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Analysis of Tools and Techniques for Drug Abuse and Overdose Analytics in Local Communities

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***Abstract*—Drug abuse and overdoses are causing havoc in all 50 states. Some of the states and communities are spellbound by the addiction. According to the Centers for Disease Control and Prevention, more than 67,000 people died from drug overdoses in 2018, putting it at the top of the list of injury-related deaths in the United States. Approximately 70% of these deaths were involved in a prescription or illicit opioid. Drugs such as Fentanyl and prescription opioids resulted in more fatalities than all other drugs that include Heroin, Methamphetamine and Cocaine (NIH Overdose Death Rates. (2019)). The nation-wide, state-wide, and the local community-wide agencies are trying to analyze, control, and carry out measures to control this epidemic. The means of collecting localized data at the ground level is to find the local root causes that are driving the people toward the drugs and identifying the impact of the measures put-up by government agencies are lacking. We analyzed various tools and techniques in our study and identified various issues and challenges that can be adapted to localized communities for detailed drug abuse and its extent to the community. To resolve the issues, we collected and analyzed the data from multiple law enforcement agencies: City of Muncie Police Department, Delaware County Sheriff's Office in Indiana and Montgomery County Sheriff's Office in Ohio. These agencies provided the overdose data from 2016 to 2018 in Muncie and Delaware County and 2017 – 2018 in Montgomery County. The R statistical package was used to process and analyze the data to understand how overdoses spread in the local communities.**

I. INTRODUCTION

In general, opioids are a class of drugs used in reducing pain. Prescription opioids can be prescribed by doctors to treat moderate to severe pain. The categories of opioids include natural opioid analgesics (morphine and codeine), semi-synthetic opioid analgesics (oxycodone, hydrocodone, hydromorphone, and oxymorphone), methadone, synthetic opioid analgesics (other than methadone, includes drugs such as tramadol and fentanyl). Fentanyl is a synthetic opioid pain reliever that is much more powerful than other opioids and is typically used for very severe cases such as advanced cancer pain. Illegally made and distributed fentanyl has been on the rise is many states. Figure 1 shows that overdose deaths involving synthetic opioids (other than methadone) increased 10% from 2017 to 2018. Lastly, the heroine is also an illegal opioid processed from morphine and extracted from certain poppy plants. Its use has also increased across the U.S. among men and women, most age groups, and all income levels. In 2017 alone, there were 70,000 fatalities in the US which is 3 times more than the number reported in 2000 [1] as shown in Figure 2.

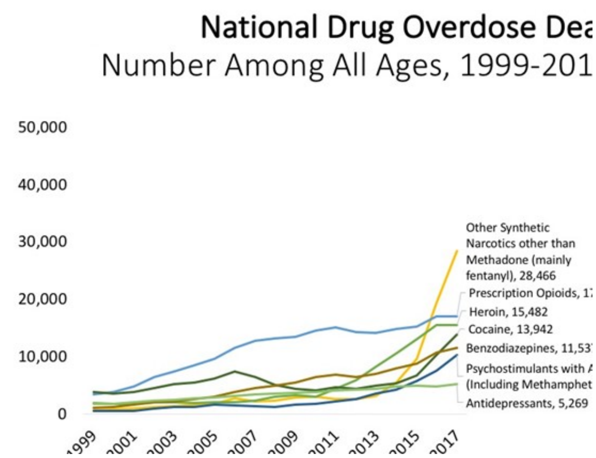

Fig. 1. Drug Overdose by various types

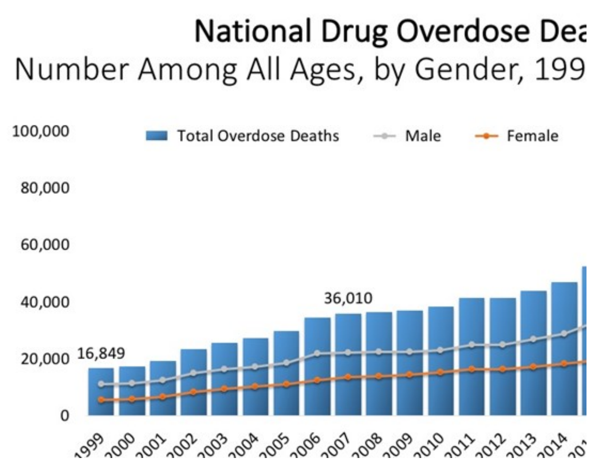

Fig. 2. Death Progression from 1999 to 2017 by drug abuse

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There are many variables that can aid in the investigation of drug overdose trends. For instance, location, type of drug, frequency of overdoses on each drug, gender, age, and socioeconomic status can help isolate and identify the aspects indicating high-risk situations. The findings from such data can be influential in creating intervention policies; identifying warning signs; and enabling prevention efforts. Researchers are using many variables and combinations of data analytics to understand the trends, some of them are discussed in the section below.

II. Use of Data Analytics for Analysing Drug Abuse

A. DrugTracker

A team at The New Jersey Institute of Technology (NJIT) had developed a real-time data analytics tool for evaluation of drug abuse trends to aid treatment centers and counsellors in identifying and treating drug abuse. DrugTracker is a community-focused drug abuse monitoring and support system. It monitors online platforms (Twitter and Reddit) and combines the information with geospatial data to determine the location of illicit drug use or changes in the landscape. DrugTracker allows organizations to detect risk behaviors cited on social media and analyse the behaviors by questioning consolidated and live datasets with keywords. Results are examined through a web-based user interface providing heat maps and statistical charts [2].

B. Hadoop and Hive

A state health agency worked with World Wide Technology (WWT) to analyse the personal information to assess patient risk for opioid abuse and opioid-related mortalities. WWT collected five years of hospital discharges, births, deaths, state trauma registries, and emergency medical services records. Data sources were combined using Hadoop Distributed File System (HDFS) and Hive SQL. Tableau dashboards were used to visualize prominent aspects of the data and allowing demographic and geographic patterns of opioid-related hospital encounters and potential opioid abuse predictors that need identification. Multivariate graphical analysis shows age and income (to a lesser degree) to be the most prominent demographic factors. The highest rates of opioid-related hospital encounters and opioid-related deaths were correlated to middle-aged individuals and lower to medium household income populations. In addition, investigators plotted opioid-related incidences on a map of the state divided up by zip codes and counties. Such analysis revealed a distinct geographic correlation of opioid-related hospitalizations. Along with that, it was identified that multiple zip codes contained high rates of opioid abuse in relation to the overall state. Yet another aspect they developed from their data was a risk model, which predicted the risk of the patient to abuse opioids, or die from future use. Researchers used gradient-boosted decision tree classification (a machine learning algorithm) to identify areas of the patient medical history that were indicative. From this model, there were ten attributes identified as "predictors." These included: individuals between 44-60 years old are 71% more likely to abuse opioids in the future; patients with at least one non-opioid drug-related hospitalization in the past five years are 176% more likely to abuse in the future; the risk of opioid abuse and related mortality increases for patients with multiple hospitals discharges for any reason; individuals discharged more than three times in the past five years are 118% more likely to be admitted due to opioid-related events; patients with more than seven discharges are at 212% greater risk; and lastly, patients with a history of unspecified anxiety in the past five years are 1895 more likely to be hospitalized for opioid use [3].

C. INSPECT based analysis

Ray, B. et al., [4] examined accidental opioid overdoses using multiple sources of data over the course of six years (2010 through 2015), in Marion County, IN. Mortality files on drug-related deaths rely on the International Classification of Diseases, 10th Revision (ICD-10) codes and specific opioid substances related to fatalities is unidentifiable. With that being said, the researchers used mainly toxicology reports from the county coroner along with earlier research designs to obtain toxicology data. Then they examined whether opioid-related overdose trends are driven by changes in synthetic opioid prescriptions or illicit drug markets using data from the Indiana Scheduled Prescription Electronic Collection and Tracking Program (INSPECT) and the Marion County Forensic Services Agency's (MCFSA) screening of drug evidence. Using these aspects of information, they were able to identify the nature and source of opioid overdoses better and provide policy recommendations. The data come from MCCO, which gains jurisdiction over the cases when it is classified as a result of the casualty or violence or has died in apparent good health or found dead. Between January 1, 2010, and December 31, 2015, The MCCO provided 1256 case numbers of individuals established to have died of an accidental drug overdose in the county. Researchers then obtained death certificates to capture sociodemographic variables (age, race, gender, marital status) and toxicology reports for 1199 of the cases, and of these 918 cases involved opioids. Toxicology reports also indicated whether an opioid was present in the decedent's system at the time of death. The researchers recorded the following opioids: heroin (6-monoacetylmorphine), morphine, codeine, oxycodone, hydrocodone, oxymorphone, hydromorphone, and fentanyl. Along with the data resources above, they additionally analyzed prescription drug trends and drug crime lab results from the Indiana Scheduled Prescription Electronic Collection and Tracking Program (INSPECT) because licensed pharmacies were required to report the prescription and dispensation of specific drugs, with prescription opioids, included. Lastly, information from the Marion County Forensic Services Agency (MCFSA) to look at the changes and availability in illicit drug markets. MCFSA executes speculative and conformational analysis of substances seized by the Indianapolis Metropolitan Police Department (IMPD). Researchers state that such data doesn't allow for presenting all arrests made for possession and/or distribution of opioids, however they still approximate measures for changes in the

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patterns of illicit drug abuse. The analytic plan used for this research suggests opioid abuse to be steered by the prescribing rates of the substances, with that being said the goal was to examine whether the changes in prescription opioids are related to the opioid-related mortalities and illicit drug detection. Through their research and data analysis, they found that opioids were largely linked to the increase in drug-related mortalities. From toxicology reports, they were able to pinpoint the specific opioid-related substances distinguished in these deaths. At the time of this study, heroin and fentanyl were the most common accidental drug overdose substances, passing up prescription opiates being the leading cause back in 2010. To put this into perspective, the researchers state that by the time of this study, heroin-related deaths were nearly equal to the number of deaths related to all substances combined. They also found polydrug intoxication to be common more so amid the prescription opiates than illicit opioids. However, they did not gather data on all legal and illegal substances with the potential to interact with opioids, such as benzodiazepines. The forensic data collected from law enforcement along with prescription drug monitoring data, they were able to better identify trends in opioid-related mortalities. INSPECT data from 2010 to 2015 found steady reductions in prescription opiates, with fentanyl being of highest decline. The MCFSA data identified a pattern in heroin and fentanyl corresponding to the coroner's toxicology reports. The heroin detection rates nearly tripled and fentanyl increased from 4 cases to 60 by 2015.

Helmick, R. [5] analyzed the race-specific mortality rates between blacks and whites in Indiana to identify possible racial inequalities as well as to investigate trends in drug involvement in overdose deaths among black individuals. From 2013 to 2019, drug overdose deaths were identified using the death ICD-10 codes and taken from the Indiana State Department of Health's annual finalized mortality dataset. Death rates for race-specific overdoses were calculated and compared among racial groups and drug overdose mortalities in blacks were examined for temporal tends and by the types of drugs involved. Results showed from 2013-2017, drug overdose death rates in the white population increased from 17.05 to 27.28 per 100,000 whereas blacks increased at a higher rate going from 10.74 to 30.62 per 100,000. There was also an increase seen across all drug categories; opioids (3.05 to 18.62), cocaine (1.76 to 10.62), benzodiazepines (0.32 to 3.08), and psychostimulants other than cocaine such as amphetamines (0.16 to 1.69), all of which were per 100,000.

Al Achkar M., et al [6] examined the impact of Indiana's emergency prescribing regulations on prescription opioids where they intended to compare volumes of prescribed opioids before and after the Indiana emergency rules as well as arrange the changes in opioid prescribing by patient and provider subgroups. Emergency rules affected by the patient gender, age, payer, and zip code level combined with measures of socioeconomic status are also considered. Data were obtained from the Indiana Prescription Drug Monitoring Program (PDMP), which is Indiana's Prescription Electronic Collection and Tracking Program (INSPECT). The INSPECT records include patient ID, zip code, gender, birth year, the date the prescription was written, the date the prescription was dispensed, quantity dispensed, number of days supplied, pharmacy ID, pharmacy zip code, provider ID, provider zip code, payer, National Drug Code (NDC), and drug name. On December 15, 2013, Indiana put into effect emergency prescribing rules that are applicable to the patients who were prescribed for more than three consecutive months if they fall within one of two classifications; (1) >60 opioid-containing pills per month, or (2) a morphine equivalent dose >15mg/day. The researchers obtained data for all opioids dispensed in the state of Indiana 1079 days before the emergency rules (January 1, 2011) and 325 days after the policy (November 6, 2014). INSPECT data was conjoined with census data to identify socioeconomic status. Researchers analysed their data with an interrupted time series analysis (ITSA) to identify the association between the Indiana emergency rules and opioid prescribing. Additionally, analyzes were differentiated by patient gender, age groups, ranges of opioid dosages, and payers, and examined the implication of combining recipients' and practices' yearly per-capita income by zip code. The policy's reasonable impact was also examined, within each decile of daily average MED (morphine equivalent dose) of dispensed opioids per recipient. Lastly, the eight most commonly prescribed opioids were assessed as well, including hydrocodone, oxycodone, morphine, methadone, fentanyl, oxymophone, nuprenorphine, and hydromorphone. Through their research, the authors found Indiana's emergency rules to be associated with a decrease in the volume of accumulative opioid prescriptions and in the average number of opioid MED per patient. Along with that comes a decrease in inappropriate opioid dispenses and a decrease in opioid misuse and non-medical use. The emergency rules revealed a decrease in levels and trends for both genders, however more so for men than women, despite the fact that more women are prescribed opioids. As for patient age, there was nearly a 10 times larger decrease in ages 0-20 years old. Insurances showed the largest decline in Worker's Compensation, then Medicare and Medicaid. They also found a large negative impact of socioeconomic status, with higher amounts being prescribed in patients on the lower end as well as higher levels of opioid prescriptions being linked with higher aggregate income levels. Emergency rules also showed decreases in the daily MED per patient of all dispensed opioids and with the majority of each drug, except for morphine, fentanyl, and buprenorphine.

D. Spatiotemporal analysis using EMS Dispatches

Li Z. R. [7] examined the temporal and geographic variation in overdose emergencies in Cincinnati, Ohio from August 2015 to January 2019. The researchers present a spatiotemporal analysis of the locations of reported heroin-related incidents associated with EMS dispatches in the city and the spatial and temporal variability was assessed as a function of economic and demographic covariates, accessibility of medical facilities, and features of the built environment. A Bayesian discrete space-time regression model was used at the census block group level to account for the spatial and temporal correlation that cannot be explained by geographic and demographic covariates. The EMS call records labeled as "heroin-related" were mapped to the census block groups using the GPS locations, allowing the researchers to relate the number of incidents to demographic and socioeconomics variables. The covariates used in each block group include variables such as population size, percentage of the population by gender, age group, race, and education, median household income, per capita income, percentage of households below the poverty level, and median home values. For each block group, they also examined accessibility to health facilities and the built environments they were in by quarter miles, from bus stops, to park areas, and the number of fast-food restaurants. Zoning maps of the area was also obtained and put into nine categories: single-family housing, multiple-family, and institutional residential, office, commercial, urban mixed use, downtown development, manufacturing, riverfront, and planned development. Time-varying covariates were also obtained and included monthly counts of crime incidents per resident in each area and monthly average temperature, and total rain to account for seasonal variations. The researcher's results show a total of 6,264 incidents within the block group boundaries. Their analysis revealed higher numbers of heroin-related incidents were linked with features of the built environment. The proportion of the male population, along with those aged 35-49 and the distance to pharmacies were all positively related to the number of suspected heroin-related emergency calls. While on the other hand, the proportion aged 18-24, the proportion of the population with a minimum of bachelor's degree, median household income, number of fast-food restaurants, distance to hospitals, and distance to opioid treatment programs all had negative correlations.

III. Use of R for Analysis

In our research, we used R [8] to manipulate, calculate, and graphically display drug-related overdoses and deaths. In spatial statistics, the ability to visualize data through geographic context is invaluable, which can be achieved efficiently using R. Using R with google APIs and libraries (ggmap, ggplot, geoencoding and geom), heatmaps that are needed to analyze data were plotted. With the help of local police (Muncie, IN) and sheriff's department (Montgommery County, OH), we obtained drug overdose-related raw data. We fine-tuned it initially, geoencoded the data, and used R to plot the heatmaps.

Figure 3 shows the plotted overdose locations from 2016 to 2018 in the Muncie area, Figure 4 shows the plotted overdoses in the Dayton area.

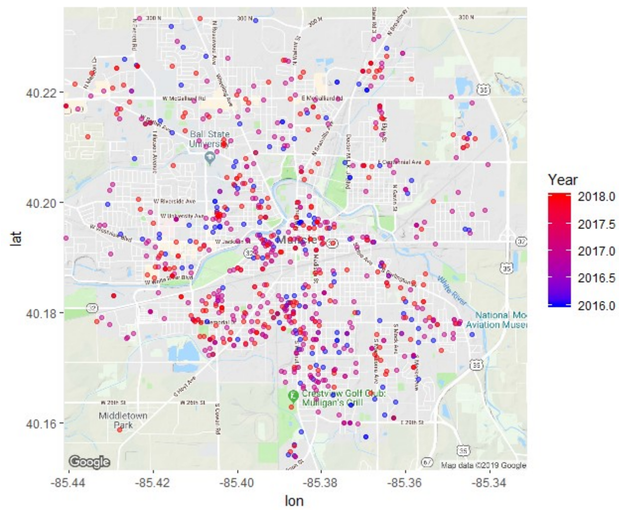

Fig. 3. Drug abuse pattern in city of Muncie, IN from 2016 – 2018

The plots reveal the progression of drug abuse from 2016 to 2018 (blue to red in color) in various neighborhoods. The data plots are invaluable for various NGOs and government officials. As of now, we are making plots available to NGOs concentrating on the needle exchange programs and the distribution of Narcan [9].

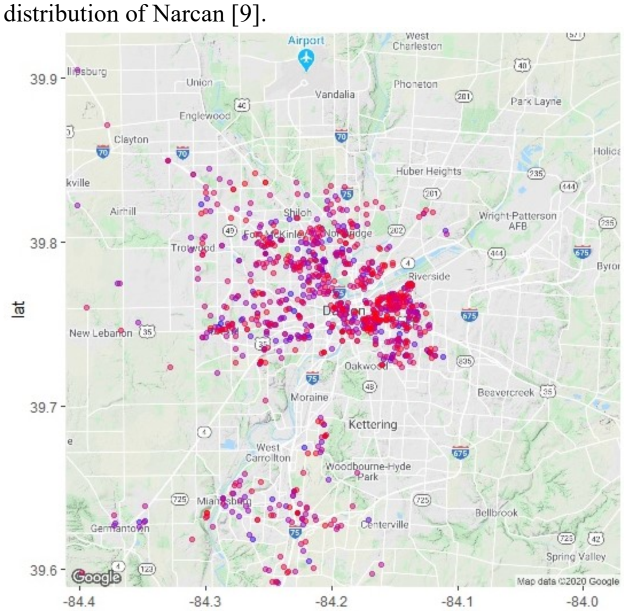

Fig. 4. Drug abuse pattern in the city of Dayton, OH from 2016 – 2018

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IV. Future Work

Even with the data we collected, it is not enough to predict future drug overdoses and the impact measurement of reforms implemented by the agencies.

In the future, we anticipate working closely with Delaware County's Department of Health and the Muncie Police Department to collect data and add more questionaries' for all the drug-related incidents. We would like to use this collected data to analyze various patterns of the individuals involved (by age, sex, socio-economical, race, location, etc.…), and to identify longitudinal patterns of drug abuse progression across Delaware and Montgomery counties.

Due to various regulations such as HIPAA, the data needed for further analysis is hard to collect. We are collecting data sets from health departments, INSPECT projects, coroner offices in Indiana. We plan to correlate with the previous data sets collected and the new ones to obtain more detailed, real-time data analytics.

We will also try to identify fentanyl effect mixed with traditional drugs through the study. We also plan to work with local community volunteers and involve in the programs such as needle exchange, Narcan distribution and study the impact of these measures in the community.

V. Conclusion

Drug abuse and overdoses are a pandemic that is effecting the United States unlike any other disaster before. People, administration, and NGOs are unable to identify the progression and effects in localized communities to address the epidemic issue. Most of the studies are identifying aftereffects of drug abuse and overdoses. In our study, we addressed the future progressions such as opioid pills to heroin and to fentanyl of the individual users and community. Also, these studies can be made available to drug enforcement agencies. Using R, we effectively projected in a community how the progressions happened over the years. In the near future with additional data set integration, we can pinpoint the root causes in a community.

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