

Understanding the factors related to the opioid epidemic using machine learning

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Abstract—In recent years, the US has experienced an opioid epidemic with an unprecedented number of drugs overdose deaths. Research finds such overdose deaths are linked to neighborhood-level traits, thus providing opportunity to identify effective interventions. Typically, techniques such as Ordinary Least Squares (OLS) or Maximum Likelihood Estimation (MLE) are used to document neighborhood-level factors significant in explaining such adverse outcomes. These techniques are, however, less equipped to ascertain non-linear relationships between confounding factors. Hence, in this study we apply machine learning based techniques to identify opioid risks of neighborhoods in Delaware and explore the correlation of these factors using Shapley Additive explanations (SHAP). We discovered that the factors related to neighborhoods' environment, followed by education and then crime, were highly correlated with higher opioid risk. We also explored the change in these correlations over the years to understand the changing dynamics of the epidemic. Furthermore, we discovered that, as the epidemic has shifted from legal (i.e., prescription opioids) to illegal (e.g., heroin and fentanyl) drugs in recent years, the correlation of environment, crime and health related variables with the opioid risk has increased significantly while the correlation of economic and socio-demographic variables has decreased. The correlation of education related factors has been higher from the start and has increased slightly in recent years suggesting a need for increased awareness about the opioid epidemic.

Index Terms—Opioid Epidemic, Substance Use Disorder, Addiction, Machine Learning, Public Health

I. INTRODUCTION

For about 30 years, the United States (U.S.) has suffered a widespread crisis of opioid addiction and overdose deaths. In 2019 alone, more than 50,000 Americans lost their lives to opioid overdose [1]. This is an almost 200% increase in deaths compared to just a decade ago (16,651 people in

2010) [2]. Subsequently, there has been a significant effort to elucidate the factors driving this epidemic and enact strategies to combat it. Led by the White House's Office of National Drug Control Policy [3], federal agencies such as the Drug Enforcement Agency (DEA), the Centers for Disease Control and Prevention (CDC), the Department of Health and Social Services (DHSS), and the National Institutes of Health (NIH) have taken several initiatives to address these problems [4]. Despite these initiatives, there has been a consistent increase in deaths from both legal and illegal opioids [5], [6]. Traditionally techniques such as Ordinary Least Squares (OLS) and Maximum Likelihood Estimation (MLE) are not well suited to exploit the increasingly non-linear relationships between various neighborhood-level indicators of opioid overdose [7]. Machine learning techniques coupled with widely available neighborhood level surveillance data can be a valuable tool to model these non-linear relations. Hence, in this study we utilize the Random Forest [8] to build a model to identify the opioid risk of neighborhoods across Delaware. We use socio-demographic data from the US Census, crime data from the Delaware Criminal Justice Information System (DELJIS), and opioid overdose data from Delaware Division of Forensic Science (DFS) [9]. Understanding the factors driving the epidemic is very important in formulating effective intervention strategies. Therefore, we use recent advancements in model interpretability to analyze our model [10] and understand the factors it considers important in identifying the opioid risk. In addition to understanding the globally important factors, we also compare the change in these factors over the years to understand the changing dynamics of the opioid epidemic.

II. METHODS

A. Outcome variable — Opioid risk

In this study our goal was to use machine learning methods to identify neighborhoods (i.e. census tracts) in Delaware at an increased risk of overdose deaths and understand which neighborhood-level factors were correlated with them. Delaware, a small state located in north-eastern part of the country, has been among the worst affected states by the epidemic. It has consistently ranked in the top ten states for highest overdose death rate, and in 2018 reported the second-highest overdose death rate in the nation [5]. With its mix of urban regions to the north and rural regions to the south, Delaware is a microcosm to discover insights that might be applicable to the larger U.S. [11].

For this study we built a longitudinal dataset of [census-tract + year] combinations containing 1444 observations for overdose deaths at census tract level from 2013 to 2019. We use the overdose death data from the Delaware Opioid Metric Intelligence Project (DOMIP) [9].

While substance abuse in the U.S. has increased in recent years, research shows it is still patterned by region [12]. This is true in Delaware as well, where some neighborhoods experience a higher level of opioid-related overdose deaths compared to others. This results in data having a semicontinuous distribution with a large proportion of neighborhoods (50%) having no deaths. When studying data with a large proportion of zeros, one cannot use commonly used methods such as linear regression as the resulting model will be biased towards zeros. Ideally, it is advised to adopt a two-part model where we fit two models — A) Classification model to differentiate between zero and non-zero values, and B) Regression model to model the death rate [13].

Since our goal in this study was to identify neighborhoods with an increased opioid risk, and not predict the death rate, we decided to discretize the continuous outcome variable i.e., opioid overdose deaths to a categorical variable named opioid risk having two categories — High and Low. In consultation with subject-matter experts, we decided to specify any neighborhoods having opioid overdose death rate equal to or above 75th percentile to be in the High-risk category and any neighborhoods having opioid overdose death rate less than 75th percentile to be in the Low-risk category.

B. Determinants of opioid risk

In recent years, research has found social and environmental factors play an important role in determining the health of individuals in a neighborhood [14], including opioid consequences [15]–[18]. Such influential neighborhood-level characteristics can include population density, racial and gender diversity, and measures of concentrated disadvantages such as poverty or education [15], [19], [20].

Thus, informed by prior research [12], [21]–[23] we choose fifty-five variables across six different categories — 1) Socio-demographic, 2) Environment, 3) Education, 4) Crime, 5) Economic, and 6) Health to serve as determinants of the opioid risk of a neighborhood [Table I].

We retrieved the data for all categories except the Crime category from the American Community Survey (ACS) conducted by U.S. Census Bureau [24]. We retrieved the data at the census tract level for years 2013 to 2019. For the Crime category, we use the arrests' data from Delaware Criminal Justice Information System (DELJIS) at the census tract level from years 2013 to 2019.

C. Machine learning

1) *Data preparation:* Since the ACS data is collected from surveys, it often contains missing values. A majority of the variables in our model had less than 7.0% missing values except for "Number of households with coal as the primary source of heating" and "Number of Mobile Homes" which had 26.69% and 36.92% missing values respectively. Thus, we preprocessed the predictor variables to replace missing values with their averages across the years. Then, we randomly split the data into training (80%) and testing (20%) sets. The training set contained 1155 samples of which 866 samples belonged to low risk category and 289 samples belonged to high risk category and testing set contained 289 samples of which 221 samples belonged to low risk category and 68 samples belonged to high risk category. We used the training set for hyper-parameter optimization and model training, and the testing set for evaluating the final model performance.

2) *Model training and evaluation:* Since we had limited samples for training the model we used K-Fold cross validation ($k=10$) to train and evaluate the model on all possible splits of training data while performing the hyper-parameter search. Once we had the best performing hyper-parameters, we trained the final model using these hyper-parameters and then evaluated its generalized performance on the testing data.

Since our target variable was highly imbalanced, traditional metrics such as accuracy and area under receiver operating characteristics (AU-ROC) would not provide an appropriate overview of the model performance. Therefore, we evaluated our model using area under precision and recall curve (AU-PR).

3) *Feature importance:* For the end users to have trust in the predictions, it is essential to know the factors the model considers important in making the predictions. Interpretability of machine learning models can be broadly achieved either by building simpler models that are intrinsically explainable or by post hoc analysis after training the models. The first approach sacrifices predictive performance in favor of interpretability but is not generalizable to any other types of models. The second approach preserves the predictive performance but requires additional effort to interpret the model but is more generalizable [25]. In this study, we adopt the second approach and make use of the Shapley Additive Explanations (SHAP) [10] to understand our model.

D. Results and Discussion

1) *Model performance:* We executed the hyper-parameter tuning step in the above pipeline 100 times, each time randomly changing the hyper-parameters. After 100 iterations,

TABLE I
PREDICTOR VARIABLES

Sociodemographic	Environment	Education	Crime	Economic	Health
Population Density Male and Female population [under 18 years, 18 to 44 years, 45 to 65 years, 65 years and above] Race [Black, White, Other] Home Language [English, Non- English]	Total Number of housing units Number of occupied housing units Number of vacant housing units Number of households with no vehicle Number of households with coal as primary source of heating Number of households with no fuel for heating Number of mobile homes Number of female headed households No vehicle for transport to work No public transport vehicle for transport to work	Population with education below college Population with college edu- cation, but no degree	Population arrested for vio- lent crimes Population arrested for prop- erty crimes Population arrested for so- cially important crimes Number of juveniles arrested for any crime Number of youths arrested for any crime	Median income - [All, black, white, other] Median rent Total employed population [All sectors, agriculture and mining, construction, manu- facturing, wholesale, trans- portation and warehousing, arts and recreation] Population below poverty [All, white, black, other]	Disabled population [All, males, females] Without health insurance [All, males, females, all below 18 years, all from 18 to 65 years, all above 65 years]

we sorted the results by AU-PR to obtain the best performing hyper-parameters and train the final model. Figure 1 provides an overview of the performance of the best model [AU-PR = 0.65].

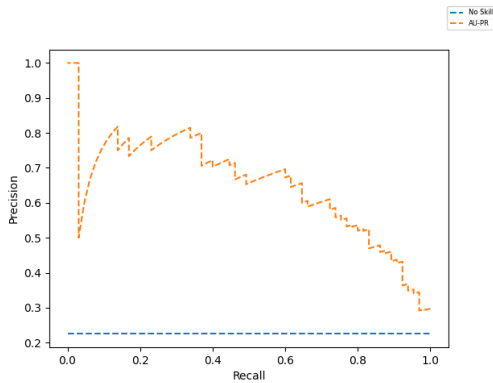


Fig. 1. The area under PR-Curve (AU-PR) is an indicator of the model performance with higher AU-PR indicating better model performance. The no-skill line indicates the performance of a model that predicts random classes regardless of the input and serves as a baseline to validate the model.

2) *Globally important community level factors:* In our pursuit to understand the factors influencing the overall opioid risk of neighborhoods, we decided to investigate the factors influencing the predictions irrespective of the geographical space or the year involved. To do so, we calculated the feature importance for every sample in the testing set. Shapley values can be either positive or negative depending on the direction in which they help the model prediction. In our case, since our model is a binary classification model, the direction of the Shapley value does not provide any meaningful information, but the magnitude of the Shapley value provides an indication of the feature's importance for the model. Hence, we convert all the feature importance to their absolute values, and then we calculated an average of every feature across the 289 samples to get an overview of the global feature importance. Table II shows the top 10 features that are globally correlated with an increased opioid risk of neighborhoods in Delaware from year

2013 to 2019.

TABLE II
GLOBALLY IMPORTANT COMMUNITY LEVEL FACTORS

Category	Feature	Importance
Environment	Number of households with no vehicle	0.045
Environment	Number of households with coal as the primary source of heating	0.029
Education	Population with no college education	0.022
Education	Population with college education but no degree	0.017
Crime	Number of people arrested for property crimes	0.014
Health	Number of males with disability	0.013
Crime	Number of people arrested for violent crimes	0.011
Economy	Median Income	0.008
Health	Number of females with disability	0.007
Socio-demographic	Number of households with English as the only language	0.007

The “number of households with no vehicles” and “number of households with coal as a primary source of heating” are primarily the indicators of urbanity or rurality of a neighborhood. Households in urban regions usually have better access to public transportation require less access to cars for daily activities [26]. On the other hand, use of coal as a source of heating is more common in rural regions [27]. These correlations are in line with existing research that has suggested that in recent years opioid epidemic has been expanding from rural regions to urban regions [28]. Higher levels of education have been associated with healthier populations [29]. Hence, “Population with no college education” being one of the top factors is consistent with past research. Prior studies have also shown opioid-related overdose mortality is significantly higher in adults with a disability attributed to the misuse of opioids prescribed for pain relief [30]. This is evident in our model were health related variables —“Number of males with disability” and “Number of females with disability” are among the important features. For socio-demographic variables, “Number of households with English as the only language” and “White population” are congruent with the existing research that has suggested the opioid epidemic has primarily affected non-Hispanic white middle-aged male population [31].

Our most interesting observation, though, is that crime-related variables have a significantly higher correlation with the opioid risk than socio-demographic, health or economic variables. This could be an indication of the ongoing shift in the nature of the epidemic from legal prescription opioids to illegal synthetic opioids, at least with respect to the cause of overdose deaths.

Individual correlations of neighborhood factors with opioid risk, though very important, do not provide a complete picture. Often, these individual neighborhood factors can be grouped into concepts/categories that embody a particular facet of our communities. Hence, we also calculate aggregated feature importance according to these concepts or categories. Figure 2 shows the relative importance of six categories in identifying the opioid risks of neighborhoods in Delaware from year 2013 to 2019.

The environment is the most important factor in determining the overall opioid risk. It is followed by education and crime related factors suggesting an ongoing change in the nature of the epidemic from legal to illegal drugs. Socio-demographic and health related factors are equally important which might indicate that this epidemic has been primarily affecting a particular subset of the population. This is followed by economic factors which seem to have the least amount of importance in determining the opioid risk.

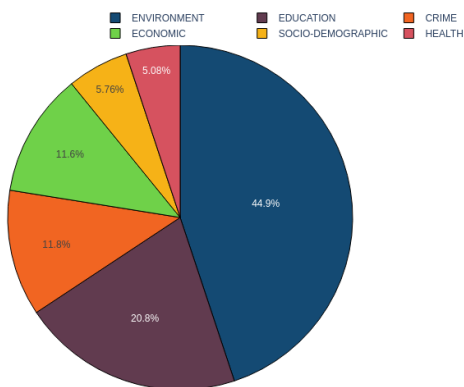


Fig. 2. Relative importance of different factors in determining the opioid risk.

3) *Change in the dynamics of the epidemic*: The Centers for Disease Control and Prevention (CDC) has characterized the U.S. opioid epidemic as having three distinct waves, with the first wave starting in 1991 [32]. This first wave was primarily attributed to the widespread use of prescription opioids, the second wave starting in 2010 was characterized by an increase in deaths due to illicit opioids such as heroin and the third wave starting in 2013 can be attributed to Illegally manufactured fentanyl — a highly potent synthetic opioid. Since then, fentanyl in combination with other drugs such as heroin and cocaine have dominated opioid related overdose deaths [Figure 3] [32].

Even though these waves were primarily attributed to different types of opioids, the underlying neighborhood factors driving each has been understudied and hence we try to un-

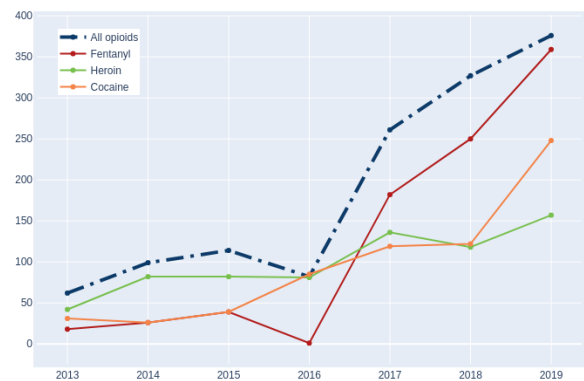


Fig. 3. Overdose deaths in Delaware from 2013 to 2019. Total number of overdose deaths have increased tremendously since 2016 and can be attributed primarily to fentanyl. Deaths due to cocaine have also been increasing steadily and have reached their highest levels in 2019. Deaths due to heroin have seen increase but not as tremendously as fentanyl or cocaine.

derstand if there were any differences in neighborhood factors driving these waves. As evident from [Figure 3], overdose deaths in Delaware have shifted after 2016. Hence, to tease out the factors that might be driving these changes, we developed two distinct models. The first model was developed to identify only heroin risk and the second model was developed to identify [fentanyl+cocaine] risk. We kept the determinant neighborhood factors constant for both the models and trained them using the same technique used to train the opioid risk model. The [fentanyl+cocaine] model had an AU-PR score of 0.67 and the heroin risk model had an AU-PR score of 0.32. The difference in AU-PR scores of both the models can be attributed to the fact that fentanyl and cocaine related deaths have increased at a much faster pace compared to heroin deaths leading to a stronger signal in the fentanyl+cocaine data.

We extracted the feature importance from both models using the same method used to extract the global feature importance in the previous section. Table III and Table IV show the top 10 factors correlated with heroin risk and the fentanyl and cocaine risk, respectively. [Figure 4] shows the difference between the factors considered important by both models.

The most striking difference between the two models is the inversion of importance of environment, socio-demographic and crime factors. For the [fentanyl+cocaine] model, the importance of environment-related variables have doubled compared to the heroin model. Taking a look at [Table III] and [Table IV], we see “Households with no vehicles” is an important factor for both the models, but “Households with coal as a primary source of heating” and “Number of mobile homes” is among the top 10 important features for [fentanyl+cocaine] model suggesting a relatively rural predominance of the fentanyl and cocaine risk.

Similar to the environment factors, the importance of crime related factors has also increased significantly. Proliferation of illegal drug markets might explain the importance of the number of arrests related to property crimes and violent offenses. Researchers have shown that violence is frequently

a defining feature of illicit markets [33]. The violence could be directed against the law enforcement officers trying to curb the illegal trade or against other market actors in an effort to gain market dominance [34]. In either case, increased importance of crime related variables might be suggestive of an active and thriving drug market in Delaware. Another contrasting feature of the [fentanyl+cocaine] model is the higher importance of health related variables such as “Number males with disability” and “Number of females with disability” which mirrors prior knowledge of opioid overdose risk being high in patients prescribed opioids for pain management [35], [36].

The importance of socio-demographic factors has decreased significantly in recent years. The heroin risk model suggests a higher predominance of heroin risk in the white population due to higher importance of “Home language English Only” and “White Population”. This is in line with the existing research that has suggested presence of significant racial diversity in the use of heroin with white population being more likely to use heroin and hispanic and black population more likely to use cocaine [37]. The [fentanyl+cocaine] model considers other racial groups (Asian, Alaskan natives and Hawaiian natives) to be more important than either white or black population (see supplementary file) suggesting a change in the population that is being affected by the epidemic in recent years.

Overall, it is evident that in the recent years, the opioid epidemic has transcended the boundaries of race and income and is affecting almost all parts of the population in some manner. Primary drivers for the opioid epidemic in recent years include variables related to the environment, crime and health as evident by their increased importance in determining fentanyl and cocaine risk. Thus, interventions targeted at addressing these factors might inform best practices in combatting the opioid epidemic.

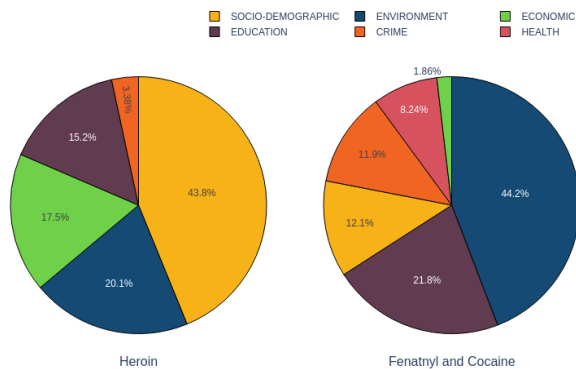


Fig. 4. Relative importance of factors in identifying Heroin risk vs Fentanyl and Cocaine risk.

E. Conclusion

In this work we have presented our approach of using machine learning to understand the factors driving the opioid epidemic. We developed a model to identify the opioid risk

TABLE III
IMPORTANCE FACTORS — HEROIN RISK

Category	Feature	Importance
Socio-demographic	Home language English only	0.028
Education	Population with no college education	0.015
Environment	Number of households with no vehicles	0.014
Socio-demographic	White population	0.010
Socio-demographic	Population density	0.009
Education	Number of people with college education but no degree	0.009
Environment	Total number of housing units	0.06
Economy	Median income of white population	0.008
Environment	Number of occupied housing units	0.007
Economy	Number of people employed in construction	0.007

TABLE IV
IMPORTANCE FACTORS — FENTANYL AND COCAINE RISK

Category	Feature	Importance
Environment	Number of households with no vehicle	0.059
Education	Population with no college education	0.033
Environment	Number of households with coal as primary source of heating	0.028
Education	Number of people with college education but no degree	0.021
Crime	Number of people arrested for property crime	0.016
Crime	Number of people arrested for violent crime	0.013
Health	Male population with disability	0.07
Environment	Number of mobile homes	0.011
Health	Number of males with disability	0.011
Health	Number of females with disability	0.009

of neighborhoods in Delaware using widely available neighborhood level data. We used Shapely Additive Explanations to understand the correlation between neighborhood factors and opioid related overdose deaths. Since the number of deaths increased dramatically after 2016, we developed two additional models to understand the factors related to this dramatic increase in deaths.

We learned that in the recent years, environment related factors were the most significant drivers of the opioid epidemic. This was followed by a significant increase in importance of crime related variables, suggesting an accelerating shift in the opioid epidemic from the legal to illegal drugs. We also determined that, in accordance with the existing knowledge, health related factors continue to be a significant determinant of opioid risk. Finally, education related factors being equally important in determining heroin as well as fentanyl and cocaine risk suggests that raising public awareness about the adverse effects of substance abuse might result in a decrease in mortality due to substance abuse.

Machine learning models though tremendously useful in determining the correlation among the predictor and target variables, are not appropriate for explaining the causal link between these variables. Therefore, the results from our study should not be used as direct evidence of the causality of certain factors in determining opioid related overdose deaths.

Instead, we think our results can serve as a guide for future studies performing an in-depth investigation into the casual relationships between these factors and the opioid epidemic.

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