, we simply combine the path instances sampled via each meta-path, and feed them into the skip-gram model [29] to learn the node embeddings.

### 2.4 Classification Model

The problem of determining if a given pair of vendors are the same individual can be considered as a link prediction in an AHIN. In this paper, motivated by [1], we propose to devise a classification model for AHIN (named $\text{vIdentifier}$ as shown in Figure 2.(d)) to predict the likelihood of the link between two nodes.

We first apply a Deep Neural Network (DNN) into node embedding to learn $f_\theta : \mathbb{R}^d \rightarrow \mathbb{R}^d$ that maps a vendor’s learned latent representation onto a low-dimensional manifold. The mapping function $f_\theta$ is defined as [1]:

$$ f_\theta : Y_u \rightarrow FC(W_{u,b_1}) \rightarrow \text{BatchNorm} \rightarrow \text{relu} \rightarrow FC(W_{u,b_2}) \rightarrow \text{BatchNorm} \rightarrow f_\theta(Y_u), $$

(2)

where $FC(W_{u,b})$ is a fully-connected layer with weight matrix $W$ and bias vector $b$, BatchNorm is described in [22], $\text{relu}(x) = \max(0, x)$ is an element-wise activation function, and $\theta = \{W_1, b_1, W_2, b_2, \ldots\}$.

Given a pair of vendors, to define a general link function $g(u, v) \in \mathbb{R}$, we consider a low-rank affine projection in the manifold space [1]: $g(u, v) = f_\theta(Y_u)^T \times M \times f(Y_v)$, where the low-rank projection matrix $M = L \times R$ with $L \in \mathbb{R}^{d \times b_1}$ and $R \in \mathbb{R}^{b_2 \times d}$, $b < d \times D$. We can factor $g(u, v)$ into an inner product $\langle L^T f(Y_u), R f(Y_v) \rangle$.

Then, we utilize the method proposed in Figure 3.(e) to conduct the optimization. The function is devised as following:

$$ Pr(\mathcal{G}) \propto \prod_{u,v \in \mathcal{V}} \sigma(g(u, v)) \cdot D_{uv} \cdot f(u, v)^\top \cdot (1 - \sigma(g(u, v)))^\top \cdot f(u, v), $$

(3)

where $\sigma(x) = 1/(1 + \exp(-x))$ is the standard logistic.

$$ f(u, v) = \begin{cases} 1 & \text{if } u \text{ and } v \text{ are the same individual} \\ 0 & \text{otherwise,} \end{cases} $$

(4)

![Figure 3: Network schema and meta-paths.](image-url)
\(D_{uv}\) is the frequency that vendors \(u\) and \(v\) co-occur within a specific window in the path instances sampled by our above proposed attribute-aware meta-path random walk.

3 EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we conduct three sets of experiments using data collections from darknet markets to fully evaluate the performance of our developed system \(uStyle-ulID\) for drug trafficker identification.

3.1 Experimental Setup

To fully evaluate our proposed method, we have collected the data from four different darknet markets Valhalla, Dream Market, SilkRoad2 and Evolution. For the former two darknet markets, we develop a set of crawling tools to scrape weekly snapshots from June 2017 to August 2017. For the rest of markets, we collect their public data dumps. After data collection, we merely retain the vendors who at least posted two different drugs, each of which should be at least with one transaction. We summarize the collected data in Table 1. Due to the anonymity of darknet markets, it is difficult to access the actual ground-truth. Similar to the approach used in [40], we propose an alternative solution: for a given vendor, we randomly split his/her posted texts and photos into two even parts to form a positive example; then we randomly match this given vendor to the other in the same darknet market to generate a negative example.

In this pseudo setting, the attribute vector attached to each vendor node is set as null. In the following experiments, we conduct ten-fold cross validations and use accuracy (ACC) and F1 as performance measures to evaluate different methods. The parameters for Vendor2Vec are empirically set as follows: node dimension \(D = 100\), walks per node \(r = 10\), walk length \(l = 80\) and window size \(w = 10\), while for the parameter of \(d\) in \(v\)Identifier is set as 30 and the remaining ones are consistent with [1].

Table 1: Information of the dataset.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Vendors</th>
<th>Drugs</th>
<th>Entities</th>
<th>Relations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valhalla (Val)</td>
<td>522</td>
<td>13,150</td>
<td>27,535</td>
<td>54,698</td>
</tr>
<tr>
<td>Dream Market (DM)</td>
<td>2,547</td>
<td>67,270</td>
<td>139,493</td>
<td>281,080</td>
</tr>
<tr>
<td>SilkRoad2 (SR2)</td>
<td>681</td>
<td>15,231</td>
<td>31,354</td>
<td>66,648</td>
</tr>
<tr>
<td>Evolution (Evol)</td>
<td>1,650</td>
<td>36,798</td>
<td>79,451</td>
<td>164,792</td>
</tr>
</tbody>
</table>

3.2 Comparisons of Different Features

In this set of experiments, we first evaluate the effectiveness of different features for drug trafficker identification.

- **Text-based features**: (1) text content only \((f-1)\), (2) writing style only \((f-2)\), and (3) text content and writing style \((f-3)\).
- **Photo-based features**: (1) photo content \((f-4)\), (2) photography style \((f-5)\), and (3) photo content and photography style \((f-6)\).

The experimental results are illustrated in Table 2, from which we can see that different features show different performances. To put this into perspective, (1) the relatedness over vendors depicted by style-based correlations \((f-2)\) and \((f-5)\) perform better than content-based correlations \((f-1)\) and \((f-4)\); (2) feature engineering \((f-3)\) and \((f-6)\) helps the performance; (3) the photo-based features \((f-4)\), \((f-5)\), and \((f-6)\) perform better than the text-based ones \((f-1)\), \((f-2)\), and \((f-3)\); (4) our proposed method \(uStyle-ulID\) which integrates different levels of semantics, leveraging both writing and photograph styles, obtains a significantly better performance.

Table 2: Comparisons of different features.

<table>
<thead>
<tr>
<th>Metric Method</th>
<th>Feature</th>
<th>Val</th>
<th>DM</th>
<th>SR2</th>
<th>Evol</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACC</td>
<td>(f-1)</td>
<td>0.780</td>
<td>0.798</td>
<td>0.782</td>
<td>0.792</td>
</tr>
<tr>
<td></td>
<td>(f-2)</td>
<td>0.792</td>
<td>0.807</td>
<td>0.795</td>
<td>0.805</td>
</tr>
<tr>
<td></td>
<td>(f-3)</td>
<td>0.803</td>
<td>0.819</td>
<td>0.806</td>
<td>0.815</td>
</tr>
<tr>
<td>ACC</td>
<td>(f-4)</td>
<td>0.795</td>
<td>0.808</td>
<td>0.796</td>
<td>0.805</td>
</tr>
<tr>
<td></td>
<td>(f-5)</td>
<td>0.807</td>
<td>0.817</td>
<td>0.808</td>
<td>0.816</td>
</tr>
<tr>
<td></td>
<td>(f-6)</td>
<td>0.818</td>
<td>0.828</td>
<td>0.819</td>
<td>0.827</td>
</tr>
<tr>
<td>(uStyle-ulID)</td>
<td>/</td>
<td>0.876</td>
<td>0.903</td>
<td>0.881</td>
<td>0.889</td>
</tr>
<tr>
<td>F1</td>
<td>(f-1)</td>
<td>0.782</td>
<td>0.784</td>
<td>0.772</td>
<td>0.784</td>
</tr>
<tr>
<td></td>
<td>(f-2)</td>
<td>0.796</td>
<td>0.788</td>
<td>0.784</td>
<td>0.790</td>
</tr>
<tr>
<td></td>
<td>(f-3)</td>
<td>0.804</td>
<td>0.809</td>
<td>0.792</td>
<td>0.797</td>
</tr>
<tr>
<td>F1</td>
<td>(f-4)</td>
<td>0.785</td>
<td>0.794</td>
<td>0.792</td>
<td>0.793</td>
</tr>
<tr>
<td></td>
<td>(f-5)</td>
<td>0.798</td>
<td>0.806</td>
<td>0.796</td>
<td>0.802</td>
</tr>
<tr>
<td></td>
<td>(f-6)</td>
<td>0.810</td>
<td>0.817</td>
<td>0.806</td>
<td>0.809</td>
</tr>
<tr>
<td>(uStyle-ulID)</td>
<td>/</td>
<td>0.865</td>
<td>0.894</td>
<td>0.868</td>
<td>0.879</td>
</tr>
</tbody>
</table>

3.3 Network Embedding Model Comparisons

In this set of experiments, we evaluate our proposed method Vendor2Vec by comparisons with several state-of-the-art network embedding models including DeepWalk [31], node2vec [18] and metapath2vec [10]. For these embedding methods, we use the same parameters as Vendor2Vec. The results from Table 3 show that Vendor2Vec consistently and significantly outperforms all state-of-the-art embedding models. The success of Vendor2Vec lies in: (1) the proper consideration and accommodation of the heterogeneous property of AHIN; (2) the advantage of the attribute setting and the proposed attribute-aware meta-path guided random walk for sampling the high-quality path instances (i.e., without the attribute information such as writing and photograph styles, the generated path instances are of low quality and less useful to our application).

Table 3: Comparisons of network embedding models.

<table>
<thead>
<tr>
<th>Metric Method</th>
<th>Val</th>
<th>DM</th>
<th>SR2</th>
<th>Evol</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACC</td>
<td>DeepWalk</td>
<td>0.703</td>
<td>0.714</td>
<td>0.699</td>
</tr>
<tr>
<td></td>
<td>node2vec</td>
<td>0.726</td>
<td>0.731</td>
<td>0.722</td>
</tr>
<tr>
<td></td>
<td>metapath2vec</td>
<td>0.741</td>
<td>0.754</td>
<td>0.744</td>
</tr>
<tr>
<td></td>
<td>Vendor2Vec</td>
<td>0.876</td>
<td>0.903</td>
<td>0.881</td>
</tr>
<tr>
<td>F1</td>
<td>DeepWalk</td>
<td>0.682</td>
<td>0.688</td>
<td>0.669</td>
</tr>
<tr>
<td></td>
<td>node2vec</td>
<td>0.703</td>
<td>0.710</td>
<td>0.692</td>
</tr>
<tr>
<td></td>
<td>metapath2vec</td>
<td>0.718</td>
<td>0.735</td>
<td>0.727</td>
</tr>
<tr>
<td></td>
<td>Vendor2Vec</td>
<td>0.865</td>
<td>0.894</td>
<td>0.868</td>
</tr>
</tbody>
</table>

3.4 Comparisons with Alternative Approaches

In this set of experiments, based on our collected datasets, we compare our developed system \(uStyle-ulID\) with alternative approaches:
(1) feeding all the features (i.e., $f_3$, $f_6$, and feature vectors of vendors and drugs) into a generic DNN [19] to make the identification (denoted as Hybrid-DNN); (2) replacing the videntifier in uStyle-uID by a generic DNN (denoted as AHIN-DNN); (3) replacing the videntifier in uStyle-uID by SVM (denote as AHIN-SVM). For the generic DNN, we implement the model in Keras [40] and retain the default parameters. The experimental results are illustrated in Table 4. From the results we can observe that AHIN-DNN added the knowledge represented as AHIN performs better than Hybrid-DNN, which shows that using meta-path based approach over AHIN is able to build the higher-level semantic connection between vendors with a more expressive view. We also note that uStyle-uID significantly outperforms other baselines, which demonstrates that videntifier indeed helps the performance compared with the generic DNN and state-of-the-art shallow learning classification model.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Method</th>
<th>Val</th>
<th>DM</th>
<th>SR2</th>
<th>Evol</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACC</td>
<td>Hybrid-DNN</td>
<td>0.831</td>
<td>0.839</td>
<td>0.833</td>
<td>0.838</td>
</tr>
<tr>
<td></td>
<td>AHIN-DNN</td>
<td>0.854</td>
<td>0.876</td>
<td>0.856</td>
<td>0.863</td>
</tr>
<tr>
<td></td>
<td>AHIN-SVM</td>
<td>0.843</td>
<td>0.851</td>
<td>0.847</td>
<td>0.848</td>
</tr>
<tr>
<td></td>
<td>uStyle-uID</td>
<td>0.876</td>
<td>0.903</td>
<td>0.881</td>
<td>0.889</td>
</tr>
<tr>
<td>F1</td>
<td>Hybrid-DNN</td>
<td>0.809</td>
<td>0.818</td>
<td>0.812</td>
<td>0.814</td>
</tr>
<tr>
<td></td>
<td>AHIN-DNN</td>
<td>0.841</td>
<td>0.864</td>
<td>0.845</td>
<td>0.855</td>
</tr>
<tr>
<td></td>
<td>AHIN-SVM</td>
<td>0.832</td>
<td>0.837</td>
<td>0.832</td>
<td>0.840</td>
</tr>
<tr>
<td></td>
<td>uStyle-uID</td>
<td>0.865</td>
<td>0.894</td>
<td>0.868</td>
<td>0.879</td>
</tr>
</tbody>
</table>

4 CROSS-MARKET DRUG TRAFFICKER IDENTIFICATION AND CASE STUDIES

To better understand and gain deeper insights into the ecosystem of drug trafficking in darknet markets, we further apply our developed system uStyle-uID for cross-market drug trafficker identification. For the detected cross-market vendor pairs, we further sample 798 pairs and validate them using conclusive evidences. Among these 798 detected cross-market pairs, 726 pairs (90.09%) are with high confidence that they are the same individuals and 22 pairs are uncertain (2.76%). As shown in Figure 4, for one of our detected cross-market vendor pairs, though "The***shop" on Evolution and "****Store" on Valhalla have different usernames, PGP keys and con-

Figure 4: An example of detected cross-market vendor pair.

to tackle the challenges of authorship identification such as [20, 40]. However, these approaches mainly relied on either stylometry analysis or photography style analysis. Different from existing works, we propose to leverage both writing and photography styles together with their contents for drug trafficker identification.

In order to depict different entities, associated attributes and the rich relationships among them, it is important to model them properly. Though HIN has shown the success of modeling different types of entities and relations [11–13, 21, 35, 42, 43], it has limited capability of modeling additional attributes attached to entities. To address this challenge, we propose to use AHIN for representation. To better address representation learning for HIN, many efficient network embedding methods have been proposed such as metagraph2vec [11], metapath2vec [10], HIN2vec [14]. However, these models are unable to deal with the attribute information associated with each entity. To address this issue, we propose Vendor2Vec to learn the desirable node representations in AHIN.

6 CONCLUSION

To combat drug trafficking, in this paper, we design and develop an intelligent system named uStyle-uID to automate drug trafficker identification in darknet markets. In uStyle-uID, we propose to leverage both writing and photography styles at the first attempt. To depict vendors, drugs, texts, photos and their associated attributes as well as the rich relationships among them, we present a structural AHIN to model them which gives the vendors higher-level semantic representations. Then, a meta-path based approach is used to characterize the semantic relatedness over vendors. To efficiently measure the relatedness over vendors in AHIN, we propose a new network embedding model Vendor2Vec which leverages complementary attribute information attached in the nodes to guide the meta-path based random walk for path instances sampling. Then, we transform the identification task into a link prediction problem and further present a learning model named videntifier to solve the problem. The promising experimental results on the collected datasets from four darknet markets demonstrate that uStyle-uID outperforms alternative approaches.

7 ACKNOWLEDGMENTS

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