TEXT MINING FOR SOCIAL HARM AND CRIMINAL JUSTICE APPLICATIONS

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To my parents.

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ABSTRACT

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Increasing rates of social harm events and plethora of text data demands the need of employing text mining techniques not only to better understand their causes but also to develop optimal prevention strategies. In this work, we study three social harm issues: crime topic models, transitions into drug addiction and homicide investigation chronologies. Topic modeling for the categorization and analysis of crime report text allows for more nuanced categories of crime compared to official UCR categorizations. This study has important implications in hotspot policing. We investigate the extent to which topic models that improve coherence lead to higher levels of crime concentration. We further explore the transitions into drug addiction using Reddit data. We proposed a prediction model to classify the users' transition from casual drug discussion forum to recovery drug discussion forum and the likelihood of such transitions. Through this study we offer insights into modern drug culture and provide tools with potential applications in combating opioid crises. Lastly, we present a knowledge graph based framework for homicide investigation chronologies that may aid investigators in analyzing homicide case data and also allow for post hoc analysis of key features that determine whether a homicide is ultimately solved. For this purpose we perform named entity recognition to determine witnesses, detectives and suspects from chronology, use keyword expansion to identify various evidence types and finally link these entities and evidence to construct a homicide investigation knowledge graph. We compare the performance over several choice of methodologies for these

sub-tasks and analyze the association between network statistics of knowledge graph and homicide solvability.

1. INTRODUCTION

Increased rates of social harm events and plethora of text-data demands the need of employing text mining techniques not only to better understand their causes but also to develop optimal prevention strategies. Over the past few years, the notion of social harm has grabbed much attention. In 2007, Paddy Hillyard and Steve Tombs played an influential role in pushing boundaries of how criminologists conceived as definition of crime [1]. Since then social harm perspective has been contemplated as a means to widen scope of rather narrowed approach that criminology offers [1–4].

Social harm events such as crime and drug use continue to remain a severe threat to societies and nations across the globe. Hence, significant research efforts have been made to underscore the utility of data mining and machine learning to address the issue [5–16]. Moreover, text based data is ubiquitous in crime description, homicide investigation and more recently online social media and discussion forums have promoted individuals to share their addiction stories.

Our primary interest in this work is to leverage data mining and machine learning techniques to better understand real-time, unfiltered criminal investigation and drug addiction data with important implication in providing necessary tools for targeted intervention.

This thesis focuses on 3 challenging problems:

- Evaluation of crime topic models: topic coherence vs spatial crime concentration
- Investigating transitions into drug addiction through text mining of reddit data
- Building knowledge graphs of homicide investigation chronologies

In the first problem we suggest two quantitative metrics, coherence and spatial concentration for the evaluation of crime topic models. Topic modeling for the categorization and analysis of crime report text allows for more nuanced categories of crime compared to official UCR categorizations [8]. We investigate the extent to which topic models that improve coherence lead to higher levels of crime concentration in dataset of crime incidents from Los Angeles.

The second problem of the thesis focuses on gathering insights into drug use/misuse using text snippets from users narratives obtained from Reddit. Drug addiction is delineated as compulsive, continued substance use despite its negative effects. Various online communities offer safe haven for individuals to seek advice, extend support and share their addiction stories. We propose a binary classifier which predicts a user's transition from casual drug discussion forum to drug recovery forums. Additionally, we propose a cox regression model that outputs likelihoods of such transitions. We found how utterances of certain drugs and linguistic features play a vital role in predicting these transitions and offer insights into modern drug culture.

The third part of the thesis discusses a framework for creating knowledge graphs of homicide case chronologies that may aid investigators in analyzing homicide case data and allow for post hoc analysis of the key features that determine whether a homicide is ultimately solved. Our method consists of 1) performing named entity recognition to determine witnesses, suspects, and detectives from chronology entries 2) using keyword expansion to identify documentary, physical, and forensic evidence in each entry and 3) linking entities and evidence to construct a homicide investigation knowledge graph. We compare the performance of several choices of methodologies for these sub-tasks using homicide investigation chronologies from Los Angeles, California. We then analyze the association between network statistics of the knowledge graphs and homicide solvability.

1.1 Thesis Outline

The remaining of the dissertation is organized as follows: In Chapter 2, we will suggest two metrics topic coherence and spacial concentration for evaluation of crime topic models. In Chapter 3, we describe transitions into drug addiction through text mining of reddit data. In Chapter 4, we describe building of knowledge graphs for homicide investigation chronologies Finally, we summarize the dissertation in Chapter 5.

2. EVALUATION OF CRIME TOPIC MODELS: TOPIC COHERENCE VERSUS SPATIAL CRIME CONCENTRATION

2.1 Introduction

Kuang, Brantingham and Bertozzi [8] recently introduced *crime topic modeling*, the application of NMF topic modeling to short (several sentence) text descriptions accompanying crime incident reports. The idea behind crime topic modeling is that crime categories resulting from the FBI Uniform Crime Reporting (UCR) categorization system may lead to a loss of information and NMF topics exhibit a more nuanced model of the text. Under the UCR system crime incidents that reflect a complex mix of criminal behaviors are combined into one of only a few broad categories. For example in the following two crime text reports from Los Angeles, CA, both reports correspond to the same category (aggravated assault) despite the fact that the two suspects exhibit different motives and behaviors.

- *S APPROACHED V ON FOOT AND FOR NO APPARENT REASON STABBED VICT IN CHEST S FLED LOC IN UNK VEH UNK DIR*
- *VICT WAS WALKING OBSD SUSP GRAB A TEMPERED GLASS CANDLE HOLDER AND THROW IT AT HER HITTING HER ON THE ARM*

In [8], non-negative matrix factorization is combined with hierarchical clustering using cosine similarity to achieve a hierarchical topic model for crime incidents. While the resulting topics are qualitatively analyzed in [8], how to evaluate and choose the

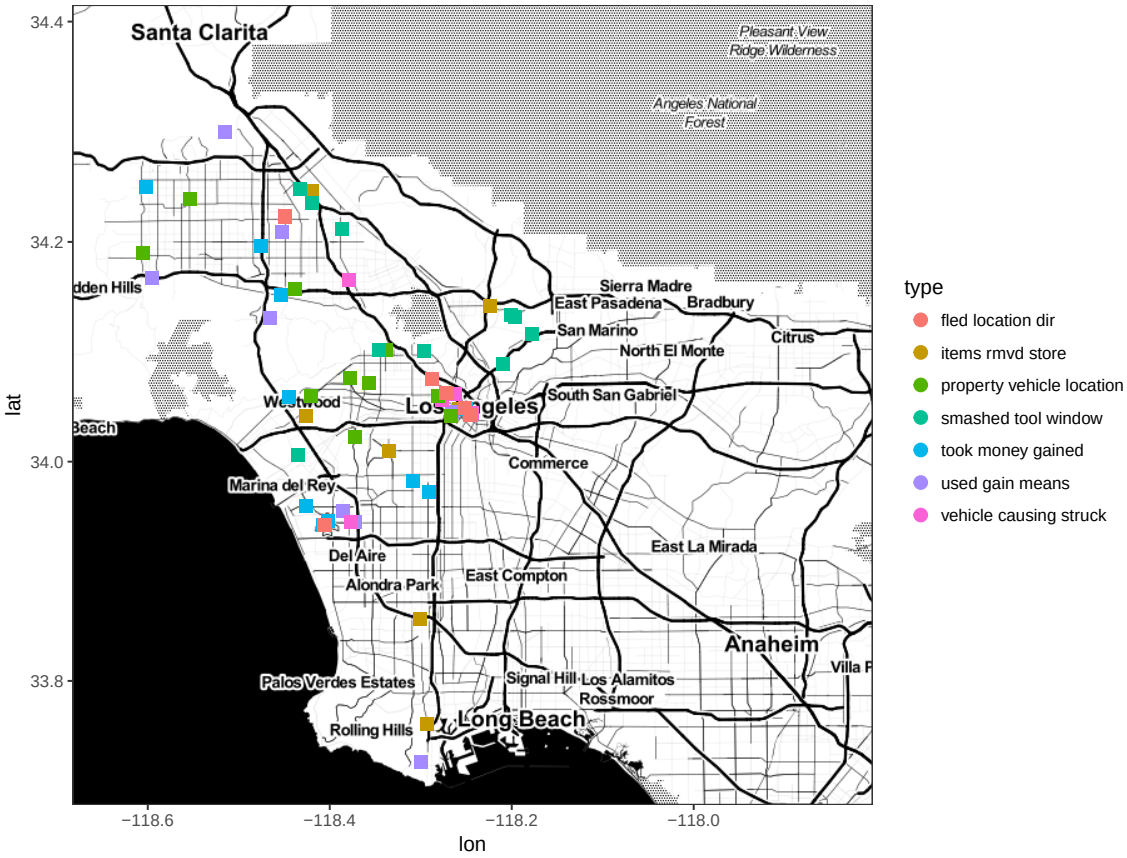


Figure 2.1.: Crime Hotspots for seven LDA topics.

appropriate topic model for crime reports remains an open question. In this paper we make several contributions along this direction:

1. We motivate two quantitative metrics: topic coherence and spatial concentration.

2. We apply the metrics to evaluate the two most popular topic models, LDA and NMF, for crime topic modeling.

3. We show that by increasing the topic coherence of crime topic models, we may also be able to increase the spatial concentration of crime, which has important consequences for hotspot policing.

Topic coherence is a standard metric for the quantitative evaluation of topic models and has been shown to have good correlation with human evaluations [17]. In our methods section we describe in greater detail coherence, but informally topics have higher coherence when co-occurring words appear more frequently in the same topic. For example, gun and shot may co-occur together in one topic while knife and stab may occur in a different topic.

However, there is also a significant spatial aspect to crime that has important implications for policing. Crime is associated with the physical environment in which it occurs, along with the behavioral and situational conditions that ultimately link suspect to victim to place [18]. Weisburd's law of crime concentration states that a small proportion of the city, known as crime hotspots (see Figure 2.1), contains the majority of criminal events [19]. Place based interventions in crime hotspots are known to lead to crime reductions in those areas and allow police to focus limited resources on a small area of the city [20]. Our hypothesis is that crime topics that have greater coherence may also have higher levels of crime concentration, facilitating more effective policing interventions. Referencing the two assault reports above, a topic corresponding to the first report may necessitate a gang intervention task force whereas the second report may belong to a mental health topic. These two topics may individually be more concentrated in space compared to when combined.

2.2 Methods

Latent Dirichlet Allocation (LDA) is a Bayesian graphical model for text document collections represented by bag-of-words [17] [21]. LDA is given by a generative

probabilistic model, where each word in a document is generated by sampling a topic from a multinomial distribution with Dirichlet prior and then sampling a word from a separate multinomial with parameters determined by the topic.

Non-negative matrix factorization (NMF) is a widely used tool for the analysis of high-dimensional data as it automatically extracts sparse and meaningful features from a set of nonnegative data vectors [22]. NMF uncovers major hidden themes by factoring the term-document matrix of a corpus into the product of two non-negative matrices, one of them representing the relationship between words and topics and the other one representing the relationship between topics and documents in the latent score topic space [23].

Coherence is a quantitative measure of the similarity of words in a topic. In particular, given a set V of topic words in a corpus (we will use the top 10 most frequent words in each topic), coherence is computed as a sum of similarity scores over all pairs of words in V. While different similarity scores may be used, we consider the intrinsic measure UMass [24] to calculate the coherence. The Umass similarity score measures the extent to which words tend to co-occur in topics together:

$$score(w_i, w_j) = \log \frac{D(w_i, w_j) + \epsilon}{D(w_j)}$$

where $D(w_i, w_j)$ is the number of documents containing both words w_i and w_j and $D(w_j)$ is the number of documents containing word w_j.

Gini index in the context of crime, is a measure of the extent to which a large percentage of crime falls within a small area percentage of a city [25] [26]. Consider a city divided into grid cells where the amount of crime falling in each cell is calculated over an observation period. The Lorenz curve is computed by rank ordering the cells by count and then plotting the cumulative percentage of crime against the cumulative percentage of land area. The Gini index, G, ranges from 0 to 1 and is the ratio of

the line of equality (representing equal hotspots across the city) and the area under the Lorenz curve. In particular, $G = 0$ corresponds to equal distribution of crime at all grid cells and $G = 1$ corresponds to maximal concentration at a single hotspot. Since, the number of crimes may be less than the number of places, we measure the crime concentration using an adjusted gini coefficient G', defined as the area between the Lorenz curve and line of maximal equality [25],

$$G' = \max(\frac{1}{c}, \frac{1}{n})(2 * \sum_{i=1}^{n} iy_i - n - 1) - \max(\frac{n}{c}, 1) + 1$$

where c is the total number of crimes, n is the total number of places, y_i is the proportion of crimes occurring in place i and, i is the rank order of the place when places are ordered by the number of crimes y_i.

2.3 Results

We analyze a data set of crime incidents in Los Angeles that spans the years 2009 to 2014. Each incident is accompanied by a date, latitude, longitude, and text description of the incident that is a short paragraph. For measuring the Gini index, we divide Los Angeles into a grid of size 100x100 and measure the number of crimes of each topic falling in each grid cell.

As part of text preprocessing we remove stop words [27]. We extend the stop-words list from the python NLTK package with common words such as victim, suspect and unknown. We discard all the stop-words and any word whose length is less than 3 characters. We then process the document term matrix using Term Frequency Inverse Document Frequency (TFIDF) weighting factors [28] to emphasize words that occur frequently, but penalizing words that occur in a large percentage of documents (for example stop words not found in our annotated list).

For each year, we sample a balanced data set of 35,000 events, 5000 events from each of seven UCR categories: vandalism, theft, burglary theft from vehicle, burglary, robbery, aggravated assault, and other. We then estimate LDA and NMF using $k = 7$ topics each for a fair comparison to the UCR categories.

Table 2.1.: Coherence vs. spatial concentration 2009-2014

type	**coherence**	**std. error**	**gini**	**std. error**
category	-0.817	0.0068	0.3308	0.0021
lda	**-0.287**	0.031	**0.360**	0.007
nmf	-0.300	0.012	0.308	0.002

In Table I we present the average coherence across years along with the average Gini coefficient. We use a weighted average where the average is weighted by the number of events in each category to take into account the fact that some topics may have more or less than 5000 events. Here we see that LDA has both the highest coherence of topics and highest gini coefficient. In Table II we display the most frequent words of each UCR crime category in 2014 and in Table III we display the same table for LDA topics in 2014. For example, the burglary theft from vehicle (BTFV) category has a coherence value of -.672 and a gini index of .282. The closest topic of LDA to BTFV is topic 5, however this topic has higher coherence of -.462 and a higher gini index of .39. There are several topics where LDA has a lower gini index, for example in the case of theft. These topics with lower gini index have lower number of events, resulting in more zero count cells, and the adjusted gini index is lower in these cases. However, in the weighted average across topics LDA has a higher over all gini index.

In Figure 2 we display coherence and the gini coefficient over time to assess the stability of these results. Here we see that LDA consistently has a higher gini index

Table 2.2.: Category 2014

coh.	gini	frequent words
-0.810	0.320	used location fled vehicle info face verbal without punched became
-0.892	0.296	vehicle fled location window used causing door damage side smashed
-0.883	0.433	property location fled removed took store entered items without paying
-0.672	0.282	vehicle property location fled removed window entered took smashed door
-0.720	0.364	prop. fled approach location took vehicle demand money removed punch
-0.894	0.257	location property fled door entered removed window open rear entry
-0.825	0.353	vehicle fled location struck head hit verbal knife causing argument

over time. For some years NMF has a higher coherence, though both NMF and LDA have consistently higher coherence than the UCR crime categories.

Table 2.3.: LDA 2014

coh.	gini	frequent words
0.000	0.467	items rmvd store phone paying business exited selected cell concealed
-0.122	0.146	used gain means smash open remove merchandise permission card ifo
0.000	0.180	took money gained secured returned parked demanded missing stated gave
-0.231	0.377	vehicle causing struck punched approached face head property verbal times
-0.462	0.390	property vehicle location removed entered door window rear entry ransacked
-0.185	0.346	fled location dir direction resid hit entered approached foot open
-0.254	0.163	smashed tool window open residence pushed res pry produced glass

2.4 Conclusion

We suggested two performance metrics for crime topic models: topic coherence and the gini coefficient for measuring spatial concentration. We showed that the choice of topic model has important implications for detecting crime hotspots. In particular, it is possible to achieve more coherent topics that simultaneously concentrate to a higher degree in space, allowing for more targeted police interventions given limited resources. For the data set analyzed in Los Angeles, our results show that LDA has the highest coherence and gini coefficient compared to NMF and UCR crime categories.

Future research may focus on the joint optimization of coherence and spatial concentration. LDA and NMF in this paper were provided with no spatial information. Methods may be developed that can improve both coherence and concentration jointly using supervised learning. Additionally, such methods may be extended to spatio-temporal models where topics and spatial hotspots evolve over time [29].

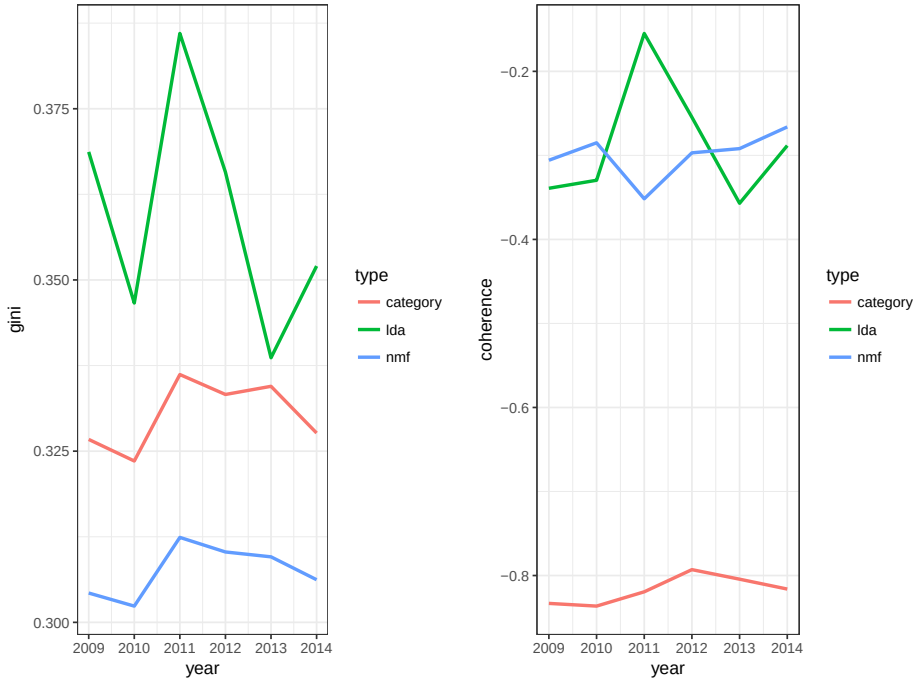


Figure 2.2.: Stability over time of coherence vs generalized gini coefficient over time.

3. REDDITORS IN RECOVERY: TEXT MINING REDDIT TO INVESTIGATE TRANSITIONS INTO DRUG ADDICTION

3.1 Introduction

The rate of nonmedical opioid use has increased markedly since the early 2000s. While recent efforts have been made to curb over-prescribing [30, 31], morbidity and mortality rates associated with opioid misuse continue to worsen [32]. Traditionally, those suffering from addiction take to support groups, such as Alcoholics Anonymous (AA) and Narcotics Anonymous (NA), on their road to recovery [33]. These groups, which provide an encouraging community and facilitate programs for addiction management and recovery, have shown significant promise in assisting substance abusers [34]. In addition to the aforementioned support groups, federal support is provided through organizations such as the Substance Abuse and Mental Health Services Administration (SAMHSA). Among others, SAMHSA offers programs such as Medication-assisted Treatment and Too Smart To Start - the former combines the use of medication and behavioral therapy in the treatment of substance abuse and the latter is a public education initiative which deters underage alcohol use.

More recently, communities have been established in online social media and discussion forums including Reddit, MedHelp, Twitter and `Drugs-Forums.com`, among others. Enacted and internal stigmatization addicts must face [35, 36] in conjunction with the convenience, privacy, and anonymity of such online communities may be explanations for their rapid expansion. These online hubs offer havens for individuals to

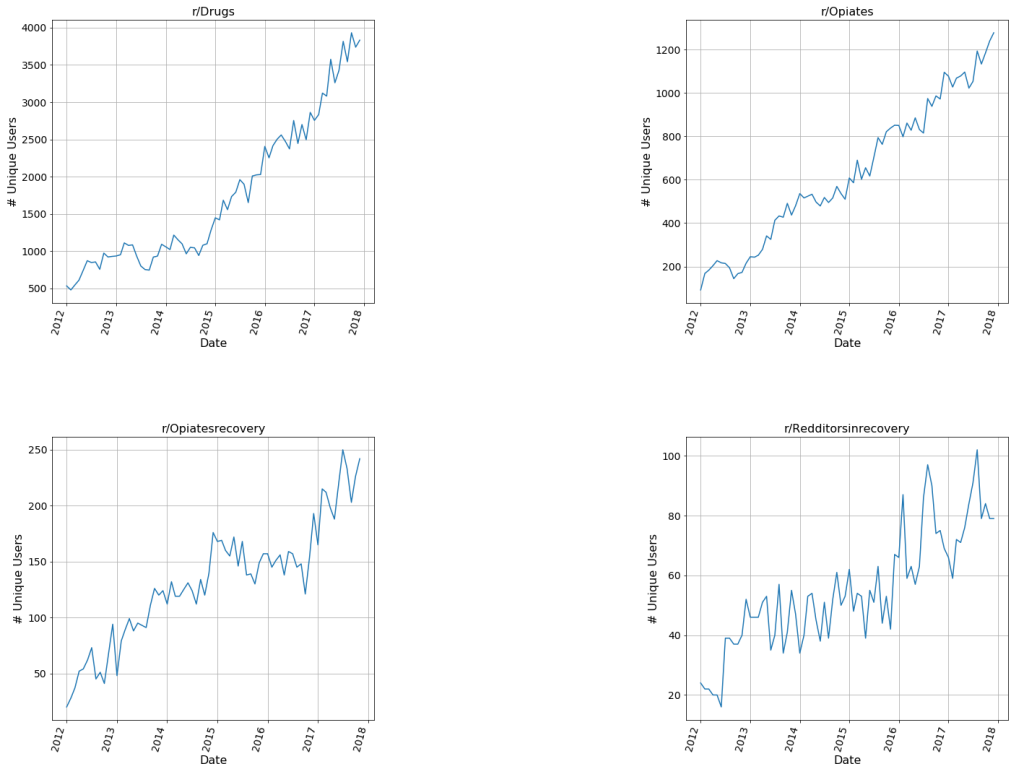
seek advice, extend support, and share their addiction stories without fear of recourse or judgment. A previous study suggested that these communities can be tremendous resources in the understanding, monitoring and intervening of substance abuse [37].

Earlier works underscore the utility of mining data from social media sites to understanding trends of human health and drug use [9, 11–13, 38, 39]; however, most of these works do not explore the particular transition from voluntary drug use to compulsive drug use, as well as the various factors that influence such a transition. Our research leverages machine learning and data mining techniques to better understand real-time, unfiltered user data presented to us via Reddit, and in particular, focuses on the understanding of how users transition into addiction can be predicted by using drug utterances and linguistic features contained in their Reddit posts. We present two statistical models: 1) a "transition classifier" that predicts if a user, given 6 months of content history in general drug discussion forums, will post in forums dedicated to substance recovery support in the subsequent 12 months and 2) a proportional hazards survival model which estimates a user's probability of posting in a recovery forum within the next year.

3.2 Background and Related Works

3.2.1 Drug Addiction and the Opioid Crisis

Drug addiction is characterized by the compulsive, continued use of a substance despite its negative effects. While drug consumption often begins as recreational, frequent use increases one's tolerance, ultimately altering brain chemistry, inducing heightened desires for drugs, and prompting involuntary and compulsive use. Opioids readily increase tolerance; with each use, one requires larger doses to reach the same



	Unique Users		User Post Volume	
Subreddit	% Growth 2012-2017	CAGR	% Growth 2012-2017	CAGR
Drugs	324%	34%	400%	38%
Opiates	464%	41%	657%	50%
RedditorsInRecovery	387%	37%	452%	41%
OpiatesRecovery	156%	21%	180%	23%

Figure 3.1.: Subreddit Growth, 2012 to 2017

level of efficacy. Consequently, opioids are highly addictive, contributing to the high prevalence of opioid misuse [40].

Since the early 2000s, the rate of opioid use has climbed, in large part, due to over-prescribing opioid pain relievers such as Oxycodone and Hydromorphone [41]. A pattern of over-prescribing and related overdose saw its peak in 2011 [42] when the Centers for Disease Control and Prevention (CDC) and the Drug Enforcement Administration (DEA) began to address this issue by implementing efforts to edu-

cate both medical professionals and the public on appropriate opiate use [40]. These efforts included tightening prescriptions and developing new prescription opioids that are "abuse-deterrent" [40]. While these efforts were met with declines in prescription opioid abuse, illicit opioid use—including that of Heroin and Fentanyl—continued to increase and contribute to rising opioid-related injuries and overdoses [42]. One explanation for the continued rise in illicit opioids was supposedly that increased barriers to medication prompted chronic pain patients to supplement their reduced prescription allowance via self-medication, further exacerbating opioid-use risk [42]. Since Heroin is pharmacologically similar to prescription opioids, relatively cheap, and readily available, it was an obvious replacement for those previously using prescription opioids [41]. The trends outlined here demonstrate the need for balanced prevention measures that aim to reduce opioid abuse and overdose while simultaneously maintaining access to prescription opioids and treatment programs as needed [40].

3.2.2 Using Social Media to Understand Drug-Related Issues

Mining social media data to study health and drug-related behavior is not a new concept. MacLean et al. created a model from MedHelp forums that attempts to predict addiction relapse [13]. Paul and Dredze used a factorial LDA topic model on forums from `Drugs-Forums.com` to model drug types, delivery methods, and other related aspects such as cultural and health factors in the context of recreational drug use [38]. Sarker et al. assessed the use of Twitter in analyzing patterns of drug abuse, and built a binary classifier that distinguishes whether or not a tweet contains signs of medication abuse [39]. Other studies have applied machine learning to classify users of an addiction recovery mobile application [12] and to identify distinct behavioral markers between Heroin and amphetamine dependence [43]. In the context of Reddit, Choudhury et al. used Reddit data to explore the transition between mental health

discourse and suicidal ideation, and built a classifier that distinguishes between those two states [9]. Eshleman et al. demonstrated the possibility of using a binary classifier in predicting a user's propensity to post in a recovery-related subreddit [11]. Our research expands upon this latter work by exploring various linguistic factors and drug utterances in a user's post that are predictive of transitions into substance abuse; further, we build a survival model capable of estimating the probability of such transitions, providing deeper insight into the explanatory factors involved in such shifts.

3.3 Reddit Data

`Reddit.com` (or Reddit) is an online collection of threads grouped by user communities known as "subreddits" with each covering a distinct topic. Reddit users, or "Redditors," subscribe and submit content to subreddits which interest them, and have their submitted content voted and commented on by fellow Redditors. Reddit has the added appeal of anonymity, allowing users to partake in unfiltered conversations on topics of shared interest. As of April 2018, the platform has over 330 million active users with 130 thousand active subreddits [44].

Threads on Reddit are defined by a user's initial post and the subsequent comments on the post by other users. Posts typically discuss a user's own substance use/abuse while comments primarily answer questions asked in the post and/or offer support to the post author. Since our objective is to learn about transitions into substance abuse, which requires analysis of content pertaining to a user's own situation, we restrict our analysis solely to posts.

Using the pushift.io Reddit API[1], we pulled data from January 2012 through May 2018. This dataset consisted of 309,528 posts from 125,194 unique users and included

[1]https://pushshift.io/

various attributes of each post such as content, title, author, date of post, number of comments, and number of upvotes. We focus on four major drug-related subreddits: r/Opiates, r/Drugs, r/OpiatesRecovery, r/RedditorsInRecovery. In addition to having adequate user and post volume, these subreddits host discussions on a variety of drugs. Whereas r/Opiates and r/Drugs primarily serve as forums for general drug discussion, which tend to be more casual in nature, the r/OpiatesRecovery and r/RedditorsInRecovery subreddits provide an avenue for those struggling with substance abuse and addiction to seek advice, share success and relapse stories, and support others. The measurable growth in both user base and post volume between 2012 and 2017 is exhibited in Figure 3.1. In the proceeding analyses, we will refer to r/Opiates and r/Drugs as "casual" subreddits and r/OpiatesRecovery and r/RedditorsInRecovery as "recovery" subreddits.

3.4 Transition Classification: Modelling Transitions from Recreational Use to Substance Abuse

We trained a binary classifier to model whether a user who posts only in casual subreddits in their first 6 months will eventually go on to post in recovery subreddits in the following 12 months.

3.4.1 Creating Classes

Analysis was restricted to users with at least 3 posts and who exclusively posted in casual subreddits in their first 6 months on Reddit. Of these, we found the subset of users that posted in a recovery subreddit within the next 12 months; there are 220 such users, and we label this group collectively as the CAS→RECOV class.

Figure 3.2 shows the distribution of the number of days until the first recovery post for the CAS→RECOV group.

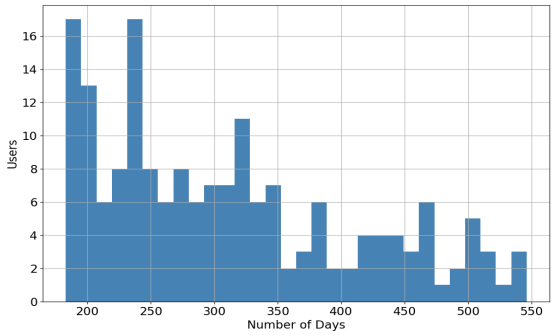


Figure 3.2.: Days Until First Recovery Post in the RECOV Group.

There are 2,836 users with at least 18 months of casual-only posts. To maintain balance between the two classes, we randomly sample 220 users from this set to form the CAS class. We then split these 440 examples into a training set (352 users) and test set (88 users).

3.4.2 Feature Selection

In applying a machine learning model for predicting users' transition from CAS → RECOV, each user should be represented by a vector. For this purpose, we extract various features from a user's posts, including dense embedding vectors obtained through $Doc2Vec$, linguistic characteristics of user posts, and drug utterances in the post. For the last two kinds of features, we use Kruskal-Wallis statistical test to determine which drug utterances and linguistic measures are significantly different between the CAS and CAS→RECOV classes. Tables **??** and **??** show the selected features and their frequency distribution.

Doc2Vec Embeddings. Text clustering and language processing applications involve algorithms that generally require the input text data to be represented as a fix-length vector. Bag-of-word models and n-gram models are often utilized to generate these vector representations due to their simplicity, but both lack contextual information. We therefore use Gensim's Doc2Vec model to create 100-dimensional vector representations for each user post [45]. The idea behind such representations was first proposed by Le and Mikolov [46], who sought to create a methodology that generates vector embeddings for texts of variable length. This unsupervised framework has been shown to outperform the bag-of-words and N-gram models in sentiment analysis and other information processing tasks.

Since predictions are based on 6 months of user posts, we aggregate the document vectors of a user's posts over this period. Let $\mathcal{D}_j$ be the set of posts made by user j in the first 6 months on Reddit (ordered by date). Then, denoting the ith post of user j by d_i^j, we use the *centroid* of the doc2vec vectors of user j's posts as a representation of the user j.

$$C_j = \frac{1}{|\mathcal{D}_j|} \sum_{i=1}^{|\mathcal{D}_j|} \mathbf{d}_i^j \ \in \mathbb{R}^{100}$$

In the above equation, $\mathbf{d}_i^j$ is the doc2vec based vector representation of d_i^j. Though simplistic, prior works [47, 48] have suggested the efficacy of using the centroid of document representations to capture meaningful content from a set of documents.

Linguistic Measures. The specific language and words one employs in speech and writing can reveal much about one's psychological and social states [49, 50]. Further, studies have shown socio-psychological and personality differences between drug and non-drug addicts [51]. To capture both linguistic components (e.g. fraction of pronouns, verbs, and articles among others) and psychological aspects (e.g. words

associated with positive/negative emotions, anger, and family/friends among others) of user posts, we use the Linguistic Inquiry and Word Count[2] (LIWC), a text analysis program that categorizes words into 93 groups which reflect different emotions, thinking styles, social concerns, and parts of speech. Though LIWC variables capture more than purely linguistic dimensions of texts, we will use the phrases "LIWC features" and "linguistic features" interchangeably hereafter for simplicity.

Keywords. We used odds ratios – a metric used in statistics to measure the association between the presence of one property with the presence of another – to find discriminative keywords for each class such as (e.g. "experiences" for CAS and "addiction" for CAS→RECOV). More concretely, if $\mathcal{W}$ is the set of all words in our training data, then the odds ratio, $OR(c, w)$, for a word, $w \in \mathcal{W}$ and class $c \in \{CAS, CAS \rightarrow RECOV\}$ is given by,

$$OR(c,w) = \frac{\frac{freq(c,w)}{freq(\neg c,w)}}{\frac{\neg freq(c,w)}{\neg freq(\neg c,w)}} = \frac{freq(c,w) * \neg freq(\neg c,w)}{freq(\neg c,w) * \neg freq(c,w)}$$

where $freq(c, w)$ is the number of posts in class c in which the word w occurs and $\neg freq(c, w)$ is the number of posts in class c where word w does not occur. The odds ratio quantifies how strongly associated w is with the class c; a higher odds ratio implies a stronger association of w with c.

We choose w to be a keyword for c if $OR(c, w) > 2$ and $|OR(c, w) - OR(\neg c, w)| > 2$. That is, w has a high OR with respect to one class and a substantially lower OR with respect to the other class. We list a sample of associated keywords for both classes in Table 3.1.

Drug Utterances. Drug utterances serve as an indicator of which drugs users are interested in and/or currently using. For each user we calculate the mentions of

[2]Language Inquiry and Word Count: http://liwc.wpengine.com/

Table 3.1.: Discriminatory keywords for CAS and CAS→RECOV class using Odds Ratio

Class	**Keywords**
CAS	friends, completely, lsd, trip, reddit, music, weird, dr, friend, experiences, ended, 100, mdma
CAS→RECOV	quit, addiction, clean, anymore, subs, suboxone, oxy, bupe

each drug (as a % of all drugs they mention). This calculation includes both formal drug names of the drug, colloquial ("street") names, and major brand names (e.g., OxyContin® is a common brand of oxycodone and "coke" is a oft-used name for cocaine). In Figure 3.3, we displays four drugs that have highly significant variation in utterance between the two classes.

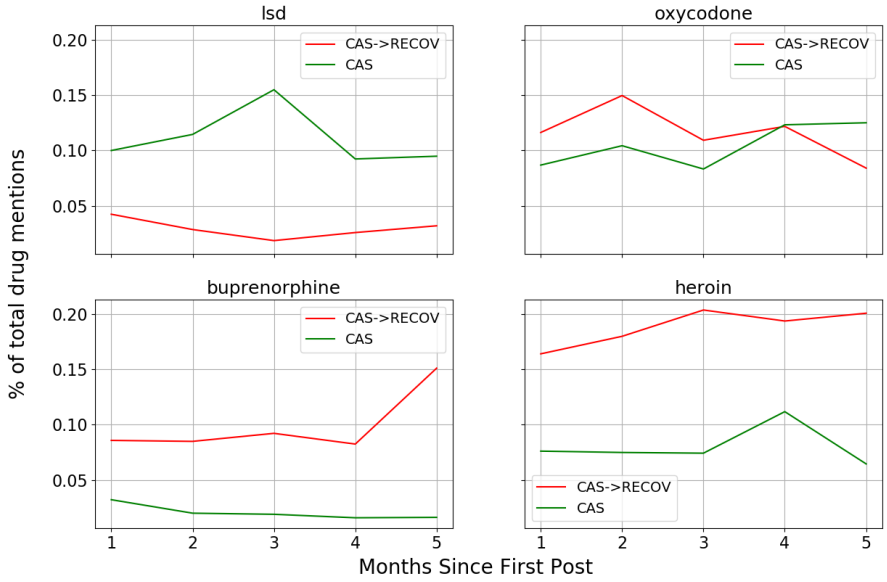


Figure 3.3.: Drugs with statistically significant variation in utterances between CAS and CAS→RECOV (p-values < 0.05 using Kruskal-Wallis test).

3.5 Survival Analysis: Predicting When Transitions are Likely to Occur

For our task, a traditional classification model predicts whether a transition would occur from CAS to CAS→RECOV. However, for such information to be useful in real-life, it is also important to know *when* such transitions might occur. This additional information can help prioritize vulnerable individuals based on their propensity to be victim of drug addiction. In this section, we present a Cox (proportional hazards) regression survival model to solve this task. This model also enables us to investigate the effect of different variables on the predicted time until one's first recovery post.

The general formulation of a survival model centers around a random variable, T (denoting time), the survival function,

$$S(t) = Pr(T > t)$$

and the hazard function,

$$\lambda(t) = \frac{f(t)}{S(t)} \quad [where\ f(t) = \frac{d}{dt}(1 - S(t))]$$

In our case, $S(t)$ is the probability that a user will last ("survive") more than t days without posting in a recovery subreddit and $\lambda(t)$ is the instantaneous rate of transitions to recovery subreddits (among those users that have never posted in a recovery subreddit) at time t. Adopting terminology commonly used in survival analyses, we shall say a user "survives" if he lasts more than 12 months without a recovery post and "fails" otherwise.

3.5.1 Right-Censored Data

Besides providing the answer whether a user will survive beyond a given time, survival model has another crucial advantage: a survival model can utilize "censored data" effectively, whereas a traditional regression model fails to do so. Censored data (also known as right-censored data) refers to observations for which the desired event has not happened yet. For instance, say, the end of observation time for our study is $\hat{t}$. Now, if a user has never posted in recovery forum within our observation period, one does not know with certainty whether that user will not post in recovery on some day $t > \hat{t}$. This is an example of *right-censored* data instances.

Our model requires users to have at least 10 posts where the first 3 were casual and not all occurring on the same day. This criteria eliminates the case of 0-day survival times, which in real-life makes little sense. In our dataset, there are 2,367 users satisfying these restrictions, and for each user, we look only at (up to) their first 12 months of posts. 165 of these users fail within the first 12 months, while the remainder are right-censored observations.

3.5.2 Cox Regression

A Cox regression model is a specific type of survival model that accounts for the effects of covariates on some baseline hazard function $\lambda_0(t)$. Formally, if we let $x^{(i)} \in \mathbb{R}^d$ be a column vector of features for user i, the *hazard* for user i is,

$$\lambda_i(t) = \lambda_0(t) \exp\{x^\intercal \beta^{(i)}\}$$

and the corresponding survival function is,

$$S_i(t) = S_0(t)^{\exp\{\beta^\intercal x^{(i)}\}}$$

where $\beta \in \mathbb{R}^d$ is a vector of trainable parameters. The data for the model can be denoted $D_{surv} = \{(y_i, \delta_i, x^{(i)}) : i = 1, 2..., n\}$ where y_i is the minimum of the censoring time C_i (end of observation time) and survival time T_i and

$$\delta_i = \begin{cases} 1 & if \quad T_i = y_i \\ 0 & otherwise \end{cases},$$

where δ_i denotes whether or not an instance is censored. We train β by maximizing the partial likelihood estimate (under iid assumption),

$$L(\beta | D_{surv}) = \prod_{i=1}^{n} \left[\frac{\lambda_0(t) \exp\{\beta^\intercal x^{(i)}\}}{\sum_{j \in \Psi(y_i)} \lambda_0(t) \exp\{\beta^\intercal x^{(j)}\}} \right]^{\delta_i}$$

where $\Psi(t) = \{i : y_i > t\}$ is the subset of users who survive past time t.

3.6 Results

In this section we provide experimental results for both binary classification and cox regression. Results for both models suggest that drug utterances and linguistic features can be indicative of one's propensity to shift towards substance abuse.

We use categorical accuracy and F1 score to evaluate the transition classifier. A baseline model, which used only Doc2Vec embeddings, achieved a modest 69.3% test-set accuracy. With the inclusion of LIWC linguistic features, drug utterances, and class-specific keywords in addition to tuning model parameters through grid search, we improved accuracy by roughly 5% (Table 3.2).

Performance of the survival model was evaluated using Concordance Index (C-Index), a standard metric often employed in survival models [52]. Concordance ranges from 0 to 1 (a higher score indicates a stronger model) and is analagous to the AUC

Table 3.2.: Transition Classifier Results Summary. Table displays test-set performance of Random Forest with 170 trees (selected using grid search and 10-fold cross validation) using different features. Model trained on users' first 6 months of posts and predicts transitions in the subsequent 12 months. Number of train and test set examples were 352 and 88, respectively.

Model	**Accuracy**	**F1 Score**
Doc2Vec	0.693	0.682
LIWC	0.659	0.659
Doc2Vec + drugs + keywords	0.716	0.725
LIWC + drugs + keywords	0.739	0.736
Doc2Vec + LIWC + drugs + keywords	**0.750**	**0.750**

score of the Receiver Operating Characteristic (ROC). Our best Cox model achieved a 0.823 C-Index on the test-set (Table 3.3), indicating a moderately strong model.

Table 3.3.: Cox Model Results Summary. Train/test split of 1,775 (1665 censored) and 592 (352 censored) users, respectively. C-Index shown for models using different feature sets. The model using drug utterances, keywords, and LIWC features performed best on training set using 5-fold cross validation and gave a test-set C-Index of 0.820. Test set data consisted of 45 observed and 592 censored examples.

Model	**C-Index**
Doc2Vec	0.790
Doc2Vec + drugs + keywords + LIWC	0.788
Drugs + keywords + LIWC	**0.820**
Test Set Performance	***0.820***

In addition to training Cox models using different feature sets, we sought to explore the explanatory strength of individual covariates by fitting a model to each individual feature (Table 3.4 presents the C-statistics from this experiment). Using this approach, we found that utterances of drugs such as Buprenorphine, Heroin, and LSD, have a stronger impact on a user's predicted survival probability relative to other drugs. This is in accordance with our earlier analysis (Figure 3.3). Similarly, LIWC dimensions such as "leisure," "time," and "focuspresent" have relatively more

predictive power (Table 3.4). These features measure the extent to which posts contain terms related to leisure activities (e.g. "cook," "chat," "movie"), time-related terms (e.g. "hour," "day," "oclock"), and terms that indicate a focus on the present (e.g "today," "is," "now").

Table 3.4.: Top 10 Explanatory Covariates

Drug Name	**C-Index**
Heroin	0.748
Buprenorphine	0.702
LSD	0.687
psilocybin	0.628
oxycodone	0.623
marijuana	0.621
Ecstasy	0.614
fentanyl	0.610
oxymorphone	0.608
amphetamine	0.597

LIWC feature	**C-Index**
leisure	0.668
Period	0.646
time	0.646
ingest	0.645
informal	0.642
netspeak	0.633
focuspresent	0.630
relativ	0.627
nonflu	0.612
money	0.610

3.6.1 Survival Predictions on the Transition Dataset

We looked once again at the 220 CAS and 220 CAS→RECOV Redditors, this time through the lens of our trained survival model. In Figure 3.4, we fix the time duration at 12 months and compare survival probabilities between the two groups. Not surprisingly, a sizable majority of the CAS group have high probability ($> 90\%$) of surviving past 12 months. We then approximated the addictive potential of certain drugs by measuring the average survival probability of users who share a common drug of choice. For example, we found that users whose top drug utterances were Ecstasy or LSD had high probability of surviving while users whose drug of choice is Heroin or Buprenorphine had a comparatively smaller chance of surviving (Table 3.5).

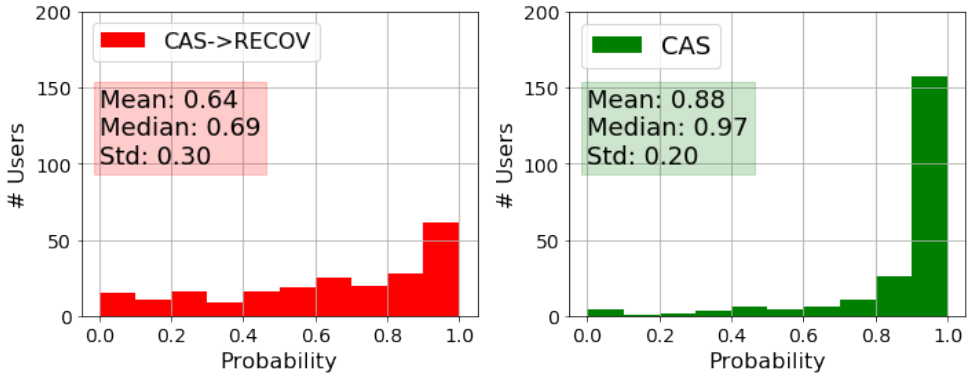


Figure 3.4.: Surviving One Year. Histograms showing the number of CAS and CAS→ RECOV users predicted to survive at least a year.

Table 3.5.: One-Year Survival Probability by Top Drug Mention

Drug Name	**Surv. Prob.**	**Drug Name**	**Surv. Prob.**
Ecstasy	0.987	fentanyl	0.820
LSD	0.981	cocaine	0.774
benzodiazepines	0.877	oxycodone	0.767
marijuana	0.872	Heroin	0.502
methamphetamine	0.824	Buprenorphine	0.498

3.7 Case Study

In this section, we illustrate one of several potential uses of our models by applying them to an actual Redditor. Figure 6 presents a profile of the user including a redacted sample of his writing, the most prevalent LIWC aspects, and most uttered drugs from his posts.

The subject is a routine user of Heroin and an active participant in r/Opiates. His top 3 drug utterances are Heroin, oxycodone, and Buprenorphine with Heroin representing approximately 35% of his total drug mentions. Referring to Table 3.5, one may expect a lower 12-month survival probability for this user relative to someone with a random drug composition. Furthermore, LIWC dimensions of the subject's posts are consistent with Redditors who do not survive 1 year. For example, users

who fail tend to have a lower "focuspresent" dimension, and our subject scores close to the $75th$-percentile in this category (Table **??**).

3.7.1 Model Predictions of Subject

Given the subject's background and profile, it is encouraging that our transition classifier labels him as CAS→RECOV. That is, using only the subject's first 6 months of casual posts, the classifier predicts he will post in recovery within the subsequent 12 months. Furthermore, our Cox model predicts a less than a 18.6% chance he will survive past 1 year (Figure 3.5), indicative of a high-risk user. Consulting the subject's entire post history, we found that he did eventually post in r/OpiatesRecovery 200 days after his first post.

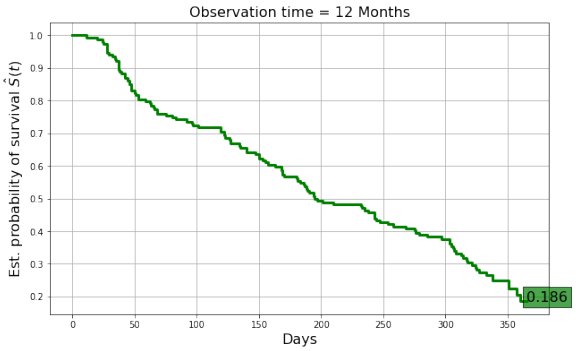


Figure 3.5.: Kaplan-Meier Curve showing surviving probability vs Days for the case study subject

3.8 Discussion

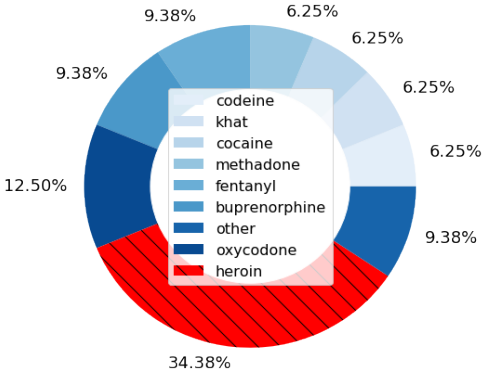
In this work, we explored transitions from recreational substance use to substance abuse using survival analysis and binary classification. In our classifier, we were able to predict whether a previously "casual" user will post in a recovery subreddit within the next 12 months. Using our survival model, we were able to uncover distinct

Initial Posts
Finished my stash off this morning as was expecting to have more by now. Just had a call..... Its not good. Hopefully tomorrow he said. HOPEFULLY..... Tonight is going to be a very long night for me.
...Ran out of **dope** last night, meaning to get more this morning. My man was out so planned on getting it while at work. But, I forgot my cash. DAMN, I have a whole night shift in front of me while starting to get sick. This sucks. Hope your all having a better night than me.
...I have aquired 15 x 100mcg **Fent** patches of the matrix type. I figured I would try smoking a bit of one and...I now know why its so easy to OD on them....Gonna be super careful with them though, lost 2 good friends over the years through **fent** OD's. Will keep posting at least once a day until their gone though. Happy nods ppl, and keep safe.

First Recovery Post
Hi guys, I figured this would be as good a place as any to post my story, and look for answers. I have been using **Heroin** on and off for about some years now...I am past the physical withdrawals now, but still really struggling with the psychological side...All my friends use, hell, most people I know use. I want to stop for my wife and son above everything else, bit finding it really hard. So, what advice do you guys have. Any will be greatly appreciated. I'm guessing I just want someone to talk to as today I am really struggling with it. Thanks

LIWC	Avg. Value	LIWC	Avg. Value
Authentic	71.261	netspeak	2.176
relativ	16.059	percept	2.028
focuspresent	13.495	leisure	1.189
Period	11.902	money	0.862
WPS	10.648	family	0.629
Sixltr	9.534	nonflu	0.579
time	8.281	sad	0.344
conj	5.841	death	0.234
informal	4.130	ingest	0.215
insight	2.491	Exclam	0.000

(a) Subset of LIWC



(b) Top Drugs

Figure 3.6.: Case Study Subject Profile

features such as specific drug utterances and linguistic features of a given post that influence a given user's probability of transitioning from recreational substance use to substance abuse. In this section, we discuss the implications of these results in informing drug use culture and possible methods of drug classifications, as well as highlight potential applications of our models in understanding drug use from the user's perspective.

3.8.1 Informing Culture and Classifications

Based on our Redditors' posts, a pattern of use was apparent: drugs such as LSD, Ecstasy, marijuana, and alcohol were often used by Redditors attending parties, music festivals, or social events in general. In contrast, opioids were commonly used as a habitual, lone activity or in smaller, low-energy gatherings. This trend learned by inspection was further supported by post-level analyses showing a co-occurrence of frequent mentions of LSD and Ecstasy and frequent use of words such as "music," "rave, " and "party." Paul and Dredze found similar results in their use of topic modeling to understand various factors, including the cultural factors, associated with certain drug use. For example, the "culture" words associated with Ecstasy include ["music", "people", "great", "rave"], while the "culture" words associated with opioids include ["life", "years", "money", "time", "shit"] [38].

Our survival model suggests that certain drug utterances were highly explanatory in influencing the probability of substance abuse – for instance, a user with higher Heroin mentions (as a percentage of total drug mentions) is associated with a higher probability of substance abuse, while higher LSD and Ecstasy mentions are associated with lower probabilities. This particular example directly conflicts with the current national drug classifications outlined by the DEA, who classifies drugs into five "schedules" based on their dependence potential as well as the level of accepted medical use. As it currently stands, drugs including Heroin, LSD, marijuana, and Ecstasy are classified as Schedule I, while most other opioids along with cocaine are classified as Schedule II. Our models, however, suggest that the drugs of choice for individuals who are likely to transition are often not the drugs labeled as Schedule I, with the exception of Heroin. Table 3.5 outlines the average "survival" probabilities associated with drugs common among our users. In our model, users whose drugs of choice are Ecstasy, LSD, and marijuana have a higher predicted survival rate which

may suggest that these drugs could be better classified as Schedule II or lower. Similarly, their lower associated survival probabilities may be justification for a higher classification for drugs like Buprenorphine, oxycodone, and cocaine.

Other studies have reached similar conclusions. The United Kingdom has similar drug classifications based on addictive potential, and places many of the Schedule I drugs as their top dangerous drugs as well. Yet Nutt and colleagues [53] found that the UK system of classification is somewhat arbitrary and not driven by scientific evidence. In their work, they reclassified the drugs listed in the UK's guidelines using potential of harms of individual drugs, and found that the top drugs with high potential of harm include Heroin, cocaine, barbiturates, street methadone, and ketamine. Their findings also disagree with UK's designation of LSD and Ecstasy in the top drug class – this aligns with our results and further suggests the higher potential of harm from opioids relative to these other drugs.

Similarly, Sarvet et al [54] discuss the increasing amount of evidence in support of the therapeutic properties of medical marijuana. According to them, medical experts, including the American Medical Association, have urged the DEA to reschedule marijuana from Schedule I to Schedule II. They argue that not only would it increase access for patients who could benefit from this form of treatment, it would also enable further research and development of cannabinoid-based medicine.

3.8.2 Limitations

In this section, we list some limitations to our work: 1) We identify selection bias in our Redditors, as they are choosing to express their opinions on Reddit and are likely much more open about their drug use/recovery progress. Since this may not be indicative of all drug users, our results may not be generalizable to the larger population. 2) We use participation in general drug forums and recovery forums as

proxies for recreational use and substance abuse, respectively. However, since there are no rules preventing abuse-related posts in our casual subreddits, these subreddits, though predominately about casual drug discussion, do contain abuse-related posts. 3) We cannot make any clinical disgnoses of drug addition or mental illness based solely on our analyses. 4) Although we made attempts to include all forms of drug names in our drug counts, there may be names that are not included, and thus we may not have captured all types of drug utterances. 5) Our research uncovers certain post-level characteristics that influence the likelihood of transitions into recovery subreddits but cannot explain *why* Redditors make these transitions.

Despite these limitations, our findings provide unique insight into drug use patterns from the perspective of users and uncovered features within one's posts that may be predictive of future substance abuse. Our work demonstrates the utility of online forums and social media sources in understanding human health and activity. Finally, the computational models that we provide can be utilized into real-life applications. For example, there can be a software App for Redditors in which they input their posts and the App returns the poster's propensity for drug abuse. Also, this App can be used as a predictive device to help counselors and psychologists in advising their patients.

3.9 Future Work

Further research in this area could focus more on the temporal aspect of a user's post sequence. Similar to the work done by Maclean et al. [13], which used a Conditional Random Field (CRF) to model phases of addiction, one could construct a sequence model using our subreddits to track users' phases of "pre-addiction" to further analyze transitions into addiction and uncover more contextual factors that influence such transitions. We hope to explore such analysis in the future.

4. BUILDING KNOWLEDGE GRAPHS OF HOMICIDE INVESTIGATION CHRONOLOGIES

4.1 Introduction

A large amount of text-based data is produced during a homicide investigation including basic descriptions of the event, evidence logs, forensic reports, maps and annotated photographs, and transcripts of investigator's notes and witness interviews. These data are compiled into a so-called "Murder Book" that summarizes the paper trail from the time the incident was reported to the time a case is closed.

In the United States nationally, around 60% of homicides are solved or cleared via arrest or other exceptional means such as death of the offender [55]. Several

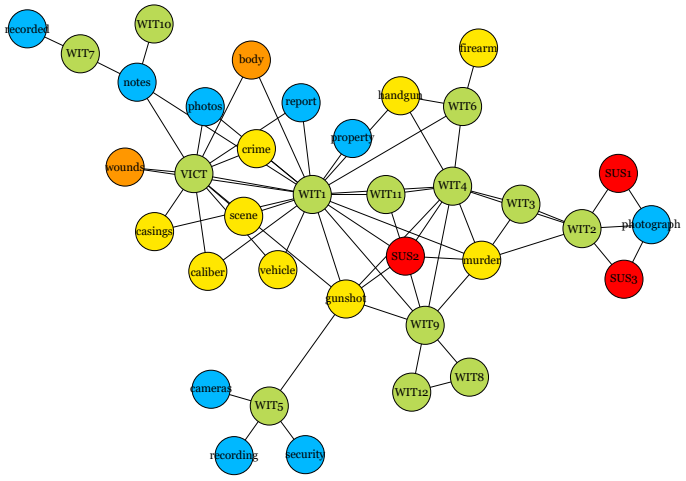


Figure 4.1.: Example knowledge graph of a homicide investigation chronology. Entities include witnesses, suspects and detectives as well as physical, documentary and forensic type evidences.

factors appear to play an important role in homicide solvability [56]. Some crimes are inherently more difficult to solve than others; clearance rates generally are lower for homicides that involve guns, are perpetrated by strangers, lack witnesses, or occur in neighborhoods where cooperation with police is strained [57–59]. The quality of police investigations also appears to matter [60]. High volumes of casework, lack of investigative resources, investigator inexperience, and variability in investigator motivation (e.g., bias) can all drive down homicide clearance rates [61, 62].

Our primary interest in this work is to understand the interactions between the characteristics of a crime, as represented by collected evidence, and the investigative process. We hypothesize that some of these interactions are non-obvious and therefore difficult to leverage using traditional methods designed to improve homicide solvability. We explore methods to construct "knowledge graphs" from text-based investigative information contained within Murder Books and evaluate the association between structural features of the resulting graphs and solvability of the cases. We see this as a precursor to methods that can be used actively during investigations to improve clearance rates for homicides that would typically go unsolved.

In Figure 4.1 we show an example knowledge graph constructed from a homicide chronology using the methods detailed in this paper. In the graph there are 3 suspect nodes, 12 witness nodes and a single node for the victim. There are 3 types of evidence nodes connected to these 16 individuals, including physical evidence nodes (yellow), documentary evidence nodes (cyan), and forensic evidence nodes (orange). Our ultimate goal is to correlate features of the network with the outcome of the investigation (whether or not it is solved).

The remainder of this paper proceeds as follows. In Section 4.2 we outline at a conceptual level an ontology for homicide knowledge graphs. In Section 4.3 we describe the data used in our study. In Section 4.4 we compare four deep learning ap-

proaches for named entity recognition in homicide investigation chronologies. We also introduce a keyword expansion methodology for extracting evidence from chronology entries. In Section 4.5 we consider two approaches for constructing knowledge graphs of homicide investigations using the entity extraction techniques introduced earlier in the paper and in Section 4.6 we analyze statistics of the constructed knowledge graphs as they relate to solvability outcomes. We discuss the implications of our findings and directions for future work in Section 4.7.

4.2 Homicide Graph Ontologies

Our approach to knowledge graph construction starts with the routine activities theory of crime [63]. RAT outlines a core ontological framework for any potential threat that arises from the normal activities that people engage in on a day-to-day basis. For crime such as homicide, RAT helps delineate the key elements and contexts that must underlie the crime. It is this underlying structure that detectives seek to capture in their investigation and that we seek to represent in a knowledge graph. The minimal elements necessary for a homicide consist of an offender (node) killing (edge) a victim (node). The homicide takes place in a setting (node), which can act upon both the offender and victim. By virtue of the fact that an offender and victim must converge in a setting for a homicide to occur, these core elements necessarily form a complete graph. The core graph can be further refined and extended based on other specific knowledge about an event. For example, the act of killing may be mediated by a weapon (node) and offenders, victims and settings each may be conditioned by other characteristics such as motives (nodes), such as jealousy, and contexts (nodes), such as alcohol and witnesses. Note that the hypothetical graph for the crime itself must have elements such as an offender (node) that exist with

certainty. A corresponding investigative knowledge graph may have elements such as a suspect (node) or evidence (node) labeled to reflect uncertainty.

There have been a few attempts to map out the ontology of graphs related to various threats [64, 65], but these remain relatively simple at present. Homicide investigations can easily generate tens-of-thousands of unique data points, suggesting that homicide knowledge graphs will include a proportional number of graphical elements. We expect the core ontology suggested above to quickly become challenging to understand and difficult to analyze for plausible causal pathways (e.g., attribution of guilt). We therefore require methods that can easily extract and accurately label investigative elements and their relationships according to a specified ontology and then use the resulting graphical structure for various investigative tasks.

4.3 Data Description

A so-called "Murder Book" is a case file management structure developed to ensure organization and standardization in homicide investigations. The Los Angeles Police Department (LAPD) has been successfully using Murder Books for nearly four decades [66]. It allows anyone involved in the investigation to find investigative reports, crime scene reports, witness list, interview transcripts, photos and other material. Every Murder Book contains a case chronology which consists of a time-ordered list of steps taken by the investigators over the entire history of the case. The chronology typically starts with an entry describing which detectives are assigned to the case and how they were notified, followed by a separate entry describing arrival at the scene and general scene description (e.g., state of the victim and initial evidence collected). A chronology typically ends with an entry describing how a case was closed (e.g., suspect arrested) or, if the case remains open, the date and time of the last case review. Hundreds of entries in between cover investigative events such as the date,

time and location of witness interviews, date of receipt of forensic reports, and date of warrant requests. Each entry in the chronology is typically a compact, text-based statement totalling no more than 120-150 words. The purpose is to provide a quick reference for the state of the investigation, rather than a sounding-board for a theory of the crime.

The dataset we analyze at present consists of the case chronologies for 24 randomly-sampled Murder Books for homicides that occurred in LAPD's South Bureau between 1990 to 2010. The data were provided by the LAPD and are analyzed under *Anonymous University* IRB Protocol #XX-XXXXXX. The 24 cases generated 2482 unique chronological entries.

4.4 Identifying Named Entities and Evidence

Named entity recognition (NER) is a framework for identifying named entities from text and classifying them into pre-defined categories. Deep learning based approaches for NER are currently state of the art and we compare four deep learning models for the task of identifying detectives, witnesses, and suspects from homicide chronologies. For a review of deep learning based NER see [67].

4.4.1 SpaCy

The first deep learning based approach we evaluate is the NER method implemented in spaCy[1], a Python based open source library that provides tools for natural language processing [68, 69]. The default NER model in spaCy utilizes subword features and bloom embeddings [70], along with a convolution neural network with residual connections.

[1] `https://spacy.io/`

Table 4.1.: NER model comparison for homicide investigation chronologies.

Model		Overall			Detective			Witness			Suspect		
		Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
spaCy	train	0.86	0.91	0.88	0.90	0.94	0.92	0.79	0.93	0.86	0.88	0.77	0.82
	valid	0.36	0.26	0.30	0.28	0.17	0.21	0.39	0.53	0.45	0.39	0.06	0.11
BiLSTM-CRF	train	0.95	0.96	0.96	0.96	0.97	0.97	0.98	0.92	0.95	0.91	**0.99**	0.95
	valid	**0.74**	**0.83**	**0.78**	**0.82**	**0.82**	**0.82**	**0.84**	0.83	0.84	0.17	**0.91**	0.29
BiLSTM-BiLSTM-CRF	train	0.98	**0.97**	0.97	**0.99**	**0.98**	0.98	**0.99**	0.94	**0.97**	0.96	**0.99**	**0.97**
	valid	0.67	**0.83**	0.74	0.64	0.70	0.67	**0.84**	**0.92**	**0.88**	0.12	0.88	0.21
BiLSTM-CNN-CRF	train	**0.99**	0.96	**0.98**	0.99	**0.98**	**0.99**	0.98	**0.96**	**0.97**	**0.99**	0.94	**0.97**
	valid	0.72	0.79	0.76	0.70	0.65	0.68	0.82	**0.92**	0.87	**0.43**	0.76	**0.55**

4.4.2 Bidirectional LSTM-CRF

We also apply a bidirectional LSTM-CRF (conditional random field) model for NER [71]. The model makes use of both past and future input features and sequence level tagging information. For the implementation of bi-LSTM and CRF, we first obtain pre-trained GloVe [72] embeddings to input into the neural network, apply a dropout to the word representation in order to prevent over-fitting [73], and then train the Bi-LSTM to get a contextual representation. The final step in the model includes applying CRF to decode the sentence [73]. We refer to this model as BiLSTM-CRF.

We also consider two alternative BiLSTM-CRF architectures. In the first alternative [74], we again obtain word embeddings using pre-trained GloVe embeddings [72] and concatenate them with character level word embeddings from a bi-LSTM model. The character level model uses a forward and backward LSTM to obtain a representation of the suffix and prefix of a word [74]. After obtaining the word representation, we apply a bi-LSTM to get another sequence of vectors providing contextual representations. Again, at the end we use a CRF to decode sentence level tag information. We refer to this model as BiLSTM-BiLSTM-CRF.

The third LSTM-CRF variant we consider uses a CNN layer instead of Bi-LSTM to derive character embeddings. We train a 1-D Convolutional Neural Network (CNN) followed by a max pooling layer to get the character level embeddings and concatenate the layer with pre-trained GloVe embeddings. The CNN is an effective architecture for extracting morphological information from characters of a word [75–77]. This word representation is then fed to a bi-directional LSTM network in order to extract a contextual word representation which is then fed to the CRF model to decode the sequence tags for the sentence. We refer to this model as BiLSTM-CNN-CRF.

Table 4.2.: Initial List for Identifying Types of Evidence in Text

Evidence Type	Keywords
Documentary Evidence	tapes, recording, surveillance, photo, video, camera, photograph
Physical Evidence	weapon, gun, knife, gunshot, caliber, casing
Forensic Evidence	dna, blood, fingerprint, autopsy

4.4.3 Application of NER to homicide investigation chronologies

We compare the above four NER models to the LAPD homicide investigation dataset. We first hand labeled 610 narrative reports from the total of 2482 reports and split them into a training set (348 reports) and validation set (162 reports). Each word in a sentence was tagged as detective (*Det*), witness (*Wit*), suspect (*Sus*) or other (*O*). All of the detectives, investigators, coroner and supervisors involved in the case were tagged as *Det*. People who were interviewed or provided information related to the case were assigned to the *Wit* label. People were tagged as *Sus* if they were under investigation at any point during the chronology (for example if a warrant was issued or they were arrested).

In Table 4.1 we show the performance of the four NER models on our dataset. We evaluate the models in terms of precision, recall and f1-score. We find that overall, the BiLSTM-CRF model has the best precision (.74), recall (.83) and f1-score (.78) on the validation data. We therefore use the BiLSTM-CRF in constructing knowledge graphs in the following sections. An example of the NER extraction is shown in Figure 4.2a.

4.4.4 Identifying Evidence using Keyword Expansion

While NER can be used to extract named entities, we use domain expertise coupled with a key word expansion to extract evidence from each sentence. We first start

Table 4.3.: Evidence List after applying Keyword Expansion

Evidence Type	Keywords
Documentary Evidence	tapes, recording, surveillance, photo, video, camera, photograph, print, letter, record, security, camera, printout, recording, report, notes, document, monitor, chronology, footage, warrant, property, picture, log
Physical Evidence	weapon, gun, knife, gunshot, caliber, casing, handgun, firearm, item, murder, crime, scene, revolver, fire, discovery, criminal, kick, crimescene, shot, kill, stab, vehicle, veh
Forensic Evidence	wound, body, polygraph, exam, examination, test, hair, impression

with a key word list of evidence classified into three types: physical, documentary and forensic evidence. The list is shown in Figure 4.2. Physical evidence includes tangible objects such as gun, knife, bullet, etc. Documentary evidence includes tapes, photos, video, etc. containing pertinent information to the case. Forensic evidence, on the other hand, includes DNA, blood, fingerprints, autopsy information, etc.

Next we used a keyword expansion [78] to extract additional keywords related to evidence from the text. In particular, we preprocessed the data by removing stopwords and eliminating any word with length less than 3 and frequency less than 5. We used Gensim Word2Vec [2] to embed each word in the remaining text and computed the similarity (distance) of each word to those in the defined list in Table 4.2. We then thresholded the similarity scores and again used domain expertise to select and prune the resulting expanded keyword list. We applied this process iteratively three times, the result of which is shown if Table 4.3. An example sentence with NER and evidence detection is shown in Figure 4.2a.

[2]https://radimrehurek.com/gensim/

4.5 Building a Knowledge Graph of Homicide Investigation Chronologies

A knowledge graph (KG) is a representation of structured information in the form of entities and relations (links) between them. Here we describe our approach to constructing knowledge graphs of homicide investigation chronologies. We utilize an end-to-end text to knowledge graph framework, t2kg, [79] to construct the knowledge graph in four stages:

1. Entity Mapping
2. Coreference Resolution
3. Entity Extraction
4. Entity Disambiguation

During the first stage an entity is mapped to a uniform resource identifier (URI). In the context of a homicide investigation, entity mapping can be viewed as identifying law enforcement detectives, witnesses, suspects and evidences from text. In the next stage, coreference resolution is the task of finding mentions in text that refer to the same underlying entity. This is done in order to capture different expressions of identical entities [80, 81]. For this purpose we use neuralcoref[3] to resolve coreference clusters. In the third stage we perform entity extraction, for which we considered the following two approaches:

1. **Triple Extraction Approach** Subject-object-relation triples are extracted using the Open Information Extraction technique implemented in the Stanford CoreNLP library. In Figure 4.2b we show an example of a sub-graph created from the paragraph in Figure 4.2a using the triple extraction approach. For example, *vehicle* keys are provided to a *witness* leading to an edge between vehicle and witness being added to the knowledge graph.

[3] `https://spacy.io/universe/project/neuralcoref`

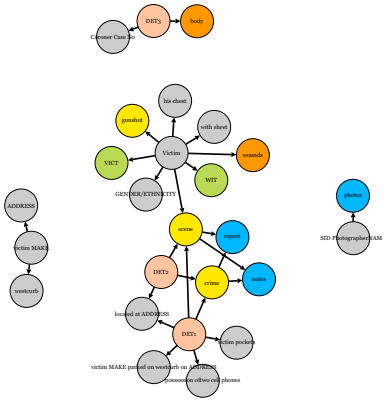
2. **Domain Knowledge** The triple extraction approach uses grammatical structure to add edges, without regard to domain knowledge or the fact that all sentences in a chronology are related. Therefore we consider an alternative approach, that we refer to as "domain knowledge," where we add a complete (fully-connected) sub-graph of all extracted entities detected in the chronology entry. We show an example of this approach in Figure 4.2c.

Coreference resolution using neuralcoref in stage 2 above is only able to resolve high level coreference clusters in the text. We therefore add an entity disambiguation stage, where identical entities are grouped together and duplicates are eliminated. In the entity disambiguation phase, multiple versions of the same entity are mapped to a unique entity identifier. For instance, entity John Middle Doe may be referenced in the text with variations such as John, John M Doe, Doe, J. Doe etc. To merge these variations we employed partial string matching. We then merged redundant entities that are identified in the triple extraction approach. For example, the triple (DET, interviewed, WIT) is merged with the triple (DET, interviewed with, WIT) into the single entity-relation tuple (DET, interviewed with, WIT).

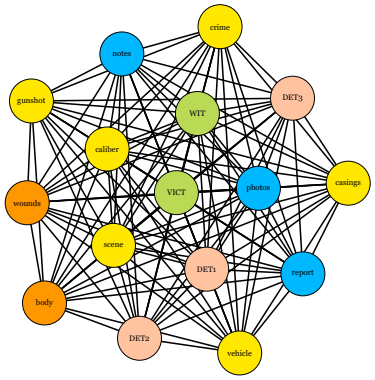
In Figure 4.5 we present example knowledge graphs for the domain knowledge approach and in Figure 4.6 we present example knowledge graphs for the triple extraction approach. In general we find that the domain knowledge graphs are more connected, given the fully connected subgraph used for each chronology entry. This can be seen in the degree distributions corresponding to each method in Figure 4.3. We also note that much of the information contained in the knowledge graphs is already present after the first week of the homicide investigation (see Figure 4.4).

DET1 and DET2 arrived at crime scene , located at ADDRESS . Victim in streetcovered with sheet . Victim identified at scene by his Sister WIT as VICT , GENDER/ETHNICITY AGE . Victim had multiple gunshot wounds to his chest , back and possibly to BODYPART . I/O 's conducted crime scene investigation See IR Report and Notes .Recoveredevidence, two .45 caliber casings . Coroner 's Investigator DET3 took charge of thevictim's body and assigned Coroner 's Case No . XXXX . DET1 took possession oftwo cell phones in victim 's pockets and searched victim 's MODEL MAKE , parked on westcurb on ADDRESS . Provided victim 's vehicle keys to WIT . SID PhotographerNAME XXXX took photos that were directed by DET1 , C # XXXX .

(a) Entity extraction using Named entity recognition and Keyword Expansion. Some text is redacted such as detective names (replaced with DET), witness names (replaced with WIT), suspect names (replaced with SUS), etc.



(b) Extracted knowledge sub-graph using Stanford OpenIE Triple Extraction approach.



(c) Extracted knowledge sub-graph using Domain Knowledge Approach.

Figure 4.2.: Building knowledge sub-graphs using Named Entity Recognition and Keyword Expansion. Text and nodes are colored by its entity type (Detective- pink, Witness- green, Suspect- red, Physical evidence- yellow, Documentary evidence- cyan, Forensic evidence- orange, Other- gray)

4.6 Association between Knowledge Graph Features and Homicide Solvability

To evaluate the quality of the knowledge graphs we construct, we investigate the extent to which knowledge graph features (statistics) are asssociated with solvability.

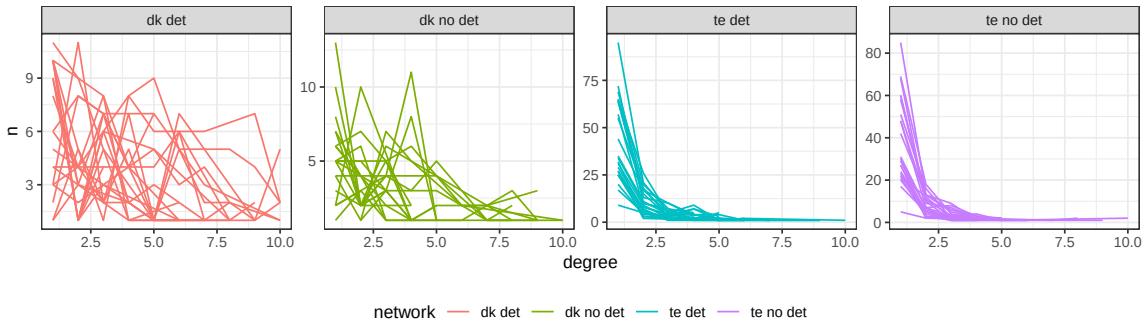


Figure 4.3.: Degree distributions of the 24 homicide investigation knowledge graphs of domain knowledge type (with and without detective nodes) and triple extraction type (with and without detective nodes).

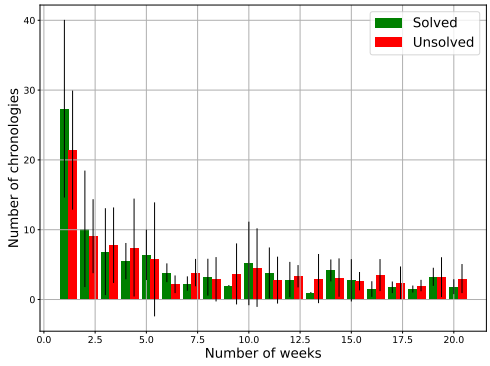
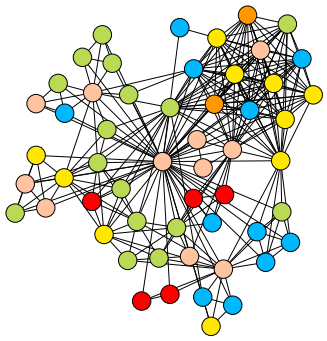


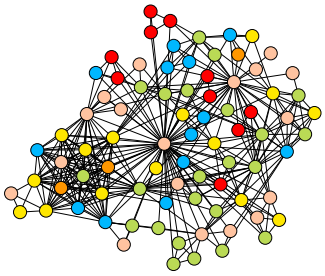
Figure 4.4.: Average number of chronology entries over first 20 weeks into the investigation.

The methods we introduce here may be stepping stones towards AI-assisted homicide investigation, where key elements of the graph may be identified as playing a role in whether the case is ultimately solved (a suspect is charged for the crime). We are cautious in avoiding the term *prediction*, given the small dataset size and our inability to disentangle causality from correlation.

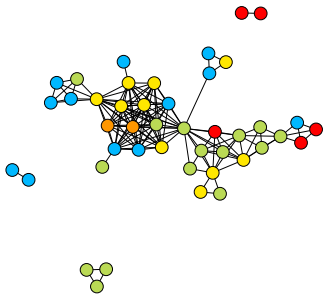
First, we create knowledge graphs for each of the 24 cases provided by the LAPD using the triple extraction and domain knowledge approaches. After the creation of the knowledge graphs, we compute network statistics for each KG, e.g., number of



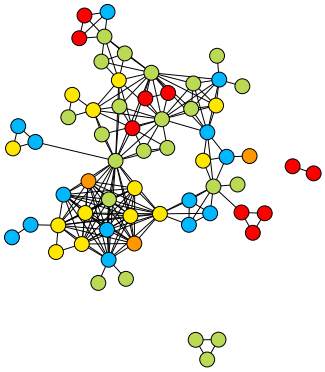
(a) Domain Knowledge Approach (including detective nodes- Week 1



(b) Domain Knowledge Approach (including detective nodes- Week 10



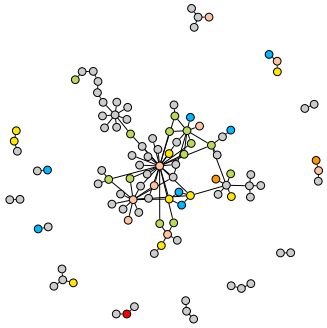
(c) Domain Knowledge Approach (not including detective nodes- Week 1



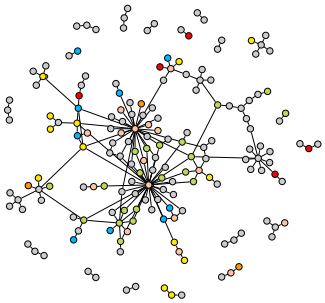
(d) Domain Knowledge Approach (not including detective nodes- Week 10

Figure 4.5.: Knowledge graph using Domain Knowledge Approach with and without detective nodes. Each node is colored by its entity type (Detective- pink, Witness- green, Suspect- red, Physical evidence- yellow, Documentary evidence- cyan, Forensic evidence- orange).

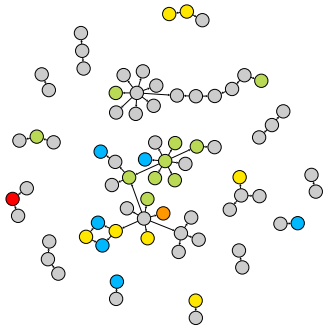
nodes, number of edges, network density. In Figure 4.7 we display the 15 network statistics we compute for each network along with the AUC of the statistic as it relates to solvability of the homicide investigation. Here we find that the number of evidence nodes, suspect nodes and average degree of detective nodes yield the highest AUC.



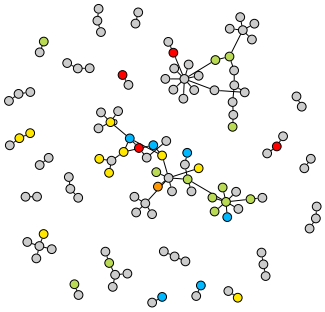
(a) Triple Extraction (including detective nodes- Week 1



(b) Triple Extraction (including detective nodes- Week 10



(c) Triple Extraction (after removing detective nodes- Week 1



(d) Triple Extraction (after removing detective nodes- Week 10

Figure 4.6.: Knowledge graph using Triple extraction approach with and without detective nodes. Each node is colored by its entity type (Detective- pink, Witness- green, Suspect- red, Physical evidence- yellow, Documentary evidence- cyan, Forensic evidence- orange, Other- gray).

For each approach (domain knowledge and triple extraction), we consider networks where detective nodes are included and networks where they are removed. While detective node based features have a high AUC score, causality may be in the wrong direction. On the one hand, an increase in the number of detective nodes may be due

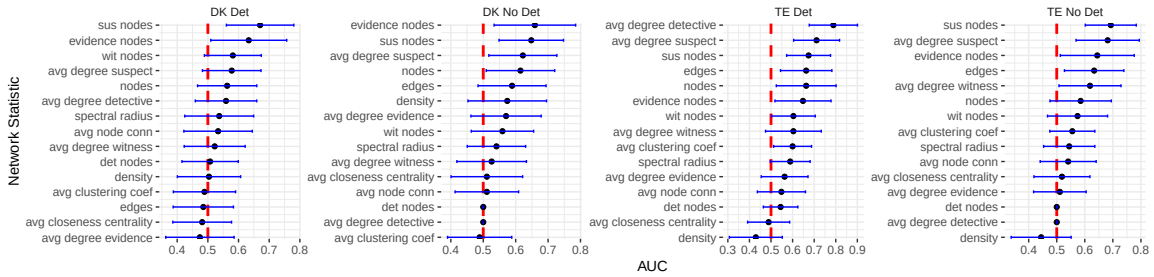


Figure 4.7.: AUC and standard error for each network statistic in week 1 of the investigation.

to the case being solvable. On the other, cases with more dedicated resources may be more likely to be solved. We show results for both types of networks.

We next evaluate a simple generalized linear model (GLM) with binary response for determining solvability:

$$\log(p(y=1)/(1-p(y=1)) = c_0 + c_1 s + c_2 e + c_3 s \cdot e \tag{4.1}$$

where s is the number of suspect nodes, e is the number of evidence nodes, and y indicates whether the homicide is solved. The features were selected based on their individual AUC scores in Figure 4.7 and limited to the top-two (averaged across network types) to prevent over-fitting.

Due to the small dataset size we use leave-one-out cross validation (LOOCV). In Figure 4.8 we show the AUC scores of the GLM model for each network type (domain knowledge vs. tripe extraction, with and without detective nodes) constructed using data up to a given week past the start of the investigation. Here we generally find that the domain knowledge approach outperforms the triple extraction approach. We also do not find much improvement in the association between the model scores and solvability past 1-3 weeks in the investigation. In the case of the triple extraction networks without detective nodes, we find that the GLM model yields AUC scores at

or below .5 (using LOOCV), indicating that the GLM model is over-fitting for that type of network.

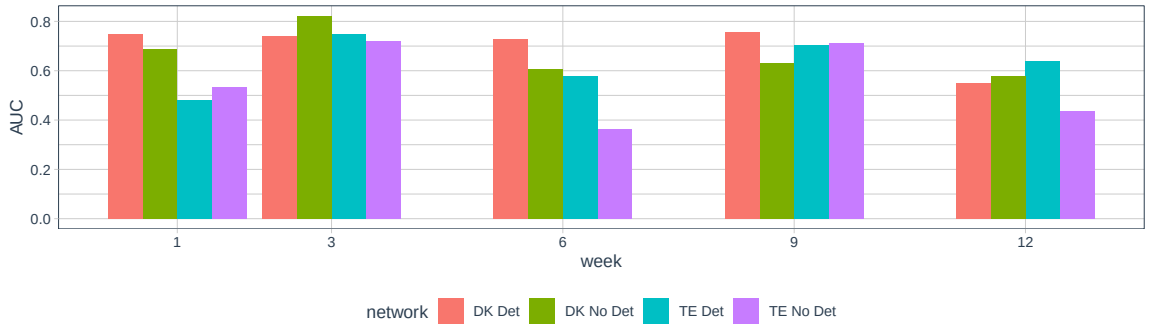


Figure 4.8.: AUC of GLM model (computed uses leave one out cross-validation) vs. number of weeks into the investigation.

4.7 Discussion

We show that it is possible to construct knowledge graphs representing homicide investigations from text-based case file information. The topological features of these knowledge graphs offers some traction in classifying whether or not homicides are solvable. Features that prove to be important in classifying homicide solvability (e.g., evidence nodes, suspect nodes) are consistent with analysis of investigative process using other methods [62]. Importantly, the results also suggest that the most significant topological structure are established early in an investigation, reinforcing the common view that cases can be divided into "self-solvers" that produce sufficient evidence at the scene and "whodunits" that do not [82].

That knowledge graph topological structures appear to provide useful information suggests that AI could eventually be used to improve solvability. It is too early to know exactly what to expect. However, we hypothesize that there will be regular structural and relational features of solved homicides that will distinguish them from

unsolved ones. When comparing graphs, we may be able to identify gaps or holes in graphical structures that, if closed, could improve the chances of a case being solved. To the extent that such graph-based insights go beyond what common investigative practice would yield, AI-assisted homicide investigation may be valuable.

A common expressed view is that solving homicides helps build community trust in police, while failure to do so erodes that trust and creates a sense of impunity among offenders [58, 59]. If AI can help improve homicide solvability, then it can also be seen to contribute to building community trust. However, the question is not simply whether such methods augment the process of homicide investigation. Rather, since homicide investigations must adhere to the policy requirements of the organization and the procedural requirements of the law, so must AI used within those investigations. For example, if we consider a hypothetical knowledge graph-based recommender system that suggests investigative steps, then those recommendations cannot violate policy or the law.

AI-assisted homicide investigation would also need to be evaluated in terms of fairness. The evidence is mixed on whether homicide clearance rates are mediated by race and gender [56, 59, 62, 83], though many expect that clearances rates are lower when the victim is a person of color [58]. In any case, AI should not introduce or amplify any clearance rate imbalances. We should also consider the possibility that AI-assisted investigation might ease clearance rate imbalances. Such imbalances may originate with the event itself if, for instance, so-called "whodunit" cases arise more often in association with certain demographic characteristics [84]. They might also appear if there is "victim devaluing" based on demographic characteristics [58, 59]. Identifying such biases in investigative knowledge graphs is a necessary and important step towards correcting for them.

Finally, we must also be aware of the potential for the miscarriage of justice. Recent evidence suggests that wrongful convictions may occur in $< 5\%$ of capital cases such as murder [85]. That wrongful convictions may also differ by race [86], demands that the contributing factors be taken into consideration in AI-assisted homicide investigations. While careful adherence to rules of evidence and procedure may offer some protection, it does not provide a guarantee. Wrongful convictions can sometimes be linked back to false witness statements, forensic error, or police misconduct [87]. Eventually, whether there are recognizable differences between knowledge graphs that include corrupted information and those that do not needs to be investigated.

Ultimately, considerations of fairness, accountability, and transparency need to be central to the development of machine learning methods for homicide investigations.

5. SUMMARY

In this work, we proposed machine learning methodologies to address social harm issues. In particular, we evaluated crime topic models, investigated transitions into drug addiction and analyzed homicide investigation chronologies using knowledge graph based framework.

The crime topic modeling exhibit a more nuanced model of crime incidents which entails the massive loss of information resulting from FBI Uniform Crime Reporting [8]. We suggested two performance metrics for the evaluation of crime topic models and demonstrated that choice of topic model has important implications for detecting crime hotspots. We showed that it is possible to achieve more coherent topics that simultaneously concentrate to a higher degree in space, allowing for more targeted police intervention given limited resources.

Another problem we explored was the transition from recreational substance use to substance abuse using voluntary generated introspective text in Reddit forums. We proposed a prediction model that provides both the classification and likelihood over time indicating a propensity of a user to become a drug addiction victim. Our study indicates user's transition into drug addiction can be predicted by the keywords and linguistic features of the his post and most frequent drug names in his post.

Furthermore, we proposed a knowledge graph based framework for homicide investigation chronologies. Homicide investigations chronology tracks the evolution of an investigation, including when and how persons involved and items of evidence became part of a case. We performed named entity recognition to determine detectives, witness and suspects from chronology entries and also extracted different

evidence types using keyword expansion. We further linked entities and evidence to construct a knowledge graph and analyzed the association between network statistics of knowledge graph and homicide solvability.

6. PUBLICATIONS

In this section, we provide the list of our publications:

1. Pandey, Ritika and Mohler, George "Evaluation of crime topic models: topic coherence vs spatial crime concentration," 2018 IEEE International Conference on Intelligence and Security Informatics (ISI), Miami, FL, 2018, pp. 76-78, doi: 10.1109/ISI.2018.8587384.
2. John Lu, Sumati Sridhar, Ritika Pandey, Mohammad Al Hasan, and George Mohler. 2019. Investigate Transitions into Drug Addiction through Text Mining of Reddit Data. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery Data Mining (KDD '19). Association for Computing Machinery, New York, NY, USA, 2367–2375. doi: https://doi.org/10.1145/3292500.3330737.

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