Detecting Opioid Users from Twitter and Understanding their Perceptions toward MAT

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***Abstract*—Opioid (e.g., heroin and morphine) addiction has become one of the largest and deadliest epidemics in the United States. To combat such deadly epidemic, there is an urgent need for novel tools and methodologies to gain new insights into the behavioral processes of opioid addiction and treatment. In this paper, we design and develop an intelligent system named *iOPU* to automate the detection of opioid users from Twitter. In *iOPU*, to model the users and posted tweets as well as their rich relationships, we first introduce a structured heterogeneous information network (HIN) for representation. Then we use meta-graph based approach to characterize the semantic relatedness over users. Afterwards, we integrate content-based similarity (i.e., similarity of users' posted tweets) and relatedness depicted by each meta-graph to formulate a similarity measure over users. Further we build a classifier combining different similarities based on different meta-graphs to make predictions. Comprehensive experiments on real sample collections from Twitter are conducted to validate the effectiveness of our developed system *iOPU* in opioid user detection by comparisons with other baseline methods. The results also demonstrate that knowledge from daily-life social media data mining could promote the practice of Medication Assisted Treatment (MAT) in opioid addiction.**

1. Introduction

Opioids are a group of drugs which include the illegal drug heroin and powerful pain relievers by legal prescription [1], such as morphine and oxycodone. Opioid addiction has become one of the largest and deadliest epidemics in the United States [2]. Americans are more likely to die of a drug overdose than in a motor vehicle accident and overdose deaths have increased every subsequent year [3]. In 2014, 4.3 million Americans age 12 and up were reported current non-medical use of prescription opioids, while 435,000 people were estimated to have opioid use disorders [4]. There was a skyrocketing increase of opioid related death in the past decade: according to National Institute on Drug Abuse (NIDA), in 2014, 18,893 Americans died from opioid analgesics and 10,574 people died from heroin overdose, both reflecting significant increase from 2001 [5]. Opioid addiction has also turned into a serious global concern because of its negative health, social and economic impacts (e.g., family breakdown, domestic violence, child abuse). Opioid addiction is a chronic mental illness that requires long-term treatment and care [6]. It is a psychiatric challenge because of high relapse and drop-out rates. Although Medication Assisted Treatment (MAT) using methadone or buprenorphine has been proven to provide best outcomes for opioid addiction recovery, stigma (i.e., bias) associated with MAT has limited its utilization [7]. Therefore, there is an imminent need for novel tools and methodologies to gain new insights into the behavioral processes of opioid addiction and treatment.

In recent years, the role of social media in biomedical knowledge mining, such as drug pharmacology [8] and interactive healthcare [9], has become increasingly important. Due to the growing use of the Internet, never-ending growth of data are generated from the social media offering opportunities for the users to freely share opinions and experiences in online communities. For example, Twitter, as one of the most popular social media platforms, has more than 140 million active users posting over 500 million 140 character tweets every day [10]. A large-scale Twitter users are willing to share their experiences of using opioids (e.g., "*I have a crippling heroin addiction and it's destroying my life*"), and perceptions toward MAT (e.g., "*heroin; I think this model of treatment (methadone) needs to be made available in the US, as it's the most effective treatment for opioid.*"). Therefore, the data from social media may contribute information beyond the knowledge of domain professionals (e.g., psychiatrists and epidemics researchers) and could potentially assist in sharpening our understanding toward the behavioral process of opioid addiction and treatment.

To combat the opioid addiction epidemic and promote the practice of MAT, in this paper, we design and develop an intelligent system called *iOPU* to automate the detection of opioid users from Twitter, where meta-graph [11] based on heterogeneous information network (HIN) are used to characterize the relatedness over users. As the moral says "*man is known by the company he keeps*", to detect if a user is an opioid user, we not only analyze his/her posted tweets but also his/her social network. For example, as shown in Figure 1, to predict whether *User-1* is an opioid user,

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using his/her posted tweet (*Tweet-1*) "*@User-3 I'll bring some heroin and needles*" may not be sufficient; however, with the information that (1) another user (*User-2*) posted the tweet (*Tweet-2*) "*@User-3 Let's shoot heroin tonight hahahah. Where's the needles at?*", and (2) both *User-2* and *User-3* are opioid users, we can conclude that *User-1* is highly possible an opioid user since he/she and *User-2* (an opioid user) both talked to the same person *User-3* (an opioid user) and also discussed the same topic (i.e., *shoot heroin*). To model the users and posted tweets as well as their rich semantic relationships, in *iOPU*, we first introduce a structured heterogeneous information network (HIN) [12], [13] for representation, which is capable to be composed of different types of entities and relations. To capture the complex relationship (e.g., as illustrated in Figure 1, two users are relevant if they have posted tweets which are talked publicly to the same person, and have also discussed the same topic), we use a meta-graph [11] based approach to characterize the semantic relatedness over users. Then, we further integrate content-based similarity (i.e., similarity of users' posted tweets) and relatedness depicted by each meta-graph to formulate a similarity measure over users. Later, we build a classifier to aggregate different similarities using Laplacian scores to make predictions. In sum, our developed system *iOPU* which integrates the above proposed method has the following major traits:

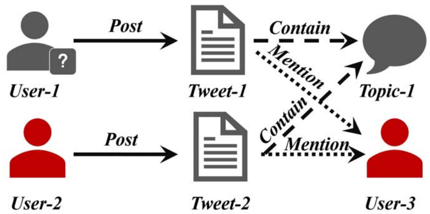

Figure 1: Illustration of an HIN.

- ***Novel feature representation and user relatedness characterization:*** Instead of using the posted tweets to describe users, we further utilize rich relationships among them to represent users (i.e., user-tweet, tweet-tweet, tweet-topic relations). Based on different kinds of relationships through different types of entities, the users will be represented by a HIN, and a meta-graph based approach will be used to depict the relatedness between users. To utilize both content- and relation-based information, we integrate similarity of users' posted tweets and relatedness depicted by each meta-graph to formulate a similarity measure over users. The proposed solution provides a more feasible way to express the complex relationships in social network than traditional approaches.
- ***Aggregation of different similarities for prediction:*** Different meta-graphs capture the relatedness between users at different views. The similarities over users defined by different meta-graphs combined with content-based information can be used to make decisions in an aggregated way. In this paper, we propose to aggregate different similarities using Laplacian scores to make predictions.
- ***A practical developed system to promote the practice of opioid addiction treatment:*** Based on the collected and annotated data from Twitter, we develop a practical system *iOPU* for automatic opioid user detection and provide comprehensive experimental studies to validate the performance of our developed system in comparisons with other alternative approaches. The results also demonstrate that knowledge from daily-life social media data mining could promote the practice of MAT in opioid addiction.

The remainder of this paper is organized as follows: Section 2 introduces our system architecture. Section 3 presents our proposed method in detail. In Section 4, based on the real sample collections and annotations from Twitter, we systematically evaluate the performance of our method in comparisons with other alternative approaches in opioid user detection. Section 5 presents the understanding of public perceptions toward MAT based on the detected opioid users using our developed system and discusses how it can help promote the practice of MAT in opioid addiction. Section 6 discusses the related work. Finally, Section 7 concludes.

2. System Architecture

We develop a system called *iOPU* (shown in Figure 2) to automatically detect opioid users from Twitter.
For ***training***, it consists of four major components:

- ***Data Collector and Preprocessor.*** We first develop web crawling tools to collect the tweets including keywords of opioids (e.g. heroin, morphine) as well as users' profiles from Twitter. Note that, to protect the users' privacy, the information of individual user is kept anonymous. For the collected tweets, the preprocessor will further remove all the links, punctuation and stopwords, and conduct lemmatization using Stanford CoreNLP [14].
- ***Feature Extractor and HIN Constructor.*** A bag-of-words [15] feature vector will be extracted to represent each user's posted tweet(s). Besides, the relationships among users, tweets and topics will be further analyzed, such as, i) *tweet-mention-user* (i.e., one user is @ (i.e. mentioned) in the tweet, which means one talks publicly to the other in this tweet), ii) *tweet-RT-tweet* (i.e., a repost of a tweet), and iii) *tweet-contain-topic* (i.e. a tweet contains a specific topic). Based on the extracted features, a structural heterogeneous information network (HIN) is then constructed. (See Section 3.1 for details.)
- ***Meta-graph Builder.*** In this module, different meta-graphs are first built from HIN to capture the relatedness between users. Then, we integrate similarity of users' posted tweets and relatedness depicted by each meta-graph to formulate a set of similarity measures over users. (See Section 3.2 for details.)
- ***Classifier Constructor.*** Given the similarity matrices over users defined by different meta-graphs combined with content-based information constructed by the previous component, a classifier is build to aggregate different similarities using Laplacian scores for automatic opioid user detection. (See Section 3.3 for details.)

For ***prediction***, given any unlabeled user, his/her posted tweets will be first extracted and the above-mentioned relationships will be further analyzed; based on these extracted features and the constructed classification model, this user will be labeled as either opioid user or non-opioid user.

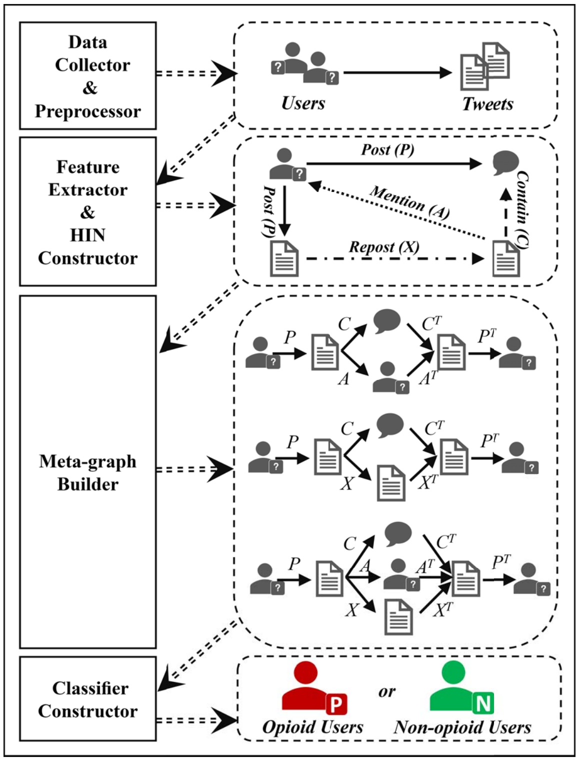

Figure 2: System architecture of *iOPU*.

3. Proposed Method

In this section, we introduce the detailed approaches of how we represent Twitter users, and how we solve the problem of opioid user detection based on this representation.

3.1. HIN Construction

As the above discussion, to determine whether a user is an opioid user from Twitter, we not only use his/her posted tweets but also his/her social network in the online communities. To characterize the relatedness of two users, we consider various kinds of relationships which include the followings.

R1: To describe the relation of a user and his/her posted tweet, we generate the ***user-post-tweet*** matrix $\mathbf{P}$ where each element $p_{i,j} \in \{0, 1\}$ denotes if user *i* posts tweet *j*.

R2: Like in the physical world, users can talk publicly to another in Twitter – if a tweet includes the symbol of @ followed by a user name, it means that the user is mentioned and talked publicly in this tweet. To describe this type of tweet-user relationship, we build the ***tweet-mention-user*** matrix $\mathbf{A}$ where each element $a_{i,j} \in \{0, 1\}$ indicates whether tweet *i* mentions user *j*.

R3: A tweet can be a repost of another tweet. To represent such relationship between two tweets, we build the ***tweet-RT-tweet*** matrix $\mathbf{X}$ where element $x_{i,j} \in \{0, 1\}$ denotes whether tweet *i* or tweet *j* is a repost of the other.

R4: To represent the relation that a tweet contains a specific topic, we generate the ***tweet-contain-topic*** matrix $\mathbf{C}$ where each element $c_{i,j} \in \{0, 1\}$ indicates whether tweet *i* contains topic *j*. In our application, we use Latent Dirichlet allocation [16] for the topic extraction of the posted tweets.

A summary of the description of above relations and elements in each relation matrix is shown in Table 1.

TABLE 1: The description of each matrix and its element.

Matrix	Element	Description
$\mathbf{P}$	$p_{i,j}$	If tweet *j* is posted by user *i*, then $p_{i,j} = 1$; otherwise, $p_{i,j} = 0$.
$\mathbf{A}$	$a_{i,j}$	If tweet *i* mentions user *j*, then $a_{i,j} = 1$; otherwise, $a_{i,j} = 0$.
$\mathbf{X}$	$x_{i,j}$	If tweet *i* or tweet *j* is a repost of the other, then $x_{i,j} = 1$; otherwise, $x_{i,j} = 0$.
$\mathbf{C}$	$c_{i,j}$	If tweet *i* contains topic *j*, then $c_{i,j} = 1$; otherwise, $c_{i,j} = 0$.

In order to depict users, tweets, topics and the rich relationships among them, it is important to model them in a proper way so that different kinds of relations can be better and easier handled. We introduce how to use HIN, which is capable to be composed of different types of entities and relations, to represent the users by using the features described above. We first present some concepts related to HIN as follows.

Definition 1. Heterogeneous information network (HIN) [13]. A HIN is defined as a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with an entity type mapping ϕ: $\mathcal{V} \to \mathcal{A}$ and a relation type mapping ψ: $\mathcal{E} \to \mathcal{R}$, where $\mathcal{V}$ denotes the entity set and $\mathcal{E}$ is the relation set, $\mathcal{A}$ denotes the entity type set and $\mathcal{R}$ is the relation type set, and the number of entity types $|\mathcal{A}| > 1$ or the number of relation types $|\mathcal{R}| > 1$.

Definition 2. Network schema [17]. The network schema for a HIN $\mathcal{G}$, denoted as $\mathcal{T}_{\mathcal{G}} = (\mathcal{A}, \mathcal{R})$, is a graph with nodes as entity types from $\mathcal{A}$ and edges as relation types from $\mathcal{R}$.

HIN not only provides the network structure of the data associations, but also provides a high-level abstraction of the categorical association. For the detection of opioid users, we have three entity types (i.e., user, tweet and topic) and four types of relations among them as described above. Based on the definitions above, the network schema for HIN in our application is shown in Figure 3.

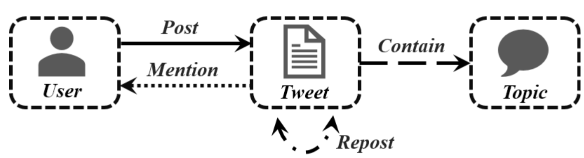

Figure 3: Network schema for HIN.

3.2. Meta-graph Based Relatedness

The different types of entities and different relations between them motivate us to use a machine-readable representation to enrich the semantics of relatedness among users. Meta-path [17] is used in the concept of HIN to formulate the semantics of higher-order relationships among entities.

TABLE 2: The description of each meta-graph.

MID	Commuting matrix $\mathbf{L}$	Description of each element l_{ij} in $\mathbf{L}$
1	$\mathbf{P}[(\mathbf{CC}^T) \circ (\mathbf{AA}^T)]\mathbf{P}^T$	# of tweet pairs posted by user *i* and *j* that contain same topics and mention same people
2	$\mathbf{P}[(\mathbf{CC}^T) \circ (\mathbf{XX}^T)]\mathbf{P}^T$	# of tweet pairs posted by user *i* and *j* that contain same topics and repost same tweets
3	$\mathbf{P}[(\mathbf{CC}^T)\circ(\mathbf{AA}^T)\circ(\mathbf{XX}^T)]\mathbf{P}^T$	# of tweet pairs posted by user *i* and *j* that contain same topics, mention same people and repost same tweets

Definition 3. Meta-path [17] . A meta-path $\mathcal{P}$ is a path defined on the graph of network schema $\mathcal{T}_\mathcal{G} = (\mathcal{A}, \mathcal{R})$, and is denoted in the form of $A_1 \xrightarrow{R_1} A_2 \xrightarrow{R_2} ... \xrightarrow{R_L} A_{L+1}$, which defines a composite relation $R = R_1 \cdot R_2 \cdot \ldots \cdot R_L$ between types A_1 and A_{L+1}, where $\cdot$ denotes relation composition operator, and L is the length of $\mathcal{P}$.

An example of a meta-path for users based on HIN schema shown in Figure 3 is: $user \xrightarrow{post} tweet \xrightarrow{contain} topic \xrightarrow{contain^{-1}} tweet \xrightarrow{post^{-1}} user$, which states that two users can be connected through their posted tweets containing same topics; another example is $user \xrightarrow{post} tweet \xrightarrow{mention} user \xrightarrow{mention^{-1}} tweet \xrightarrow{post^{-1}} user$, which denotes that two users are related by their posted tweets mentioning same users. Although meta-path has been shown to be useful for relatedness measure between users [17], [18], it fails to capture a more complex relationship, e.g., two users have posted tweets discussed the same topic and have also talked publicly to (i.e., mentioned) the same person. This calls for a better characterization to handle such complex relationship. Meta-graph [11] is proposed to use a directed acyclic graph of entity and relation types to capture more complex relationship between two HIN entities. The concept of meta-graph is given as following [11]:

Definition 4. Meta-graph [11]. A meta-graph $\mathcal{M}$ is a directed acyclic graph with a single source node n_s and a single target node n_t, defined on a HIN $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with schema $\mathcal{T}_\mathcal{G} = (\mathcal{A}, \mathcal{R})$. Formally, a meta-graph is defined as $\mathcal{M} = (\mathcal{V}_M, \mathcal{E}_M, \mathcal{A}_M, \mathcal{R}_M, n_s, n_t)$, where $\mathcal{V}_M \subseteq \mathcal{V}$, $\mathcal{E}_M \subseteq \mathcal{E}$ constrained by $\mathcal{A}_M \subseteq \mathcal{A}$ and $\mathcal{R}_M \subseteq \mathcal{R}$, respectively.

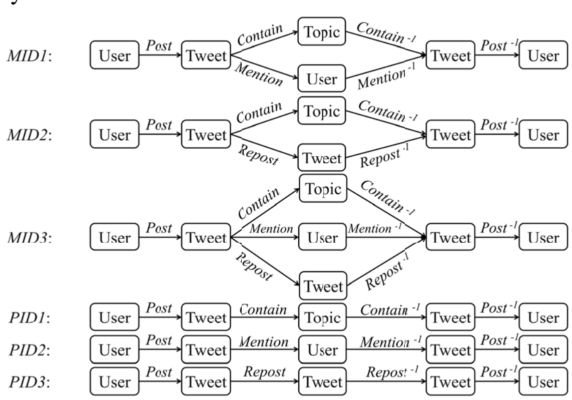

Figure 4: Meta-graphs and meta-paths

In our application, based on the HIN schema displayed in Figure 3, we generate three meaningful meta-graphs to characterize the relatedness over users (i.e., ***MID1–MID3*** shown in Figure 4). For example, ***MID1*** depicts that two users are related if they have posted tweets discussed same topics and have also talked publicly to (i.e., mentioned) same people; ***MID3*** describes that two users are connected if the tweets they posted have discussed same topics and mentioned same people, which have also reposted same tweets from others. Actually, a meta-path is a special case of a meta-graph (e.g., *PID1* and *PID2* are particular cases of *MID1*). In Figure 4, the meta-paths of *PID1–PID3* are the special cases of the constructed meta-graphs *MID1–MID3*. But meta-graph is capable to express more complex relationship in a convenient way.

To compute the relatedness over users using a particular meta-graph designed above, we use the commuting matrix [11], [17] to compute the counting-based similarity matrix for a meta-graph. Take *MID3* as an example, the commuting matrix of users computed using *MID3* is $\mathbf{L}_{\mathcal{M}_3} = \mathbf{P}[(\mathbf{CC}^T) \circ (\mathbf{AA}^T) \circ (\mathbf{XX}^T)]\mathbf{P}^T$, where **P, C, A, X** are the adjacency matrices between two corresponding entity types, $\circ$ denotes the Hadamard product [19] of two matrices. $\mathbf{L}_{\mathcal{M}_3}(i, j)$ denotes the number of tweet pairs posted by user i and user j which contain same topics, mention same people and also repost same tweets. Table 2 shows the commuting matrix of each meta-graph and the description of its element.

After characterizing the relatedness of users, we utilize both content- and relation-based information to measure the similarity over users: we integrate similarity of users' posted tweets and relatedness depicted by meta-graph to form a similarity measure matrix over users. The similarity matrix over users is denoted as $\mathbf{Q}$, whose element is a combination of content-based similarity and meta-graph based relatedness. We define the similarity matrix $\mathbf{Q}_{\mathcal{M}_k}$ based on $\mathbf{L}_{\mathcal{M}_k}$:

$$\mathbf{Q}_{\mathcal{M}_k}(i, j) = [1 + log(\mathbf{L}_{\mathcal{M}_k}(i, j) + 1)] \times tSim(i, j), \quad (1)$$

where $\mathbf{L}_{\mathcal{M}_k}(i, j)$ is the relatedness between user i and j under meta-graph $\mathcal{M}_k$, $tSim(i, j)$ represents the similarity between two users' posted tweets. A user may post multiple tweets including the keywords of opioids. Therefore, for each user, we convert his/her posted tweet(s) into a bag-of-words feature vector and then use cosine similarity measure [20] to estimate the closeness of two users' posted content.

3.3. Classifier Combining Different Similarities

Different meta-graphs capture the relatedness over users at different views, i.e., *MID1–MID3*. Since HIN can naturally provide us different relatedness with different semantic meanings, instead of using a single meta-graph to depict the relatedness between users, we propose to use Laplacian scores to weight the importance of different similarities based on different meta-graphs for user classification (i.e., whether the user is an opioid user or not).

Suppose that there are K meta-graphs $\mathcal{M}_k$ ($k = 1, 2, ..., K$), we can calculate their corresponding commuting matrices $\mathbf{L}_{\mathcal{M}_k}$ ($k = 1, 2, ..., K$). Then, we use Eq.(1) to compute the similarity matrix $\mathbf{Q}_{\mathcal{M}_k}$ ($k = 1, 2, ..., K$) based on $\mathbf{L}_{\mathcal{M}_k}$. Following [21], [22], after the normalization of each similarity matrix, we combine different similarities to form a new similarity measure:

$$\mathbf{S}(i, j) = \frac{2 \times \sum_{k=1}^{K} w_k \mathbf{Q}_{\mathcal{M}_k}(i, j)}{\sum_{k=1}^{K} w_k \mathbf{Q}_{\mathcal{M}_k}(i, i) + \sum_{k=1}^{K} w_k \mathbf{Q}_{\mathcal{M}_k}(j, j)}, \quad (2)$$

where $\boldsymbol{w} = [w_1, w_2, ..., w_K]$ is the weighted vector of different similarities based on different meta-graphs. In our application, we use Laplacian score [23] to learn the weight of each similarity, since it can be computed to reflect the locality preserving power of each feature. In this way, a new kernel is formed and we feed it to the Support Vector Machine (SVM) for classification. Note that if the matrix $\mathbf{S}$ is not a kernel (not a positive semi-definite matrix), we simply use the trick to remove the negative eigenvalues.

4. Experimental Results And Analysis

In this section, we show three sets of experimental studies using real sample collections from Twitter to fully evaluate the performance of our developed system *iOPU* for automatic opioid user detection: (1) In the first set of experiments, based on HIN schema, we evaluate the effectiveness of meta-graph based approach for relatedness measure over users by comparisons with meta-path based method; (2) In the second set of experiments, we evaluate the proposed method for aggregation of different similarities based on different meta-graphs; (3) In the last set of experiments, we systematically evaluate *iOPU* based on larger sample collection for opioid user detection. The measures for evaluation of different methods are shown in Table 3.

TABLE 3: Performance indices of opioid user detection.

Indices	Description
TP	# correctly classified as opioid users
TN	# correctly classified as non-opioid users
FP	# mistakenly classified as opioid users
FN	# mistakenly classified as non-opioid users
Precision	$TP/(TP + FP)$
Recall	$TP/(TP + FN)$
ACC	$(TP + TN)/(TP + TN + FP + FN)$
F1	$2 * Precision * Recall/(Precision + Recall)$

4.1. Data Collection and Annotation

To obtain the data from Twitter, we develop web crawling tools to collect the tweets including keywords of opioids (e.g., heroin, morphine) as well as users' profiles in a period of time. By the date, we have collected over ***4,447,507 tweets*** including keywords of opioids from nearly ***4,051,423 users*** through March 2007 to January 2017.

As heroin addiction occupies the majority of today's opioid addiction [1], in this paper, we first study the tweets containing the keyword of heroin and their related users. To obtain the prelabeled data for training, after data collection, based on the collected data, five groups of annotators (i.e., ***18 persons***) with knowledge from domain professional (i.e., psychiatrist) ***spent three months to label*** whether they are opioid users or not by cross-validations. The mutual agreement is above 95%, and only the ones with agreements are retained. The annotated data includes two sets: (1) the first dataset (denoted as $\mathbf{DB}_1$) consists of 356 users (170 are labeled as opioid users and 186 are non-opioid users) related to 2,817 tweets (1,452 are posted by opioid users and 1,365 are posted by non-opioid users); (2) the second dataset (denoted as $\mathbf{DB}_2$) with larger size includes 2,788 users (1,328 are opioid users and 1,460 are non-opioid users) related to 22,857 tweets (12,252 are posted by opioid users and 10,605 are posted by non-opioid users).

4.2. Evaluation of Meta-Graph based Relatedness

In this set of experiments, based on the $\mathbf{DB}_1$ (2,817 heroin-related tweets posted by 356 users) and the HIN schema (as described in Section 3.1), we construct three meta-graphs (i.e., *MID1–MID3* shown in Figure 4). For comparison, we also generate three meta-paths (i.e., *PID1–PID3* shown in Figure 4). We evaluate their performances for opioid user detection using SVM. For each meta-graph or meta-path, we use its related commuting matrix as the kernel fed to SVM. For SVM, we use LibSVM and the penalty is empirically set to be 1,000 while other parameters are set by default. In the experiments, we randomly select 90% of the data for training, while the remaining 10% is used for testing. The results are shown in Table 4.

TABLE 4: Evaluation of meta-graph based relatedness.

ID	Commuting Matrix	ACC	F1
PID1	$\mathbf{PCC}^T\mathbf{P}^T$	0.7525	0.7530
PID2	$\mathbf{PAA}^T\mathbf{P}^T$	0.7360	0.7265
PID3	$\mathbf{PXX}^T\mathbf{P}^T$	0.7240	0.7200
MID1	$\mathbf{P}[(\mathbf{CC}^T) \circ (\mathbf{AA}^T)]\mathbf{P}^T$	0.7785	0.7680
MID2	$\mathbf{P}[(\mathbf{CC}^T) \circ (\mathbf{XX}^T)]\mathbf{P}^T$	0.7625	0.7640
MID3	$\mathbf{P}[(\mathbf{CC}^T) \circ (\mathbf{AA}^T) \circ (\mathbf{XX}^T)]\mathbf{P}^T$	0.7835	0.7755

From Table 4, we can observe that (1) different meta-graphs have different detection performance, which can be ranked as: $MID3 \rightarrow MID1 \rightarrow MID2$; (2) each meta-graph does perform better than its corresponding meta-paths. For example, meta-paths of *PID1* and *PID2* are special cases of meta-graph $MID1$; but $MID1$ works better than *PID1* and *PID2* in the problem of opioid user detection. The reason behind this is that meta-graph is more expressive to characterize a complex relatedness over users than meta-path. This also demonstrates that we can use meta-graph with subtle differences to significantly improve the quality of relation-based features and better express different relatedness over users in our application.

4.3. Evaluation of the Proposed Method

In this set of experiments, based on the first dataset $\mathbf{DB}_1$ described in Section 4.1, we evaluate the proposed classification method combing different similarities based on different meta-graphs by 10-fold cross-validations. To measure the similarity over users, we utilize both content- and relation-based information by integrating similarity of users' posted tweets and relatedness depicted by meta-graph to form similarity measure matrix (as described in Section 3.2). We then combine all the generated similarity matrices based on different meta-graphs using Laplacian scores as the weights to construct a more powerful kernel (i.e., $ID4$) fed to SVM (as described in Section 3.3). The results are illustrated in Table 5.

TABLE 5: Evaluation of the proposed method.

ID	Method	LS	ACC	F1
ID0	SVM (content-based features)	-	0.7540	0.7610
QID1	$\mathbf{P}[(\mathbf{CC}^T) \circ (\mathbf{AA}^T)]\mathbf{P}^T$	0.8767	0.8345	0.8300
QID2	$\mathbf{P}[(\mathbf{CC}^T) \circ (\mathbf{XX}^T)]\mathbf{P}^T$	0.7113	0.8185	0.8020
QID3	$\mathbf{P}[(\mathbf{CC}^T) \circ (\mathbf{AA}^T) \circ (\mathbf{XX}^T)]\mathbf{P}^T$	0.9246	0.8415	0.8385
ID4	**Combined-kernel (3)**	-	0.8630	0.8565

From Table 5, we can see that different similarities based on the relatedness depicted by different meta-graphs perform different in opioid user detection, which can be ranked as: $QID3 \rightarrow QID1 \rightarrow QID2$. The ranking of similarity measures is the same as relatedness measures based on the meta-graphs, which further proves that the rich semantic relationships among users depicted by meta-graph can help to better estimate the closeness over users. The results also indicate that, with the content-based information (i.e., user's posted tweet(s) represented by a bag-of-words vector), each kernel formed by a similarity matrix (i.e., QID_k) performs better than the one merely constructed from the related meta-structure (i.e., MID_k). From the results, we can also observe that Laplacian score indeed helps us select important similarities, and the "Combined-kernel (3)" for test set is with 86.3% detection accuracy which works better than any single similarity. This shows that by combining different similarities using Laplacian score, it can also improve the performance.

In this set of experiments, to assess the performance of our proposed method, we also compare it with the baseline method which only utilizes content-based information as features (i.e., user's posted tweets represented by bag-of-words vectors) fed to SVM (i.e., $ID0$). From the comparisons ($ID4$ vs. $ID0$), we can see that our proposed method outperforms the classifier built only using content-based features. To check whether the overall improvement is significant, we also run 20 random trials of training and testing examples to compare *iOPU* integrated our proposed method and SVM only using content-based features. The probability associated with a paired t-Test [24] with a two-tailed distribution is 5.06×10^{-15}. This shows that the proposed method is significantly better than the baseline method we compared. The reason behind this is that, in *iOPU*, we use more expressive representation for the data, and build the connection between the higher-level semantics of the data and the final results. This again demonstrates that using *iOPU* can significantly improve the opioid user detection performance.

4.4. Evaluation based on Larger Sample Collection

Based on the larger dataset annotated by human experts (i.e. $\mathbf{DB}_2$ described in Section 4.1), we systematically evaluate the performance of our developed system *iOPU*. Figure 5 shows the overall receiver operating characteristic (ROC) curves of *iOPU* based on the 10-fold cross validations, from which we can see that our proposed framework *iOPU* achieves an impressive 0.9125 average TP rate at the 0.137 average FP rate for opioid user detection from Twitter. Note that many of the existing microblog classifications [25], [26], especially on Twitter, achieve the TP rates at the range of [0.647, 0.877].

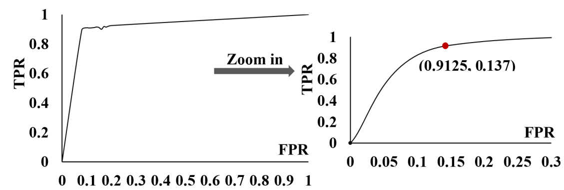

Figure 5: *Left*: ROC curve of *iOPU*, *Right*: Zoom-in.

We also further evaluate the parameter sensitivity of *iOPU* with different values of the penalty parameter C. From Figure 6, we can see that in a wide range of numbers, the performance of combined similarity is stable and not very sensitive to the penalty parameter. This indicates that we can simply tune a parameter using some training data based on cross-validation, and apply that parameter to the test set without concerning the change of the parameter affecting the online performance. We also evaluate the training time of *iOPU* with different sizes of the training data sets. Figure 7 shows the scalability of our proposed method. It is illustrated that the running time is quadratic to the number of training samples. When dealing with more data, approximation or parallel algorithms should be developed. Therefore, for practical use, our approach is feasible for real application in automatic opioid user detection.

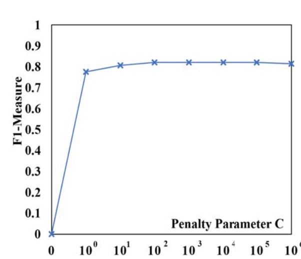

Figure 6: Parameter sensitivity of *iOPU*.

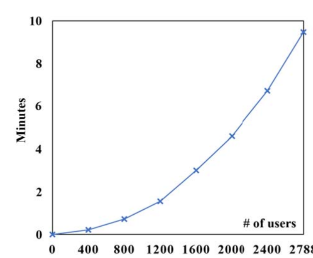

Figure 7: Scalability evaluation of *iOPU*.

5. Understanding Public Perceptions toward MAT based on Detected Opioid Users

In this section, after the automatic detection of opioid users from Twitter using our developed system *iOPU*, to better understand opioid addiction epidemic and public perceptions toward Medication Assisted Treatment (MAT), we further analyze the data and have the following findings.

Finding 1: The detected opioid users may have severe stigmas toward MAT. To understand the public perceptions of MAT, we analyze and categorize all opioid-related tweets posted by the newly detected 1,132 heroin users using *iOPU*. There are 31.07% of their posted tweets (i.e., 3,382 opioid-related tweets) related to the stigmas toward MAT. We then further analyze these tweets and Table 6 shows different stigmas toward MAT from the detected heroin users. This study also reveals that (1) many users are indecisive and may have ambivalent attitudes to MAT (e.g., "*does anyone have recovered from opioid addiction via mat methadone or suboxone please tell me*"); (2) some of them have bias toward MAT who mistakenly think of MAT as "*one drug replaced by another*"; while (3) a few users (i.e., 23 tweets posted by 5 users) have critically criticized the effects of MAT. The study also indicates that there is a remarkable treatment gap suggesting many people who need behavioral health treatment but have not received it due to various reasons (e.g., financial and psychological burden).

TABLE 6: Deep understanding of stigmas toward MATs.

Categories of the stigmas	# tweets	Percentage
Opioid addiction cannot be treated completely	931	27.53%
MAT cannot be taken safely for long-term	668	19.75%
Financial and psychological burden of MATs	516	15.26%
Side effect of MATs	501	14.91%
Medication cannot matched to each person	234	9.62%
No effect treated by MATs	23	0.68%
Others	509	15.05%
Examples of stigmas toward MATs		
1. "*How long are addicts dependent on methadone? Replace one drug for a Government provided drug?*" 2. "*heroin mat is utterly fraudulent but expensive. You can treat all you want, the users will go right back to it.*"		

Finding 2: It is important to identify influential users to advertise and promote the practice of MAT. To promote the perception of MAT, we believe it is best to first locate the group of users with apparent stigmas toward MAT and then use social network analysis to identify the most likely authoritative users that could influence the group of interests. In this study, the assumption is further validated. For the users who post their perceptions of MAT, we further analyze their social networks (e.g., their tweeps and people who like/repost/reply their tweets) and find that some of them actively interact with people on Twitter, which indicates that they could be the influential users who have the power of authoritative sources in the linked environment and thus can help promote the practice of MAT. Figure 8 shows a group of users with stigmas toward MAT (marked in red). By the analysis of their social networks, we found that some of their common "friends" (i.e., *user 1, user 2, user 3,* and *user 4*) come from the same therapy group and are in favor of MAT. In particular, *user 1* has been in the MAT program for more than 7 years, who has also tried to help others in recovery from opioid addiction. It is obvious that *user 1* could be a potential influential user who can help advertise and promote the practice of MAT.

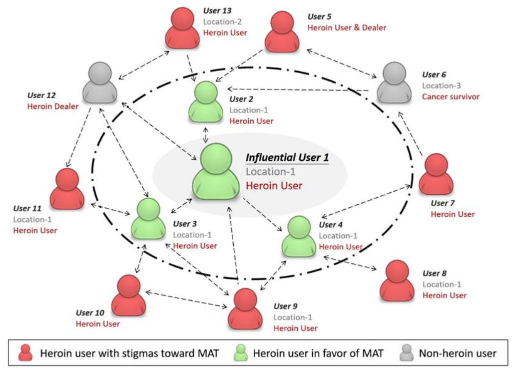

Figure 8: Identification of the influential users

The above findings based on the automatically detected opioid users using our developed system *iOPU* demonstrate that knowledge from daily-life social media data mining could promote the practice of MAT in opioid addiction.

6. Related Work

In recent years, the role of social media in biomedical knowledge mining, such as interactive healthcare and drug pharmacology, has become increasingly important. For example, based on users' posted tweets, a machine learning-based concept extraction system ADRMine was introduced for adverse drug reactions (ADRs) analysis [27]; SVM classifiers based on the content of twitter messages were built to find drug users as well as the potential adverse events [28]. Unfortunately, the application of social media data analytics into drug-addiction domain has been scarce in the literature with few exceptions [29], [30]. Different from the existing works in drug-addiction domain, in this paper, we propose to utilize not only the users' posted tweets but also the relationships among users and tweets (i.e., user-tweet, tweet-tweet, and tweet-topic relations) for opioid user detection from Twitter. Based on the extracted features, the users are represented by a structured heterogeneous information network (HIN).

HIN has been intensively studied in recent years. Typically, HIN is used to model different types of entities and relations [12], [13]. It has been applied to various applications, such as scientific publication network analysis [17], [31] and document analysis based on knowledge graph [21], [22]. Several studies have already investigated the use of HIN information for relevance computation, however, most of them only use meta-path [17], [18] to measure the similarity. Such simple path structure fails to capture a more complex relationship between two entities. To address this problem, Zhao et al. [11] proposed to use meta-graph, which is a directed acyclic graph of entity and relation types to measure the proximity between two entities. Different from existing works, in this paper, we take into consideration of different meta-graphs which characterize the relatedness over users at different views, and integrate the content-based information to formulate a set of similarity measures between users. Furthermore, a classifier is built to aggregate different similarities based on different meta-graphs for user classification. To the best of our knowledge, this is the first attempt to use meta-graph on HIN in biomedical knowledge mining, especially in drug-addiction domain.

7. Conclusion

In this paper, we design and develop an intelligent system named *iOPU* to automatically detect opioid users from Twitter. In *iOPU*, we first construct a heterogeneous information network (HIN) to leverage the information of users, tweets and topics as well as the rich relationships among them, which gives the user a higher-level semantic representation. Then, meta-graph based approach is used to characterize the semantic relatedness over users. Afterwards, we integrate content-based similarity and the relatedness depicted by each meta-graph to formulate a similarity measure over users. We then use Laplacian scores to aggregate different similarities to build a classifier for opioid user detection. The promising experimental results on the collected and annotated data sets from Twitter demonstrate that *iOPU* integrated our propose method outperforms other alternative approaches. The studies based on the detected opioid users using *iOPU* also show that knowledge from daily-life social media data mining could promote the practice of MAT in opioid addiction.

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