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Summary Sheet

The United States is experiencing a national crisis regarding the use of synthetic and non-synthetic Opioids, causing increasing damages to people's lives and health. And our objective is to describe the spread and characteristics of the synthetic opioids and take some strategies to prevent the crisis happening.

Firstly, for further use of data, we **standardized** the raw data by counting the number of reports in different states, counties as well as opioids. Based on the data, we use the **hierarchical clustering method** to cluster these opioids from their severities and influences. Besides, in order to compare the severity of opioid use in different states and counties, we defined the **Opioid-induced Social Harm Index (OSH Index)** by using **analytic hierarchy process (AHP)** method. The result shows

Secondly, in order to the changes and spread of opioid use, we established the **combined epidemic model (SIR model)** by combining the **traditional SIR model** and **gravity model**, which may affect the infectiousness of some opioids. In addition, our s**ensitivity analysis** shows that the opioid use is sensitive to the education, social life and government policies.

Finally, we build the **linear polynomial regression** model to analyze the impacts and derivatives of some important factors from the perspective of education, household conditions and marital status. The results shows that the higher the education is, the fewer the opioid use. Besides, the OSH index is negatively correlated with education, social life. And African people are more likely addicted to opioid use compared to Asian and European people.

Based the work above, we give some strategies to help U.S. government to cope with the Opioid Crisis and hope it can get better and better

Contents

Demo

Dear Chief Administrator:

Greetings! Having studied the current situation of opioid crisis, we have made the following results and insights to this specific problem.

Here is the rankings of the life threatening opioids that are popular in KY, PA, WV, VA and OH.

$[Heroin, Methadone, Oxycodone, Hydrocodone]$

By referring to the rankings of these four opioids, we created the Opioid-induced social harm (OSH) Index which could reflect the opioid harm on society. We found out the general trend of total drug reports in both county and state is decreasing over time.

By defining the threshold value (using OSH Index) and evaluating the total drug reports in each state, we conclude that the opioid spread is most likely to start from Ohio State, and the year that those states will reach the threshold value is shown below.

County	The year when the threshold is met
Ohio	2035
Virginia	2045
Pennsylvania	2040
Kentucky	2042
West Virginia	2080

With our results, we have some suggestions for the prevention of further spread of opioids:

1. The U.S. government should arrange more budgets on public colleges and graduate schools.
2. The U.S. government can legalize the medical use of some pain-relieving substances.
3. It is essential to provide various social life to those elder people living alone.

1. Introduction

1.1 Background

The United States, especially the Appalachia region, is experiencing a crisis regarding the use of synthetic and non-synthetic opioids.

The Opioid Crisis in the Appalachia region stems partially from socio-economic reasons, such as lack of education and poverty. In the past, coal industry drew much of the original population to the region. With the United State relying less upon coal for energy, coal jobs suffered and some people left for better opportunities. The result was crippling poverty and lack of education that still exists today. Where hope has left the region, addicting opiates have entered.

The Opioid crisis affects the U.S. population health and its economy. If the opioid crisis spreads to population cross-sections, filling in skill-demanding positions will be affected; if the crisis spreads within elders, health care costs and assisted living facility staffing will also be affected.

1.2 Restatement of Problem

We will model the reported synthetic opioid and heroin incidents of counties located in the five states (Ohio, Kentucky, West Virginia, Virginia, and Pennsylvania). We are not only required to describe and predict the spread of opioid usage, but are also required to associate the spread with U.S. Census socio-economic factors and propose strategy for countering the opioid crisis.

The problem can be analyzed into three parts:

- Describe opioid spread and characteristics, identify its origin, and predict future concerns
- Modify the model to include socio-economic factors if associated with opioid usage
- Identify a strategy for countering the opioid crisis, use the model to test its effectiveness, and identify parameter bounds

1.3 Literature Review

Opioid use disorder has reached epidemic levels in the United States, with a 200 percent increase in overdose deaths from opioid and heroin use between 2000 and 2014 (Robin Ghertner and Lincoln Groves, Ph.D., 2018). Base on this literature, we incorporate the rapidity of spread as a characteristic in our model while SIR Model serves as a reference.

Literature provides information regarding correlation between opioid spread and socio-economic factors: Poverty, unemployment rates, and the employment-to-population ratio are highly correlated with the prevalence of prescription opioids and with substance use measures (Robin Ghertner and Lincoln Groves, Ph.D., 2018).

Literature also exhibits severe consequences regarding the crisis: Overdose death rates involving opioids have risen dramatically, with deaths due to synthetic opioids other than methadone doubling from 2015 to 2016 (Robin Ghertner and Lincoln

Groves, Ph.D., 2018). Therefore, we propose a countering strategy.

2. Assumptions and Notations

To simplify the real life situation, we will make the following assumptions as a start of the model construction:

- **The county location data are correct as provided.** Typically, when law enforcement organizations submit these samples, they provide location data (county) with their incident reports.
- **All opioids provided will not be affected during transportation.** This ensures that drugs can be spread in the five states regardless of traveling distance and other conditions.
- **The larger the county's total opioid reports difference (absolute value) between 2010 and 2017, the better that county reflects opioid spread's varying pattern within state between 2010 and 2017.** We assume that significant increases and/or decreases in several counties' total drug reports (from 2010 to 2017) are representative of the state's change of spreading pattern.
- **The smaller the county's total report difference (absolute value) between 2010 and 2017, the better that county reflects opioid spread's stable pattern within state between 2010 and 2017.** We assume that small or no changes in several counties' total drug reports (from 2010 to 2017) are representative of the state's table spreading pattern.
- **There is geographical distance decay in the spread of opioids.** With increasing distance, there are less spread of opioids among places.
- **Earth is an approximate sphere.** We can calculate the distance between points on Earth by math equations regardless of Earth's ellipsoid shape.
- **Drug identification threshold levels which government concern occur by the mean value of the five states' opioid-usage.** This help us predict when government concern occur (usage exceed threshold) in states given.

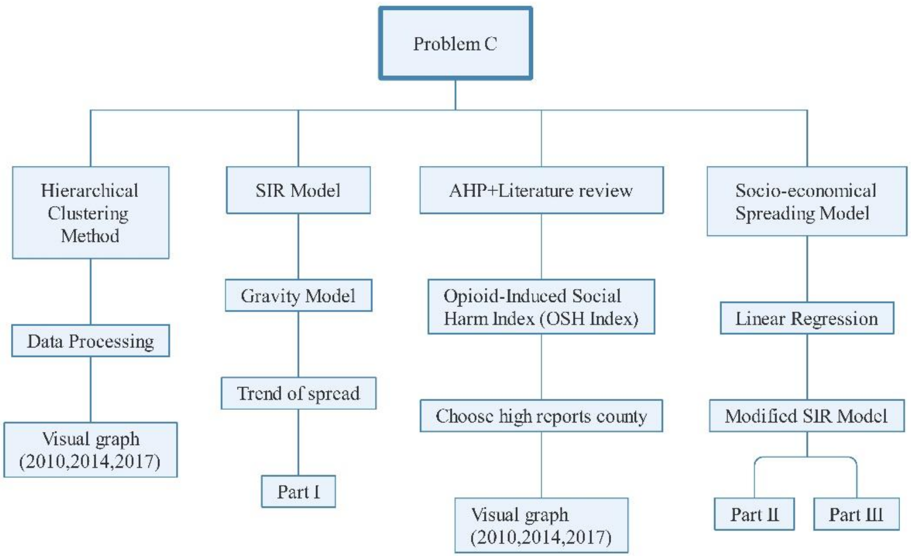
Symbols	Units	Definition
	Data Processing	
x	1	Amount of opioid reports in a county in 2010
x'	1	Amount of opioid reports in a county in 2017
D	1	Amount difference from 2010 to 2017
D_A min	1	Positive minimum difference
D_B min	1	Negative minimum difference
R	1	Difference range
	Distance Calculation	
r	km	The radius of the Earth
d	km	The real distance between two states or counties

Gravity Model		
G_{ij}	1	Size of the interaction
P_i	1	Size of the index of every thousand people in state *i*
P_j	1	Size of the index of every thousand people in state *j*
k	1	Constant of the Gravity Model
SIR Model		
I	1	Group that abuse drugs
S	1	Group that are vulnerable to addict to opioids
L	1	Group that addicted to opioids and then give them up
a	1	Probability of infection of *S*
b	1	Probability of recovery of *I*
Modified SIR Model		
Y	1	Dependent variable
$x_1, x_2, x_3 \dots x_n$	1	Independent variable
ε	1	Residual in the equation

3. Models

3.1 Model Overview

Based on the analysis above, the total process of our work are shown as follows:



3.2 Opioid geographical spreading Model

3.2.1 Data Processing I: Spread in Breadth

a. Hierarchical Clustering Method

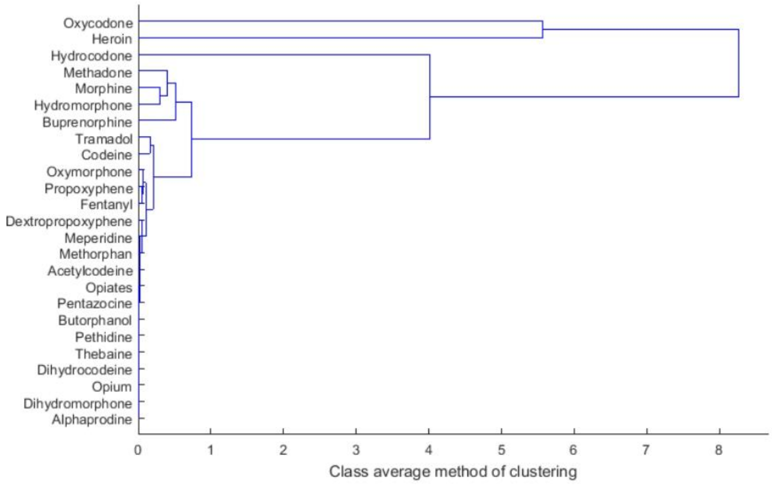
We want to divide all types of opioid provided into four clusters base on their spread in breadth. The more an opioid being reported, the more it is spread in breadth. Thus, the **Hierarchical Clustering Method** is applied to those types of drug with the reports each opioid in five states respectively and in Appalachia region as general (sum of five states). In this way, we may obtain a 6-dimension coordinate for each drug. At this point, we use **Euclidean Distance**, where the distance is defined as the following:

$$\|a-b\|_2 = \sqrt{\sum_i (a_i - b_i)^2}$$

We choose **Average Linkage Clustering:**

$$\frac{1}{|A|.\,|B|}\sum_{a\in A}\sum_{b\in B} d(a,b).$$

The result is shown below:



We have four clusters: the first three clusters are Oxycodone, Heroin, and Hydrocodone, and the fourth cluster (we refer to it as "Miscellany") is the combination of all other opioids provided. For modified SIR Model I, we use these four opioid clusters instead of all specific opioid types.

b. Representative Data Selection

We use macroscopic perspective to analyze opioid spread in breadth between states; besides, we use microscopic perspective to analyze its spread within states.

When presenting reports amount in the fourth cluster "Miscellany", we select six representative opioid types. Since other opioids are seldom reported, we may neglect their impact.

When processing data to describe opioids' spreading pattern, we select thirteen representative counties that reflect both varying and stable patterns:

Arrange D in descending order from D_1 to D_n.

(1) Ten representative counties of varying pattern:
According to our assumption, the larger the county's total report difference (absolute value) between 2010 and 2017, the better that county reflects opioid spread's varying pattern within state between 2010 and 2017.

According to our notation, $D = x - x'$. We select ten counties that has D_1, D_2,

D_3, D_4, D_5, D_n, D_{n-1}, D_{n-2}, D_{n-3}, D_{n-4}, respectively.

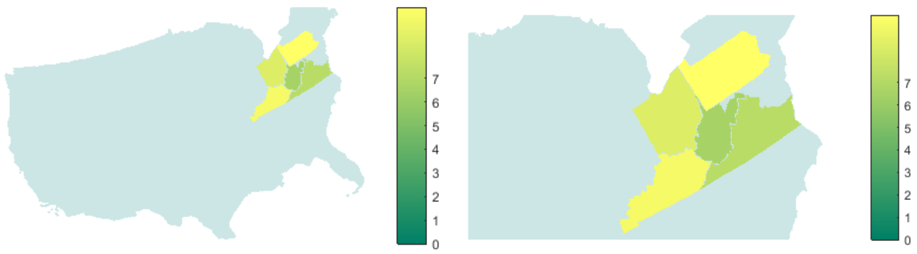
(2) Three representative counties of stable pattern:
According to our assumption, the smaller the county's total report difference (absolute value) between 2010 and 2017, the better that county reflects opioid spread's stable pattern within state between 2010 and 2017.

According to our notation, $R = (D_1 - D_n) > 0$. We first select counties that satisfy the condition below:

$$D \in \left[D_A\ min + 1\%R, D_B\ min - 1\%R\right]$$

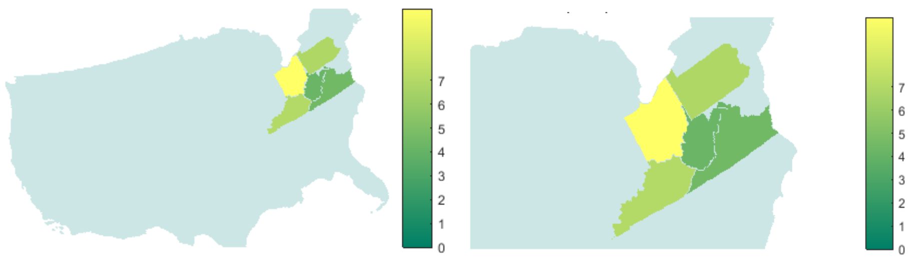
Then, from the previous set of selections, we select counties with the three top x values. Therefore, thirteen representative counties for analyzing opioid spread from 2010 to 2017 are selected.

In macroscopic view, we visualize five states' opioid spread (in breadth) of four opioid clusters' report amount as below. The degree of opioid spread is represented by colors, green stands for low quantity of total drug reports, while yellow represents high quantity of total drug reports.



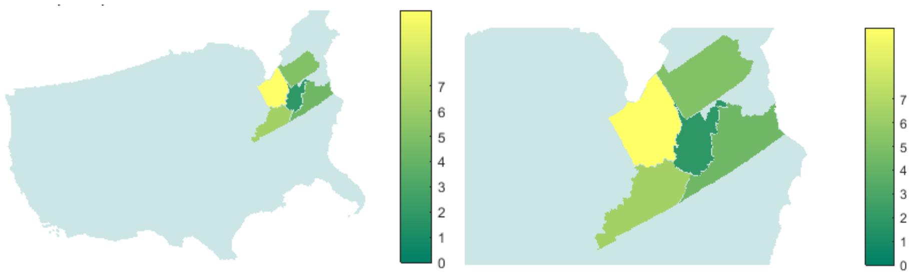
Opioid reports per thousand people in the five given states in 2010

As the figure shows above, we could clearly see that in the year 2010, PA and KY have relatively large numbers of total drug reports. VA is not affected that much compared with other four states.



Opioid reports per thousand people in the five given states in 2014

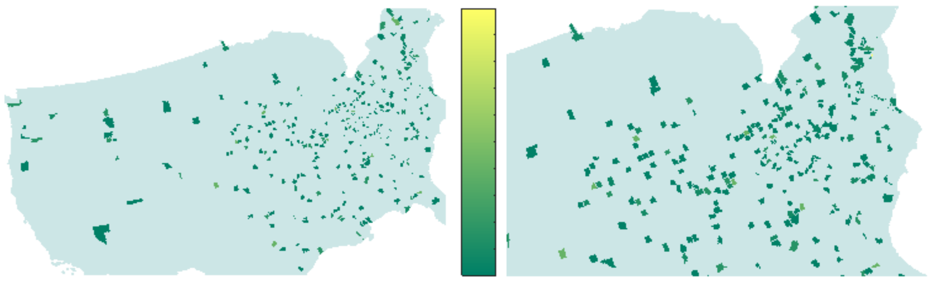
In the year 2014, due to the external factors, the degree of opioid spread varied in the five states. There is a similar pattern in PA, WV, KY and VA those four states, where the total number drug reports all decreased to some extent compared to the data in 2010. However, there is one exception, which is Ohio State, the total reports slightly increased during these 4 years, which indicates that the opioids addiction is more severe in Ohio State.



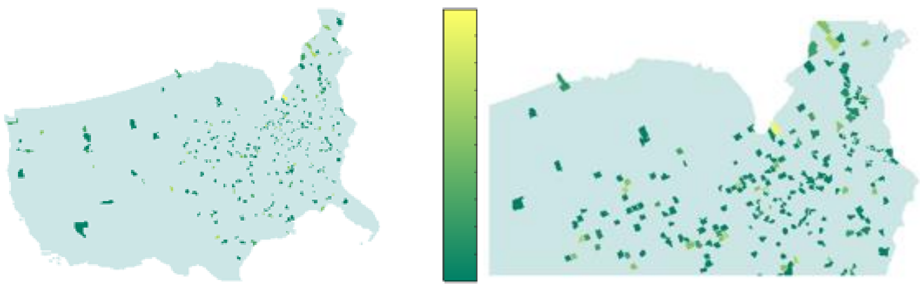
Opioid reports per thousand people in the five given states in 2017

The total number of drug reports in almost remains the same compared the data from year 2014 to 2017. Comparing the three graphs above, we can conclude that spread of opioid use is restricted strictly in KY, WV and especially in VA over time because the total number of drug reports decreased constantly. In contrast, the opioid abuse spread rapidly in Ohio State and more people are addicted to the opioids.

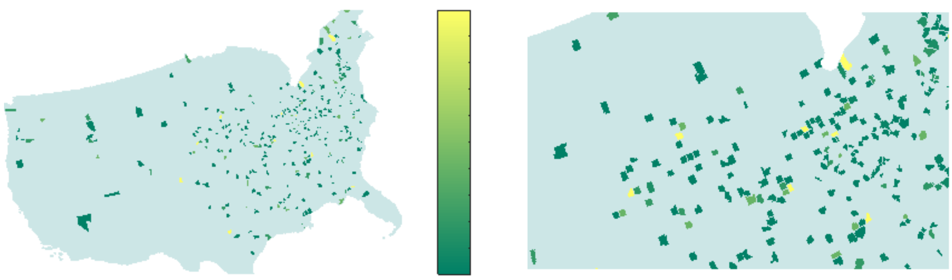
In microscopic view, we visualize selected counties' (counties are selected from each state) opioid spread (in breadth) of four opioid clusters' reports amount as below.



Total opioid reports in selected counties in 2010



Total opioid reports in selected counties in 2014

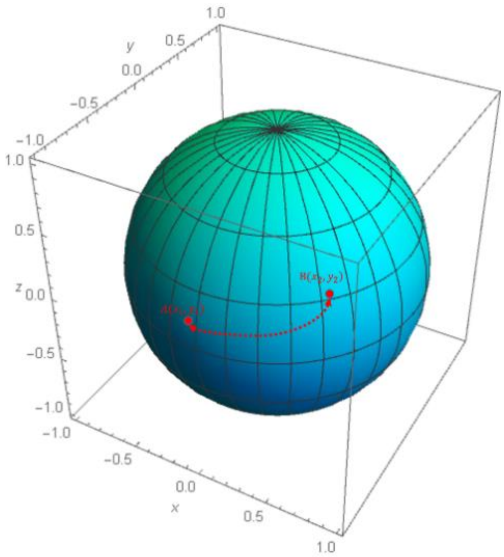


Total opioid reports in selected counties in 2017

According to the graph above, we can obviously observe that Philadelphia has the greatest number of total county opioid reports from year 2010 to 2017, followed by Hamilton in Ohio State. Besides, there also exists a similar pattern for the counties that we selected. The total opioid reports continue to drop, which indicates that the spread of opioids is bring controlled.

3.2.2 Modified SIR Model I

a. Distance between two states or counties



(x_1, y_1) , (x_2, y_2) denotes the longitude and latitude of two sites, respectively. Given geographic coordinate, we could establish the three dimensional rectangular coordinate system, and their coordinates can be shown as follow:

$$A(R\cos x_1 \cos y_1, R\sin x_1 \cos y_1, R\sin y_1)$$

$$B(R\cos x_2 \cos y_2, R\sin x_2 \cos y_2, R\sin y_2)$$

Where R represents the radius of the Earth.
The real distance between A, B is:

$$d = R\arccos\left(\frac{\overrightarrow{OA}\cdot\overrightarrow{OB}}{\left|\overrightarrow{OA}\right|\cdot\left|\overrightarrow{OB}\right|}\right)$$

That is, in simple form:

$$d = R\arccos[\cos(x_1 - x_2)\cos y_1 \cos y_2 + \sin y_1 \sin y_2]$$

b. Gravity Model

Generally speaking, the closer the States and counties are, the greater the interaction between them; and the farther they are, the smaller the interaction between them, which is similar to the gravitational model. Therefore, this paper uses the gravity model in physics for reference, and establishes the gravity model of the interstate effect of opioid abuse.

$$G_{ij} = k\frac{p_i p_j}{d_{ij}^2}$$

Gij denotes the size of the interaction, *k* denotes the constant of the Gravity Model, *Pi* and *Pj* denote the size of the index of every thousand people in states *i* and *j*, respectively, and *Dij* denotes the distance between the two states.

c. Building SIR Model

In fact, the population as a whole can be divided into three groups: the first group, denotes by *I* (infected), is the ones who abuse opioids,; the second group, denotes by *S* (susceptible), is the ones who are vulnerable to addict to opioids; the third group, denotes by *R* (removed), is the ones who are one addicted to opioids and them give them up (if no policy is applied to restrict the use of opioids or heroin, the third group can be considered non-existent). Therefore, the changing process of *S* (second group) is

$$\frac{dS}{dt} = -aS(t)I(t)$$

The changing process of *I* (first group) is

$$\frac{dI}{dt} = aS(t)I(t) - bI(t)$$

The changing process of *R* (third group) is

$$\frac{dR}{dt} = bI(t)$$

Here *a* and *b* denote the probability of infection of *S* and the probability of recovery of *I*, respectively. Further, the *S*'s infection probability is related to the interstate influence: the higher the rate of addiction in the nearby state, the more likely it is to affect the population in the state through various channels. Therefore, *a* is a function of *G* as below：

$$a = a(G)$$

The probability of recovery is obviously related to government policy and organization supervision. We use *P* to denote the impact of policy as below:

$$b = b(P)$$

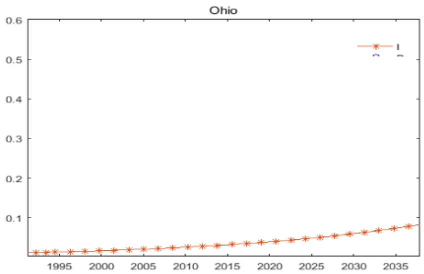
The Modified SIR Model I, which is also the Opioid Geographical Spreading Model, is below:

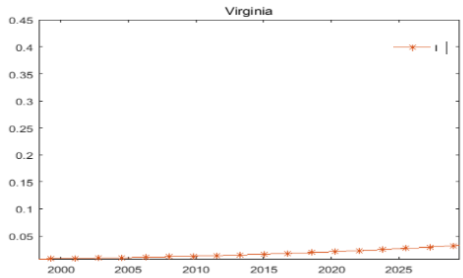
$$\begin{cases} \frac{dS}{dt} = -aS(t)I(t) \\ \frac{dI}{dt} = aS(t)I(t) - bI(t) \\ \frac{dR}{dt} = bI(t) \\ a = a(G), b = b(P) \\ d = R\arccos[\cos(x_1 - x_2)\cos y_1 \cos y_2 + \sin y_1 \sin y_2] \\ I_{ij} = k\frac{p_i p_j}{d_{ij}^2} \end{cases}$$

d. Predict Starting Location

We use our model to create a graph to predict the condition 20 years before the 2010.

The graph on the left is a prediction of the year when opioid abuse started in Ohio Stated based on the total drug reports from 2010-2017. The red line stands for people who abuse drugs. We can clearly see from the graph that 1990 is the approximate year when opioid started to spread in Ohio State. We compared five graphs from those five states, and we conclude that Ohio State is the state where the opioid spread might have started.





For instance, here is a graph of Virginia State on the left, the value reaches zero approximately at 2000, which indicates that the opioid started to spread in Virginia around 2000. This means that opioid starts in Ohio State earlier than Virginia State.

We modified the SIR Model by applying Gravity Model, which is in accord with our assumption that there is geographical distance decay in the spread of opioids.

3.2.3 Data Processing II: Spread in Depth

a. Selecting Opioids by Degree of Social Harm

We select four opioids (Oxycodone, hydrocodone, heroin, and methadone) from the ones chosen in *Data Processing I* base on their degree of social harm.

According to *National Heroin Threat Assessment Summary* (DEA Intelligence Report, 2015), Heroin is far more deadly to its users than other opioids while Oxycodone and Hydrocodone will only slightly affect users' health, such as resulting in shallow or light breathing. Literature also shows that Methadone is likely to cause serious or even life-threatening breathing problems.

Therefore, we conclude that Heroin will be the most threatening opioid, followed by Methadone, Oxycodone, and Hydrocodone. For modified SIR Model II, we use these four opioids instead of all specific opioid types.

b. Representative Data Selection

We want to select total drug reports that can best represent the spread of relatively harmful opioids. As a result, we first select two counties with the highest total drug reports (2017) in each state, as those counties have the most opioid spread in breadth. Then, we use the selected ten counties' Heroin, Methadone, Oxycodone, and Hydrocodone reports, as these reports best represent opioids' spread in depth (social harm)

3.2.4 Analytic Hierarchy Processing

a. Opioid-induced Social Harm Index (OSH Index)

In the previous section, we found four types of opioids (Oxycodone, Heroin, Hydrocodone, and Methadone) that have relatively serious social harm. However, simply measuring the spread of states' and counties' reports cannot reflect different opioids' different degree of harmful effects in and between states. We weight selected opioids base on their degree of social harm. Opioids with greater social harm may contribute more to the overall index we defined.

At this point, we introduce the Analytic Hierarchy Process (AHP) to calculate the weight of each drug in the index.

Through research, we get information about the four selected types of opioids' social harm. In this way, we can do pairwise comparison and get a judging matrix as below:

	Oxycodone	Heroin	Hydrocodone	Methadone
Oxycodone	1	1/7	3	1/5
Heroin	7	1	7	3
Hydrocodone	1/3	1/7	1	1/5
Methadone	5	1/3	5	1

As the Consistency Index equals 0.076, and Consistency Ratio equals 8.45% which is less than 10%. The subsequent priority vector is valid:

$$\text{Priority vector: } [0.091,\ 0.5741,\ 0.0523,\ 0.2821]$$

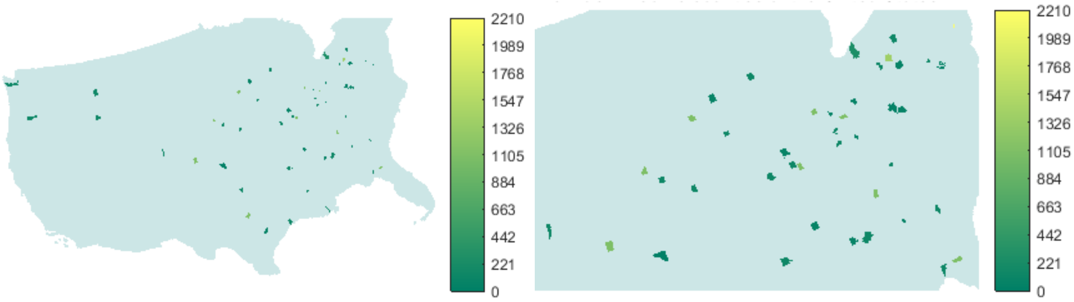
This means that the weights for Oxycodone, Heroin, Hydrocodone, and Methadone are 0.091, 0.5741, 0.0523, and 0.2821, respectively. From this, we may define an Opioid-induced Social Harm Index (OSH Index):

TDR = Total Drug Report
OSH Index=
$0.091 \times (\text{Oxycodone TDR}) + 0.5741 \times (\text{Heroin TDR})$
$+0.0523 \times (\text{Hydrocodone TDR}) + 0.2821 \times (\text{Methadone TDR})$

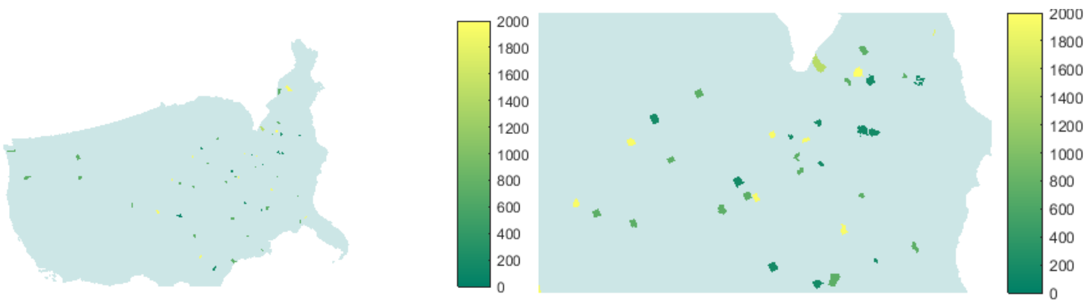
The OSH Index table for the ten counties we select is below:

State	County	Oxycodone	Heroin	Hydrocodone	Methadone	Index
PA	Philadelphia	865	5075	24	25	3001.0127
	Allegheny	167	1894	70	13	1109.9542
KY	Jefferson	80	1031	133	2	606.7372
	Fayette	46	375	15	15	224.5125
OH	Cuyahoga	397	2528	24	24	1495.6759
	Hamilton	270	3970	83	20	2313.8649
VA	Fairfax	90	307	20	7	187.5044
	Prince William	82	270	20	5	164.9665
WV	Kanawha	56	202	22	1	122.5249
	Wood	1	144	8	0	83.1803

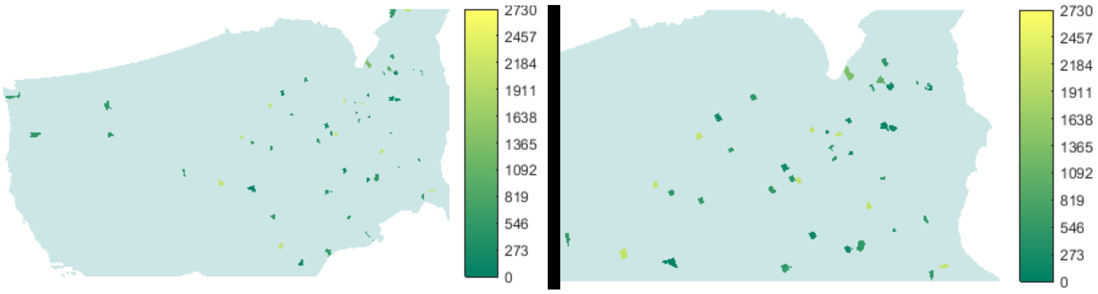
We visualize OSH Index in some counties as follow. Since other counties' name may coincide with the ten counties' we selected, the number of spots on the graph are apparently greater than ten. But we are going to focus on the spots within the five states provided (PA, KY, OH, VA, and WV). The following graphs exhibit OSH Index increase in some counties from 2010 to 2017.



Opioid-induced Social Harm (OSH) Index some counties in the United States in 2010



Opioid-induced Social Harm (OSH) Index some counties in the United States in 2014



Opioid-induced Social Harm (OSH) Index some counties in the United States in 2017

As the figure shows above, we could see it clearly that the OSH index for Philadelphia, Cuyahoga, Hamilton and Jefferson increased slightly over time. This indicates that opioid abuse is having a significant impact on these counties, and the situation is getting worse each year. While other counties, for instance Fairfax, Wood, Prince William generally remains the same, so the social harm of opioid abuse relatively remains the same.

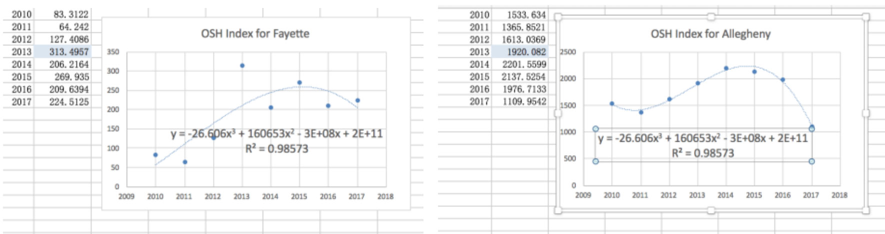
b. Prediction: Government Concerns

According to our assumption, we determine drug identification threshold levels which government concern occur by the mean value of the five states' opioid-usage.

Our OSH Index versus Time Plot is below, with **polynomial regression** line.

When applying polynomial regression to find relationship between the time and the OSH Index of top two counties for five states, we discover some good empirical results. When the degree of polynomial reaches three, the value of R^2 goes up drastically to more than 0.9 for most counties; however, when the degree increases to four or five, the value of R^2 merely grows to a very small extent. Thus, we think that the three degree polynomial may be the most suitable for the counties to **empirically** predict the OSH Index for those counties in the future.

Here are some typical graphs:



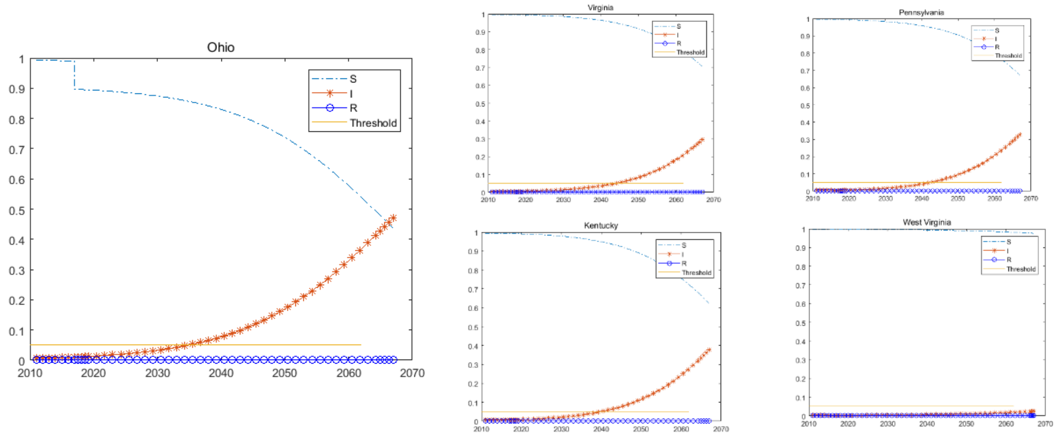
Polynomial Regression: OSH Index v.s. Time Plot

From the graphs above, we can predict that social harm will continue in the future. Despite a decrease in harmful effects, opioids will still lead to government concern in the future, since the peaked OSH Index will damage the society and the society have a harm resilient capacity. The cumulative damage will ultimately result in government concern in population health and economy: there will be difficulties in filling in skill-demanding jobs and covering healthcare costs.

While predicting the place and time for the predicted concern to occur, we can look at the Modified SIR Model I below and see when it exceeds the drug identification threshold level we determine.

If there is no external opioid-usage policy, people with addiction will have great difficulty to give opioids up, that is, $b = 0$. In this case, Modified SIR Model I Prediction for the five state is below.

Therefore, we predict the concern will occur around 2034 in Ohio, around 2040 in Kentucky, around 2041 in Pennsylvania, around 2042 in Virginia, and after 2070 in West Virginia.



Modified SIR Model I Prediction for the Five States with Threshold

3.3 Opioid Geo-socio-economical Spreading Model

3.3.1 Regression Model

In this part, the regression model for evaluating the influences of opioid use and addiction will be built to find the indicators.

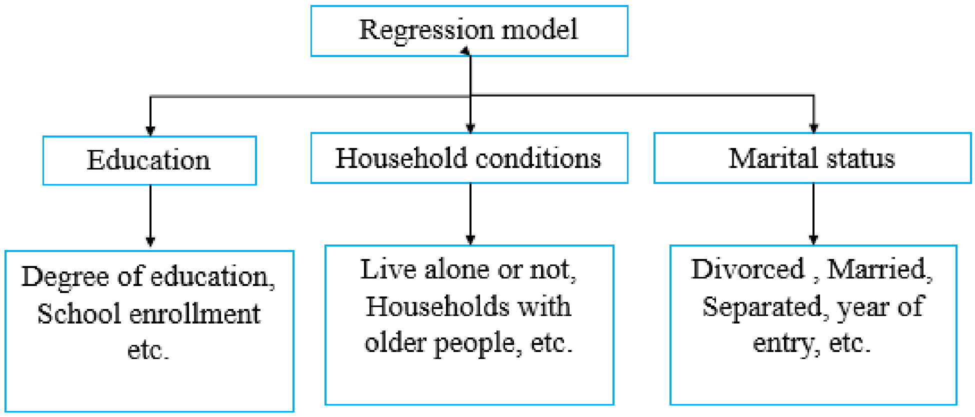
The model can be shown as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \cdots + \beta_n X_n + \varepsilon$$

Where Y represents the dependent variable, $X_1, X_2, \cdots, X_n$ represents the independent variable, and ε represents the residual in the equation. And in this analysis, based on the given data, we regard the index per 1000 as the dependent variable, which can be affected by some factors such as education, age, native born or not, etc.

a. Variable selection

Dependent variable: in this regression model, our dependent variable is the index per 1000 people. As you could imagine, if some factors do have some impacts on the increase or decrease of the index, it can explain why and how opioid use got to its current level. We select variable as follow:



We build the regression model from three dimensions: education, household conditions, and marital status. There are 22 independent variables in total.

b. Hypothesis

Base on the literature, we give the following hypothesis:

Hypothesis 1	The higher the education is, the fewer in opioid use and addition
Hypothesis 2	If a person lives alone, it is more likely for he or she to addict to opioids
Hypothesis 3	People from Africa are more likely to become addicted to opioids than people from other countries

3.3.2 Regression results

By using Matlab, the regression results are shown as follows:

Variable	Variable	Coefficient	T-statistic	P-value
HC03_VC85	Percent; EDUCATIONAL ATTAINMENT - Less than 9th grade	-0.15703	-0.15851	0.87411
HC03_VC94	Percent; EDUCATIONAL ATTAINMENT - Percent bachelor's degree or higher	-0.23133	-0.372	0.710028
HC03_VC88	Percent; EDUCATIONAL ATTAINMENT - Some college, no degree	-2.06608	-1.54237	0.123525
HC03_VC04	Percent; HOUSEHOLDS BY TYPE - Family households (families)	-2.31408	-0.67908	0.497353
HC03_VC07	Percent; HOUSEHOLDS BY TYPE - Family households (families) - Married-couple family	3.342747	1.586238	0.113225
HC03_VC18	Percent; HOUSEHOLDS BY TYPE - Households with one or more people 65 years and over	-0.47723	-0.23077	0.817577
HC03_VC17	Percent; HOUSEHOLDS BY TYPE -	0.697522	2.35673	0.00425

	Households with one or more people under 18 years			
HC03_VC14	Percent; HOUSEHOLDS BY TYPE - Nonfamily households - Householder living alone	0.546274	0.168052	0.8666
HC03_VC15	Percent; HOUSEHOLDS BY TYPE - Nonfamily households - Householder living alone - 65 years and over	1.808351	1.92786	0.047823
HC03_VC40	Percent; MARITAL STATUS - Divorced	-2.02837	-1.11029	0.26733
HC03_VC36	Percent; MARITAL STATUS - Never married	-0.78613	-0.76669	0.443577
HC03_VC44	Percent; MARITAL STATUS - Now married, except separated	-1.91721	-1.17741	0.239509
HC03_VC38	Percent; MARITAL STATUS - Separated	-3.33123	-0.83566	0.403689
HC03_VC80	Percent; SCHOOL ENROLLMENT - College or graduate school	-3.53233	-3.26298	0.001167
HC03_VC78	Percent; SCHOOL ENROLLMENT - Elementary school (grades 1-8)	-4.96612	-3.1501	0.001715
HC03_VC77	Percent; SCHOOL ENROLLMENT - Kindergarten	-2.99531	-1.15981	0.246598
HC03_VC159	Percent; WORLD REGION OF BIRTH OF FOREIGN BORN - Africa	0.193544	1.932654	0.045872
HC03_VC158	Percent; WORLD REGION OF BIRTH OF FOREIGN BORN - Asia	-0.40213	-0.97027	0.332314
HC03_VC157	Percent; WORLD REGION OF BIRTH OF FOREIGN BORN - Europe	-0.1683	-0.41302	0.67974
HC03_VC161	Percent; WORLD REGION OF BIRTH OF FOREIGN BORN - Latin America	-0.22346	-0.56564	0.571854
HC03_VC151	Percent; YEAR OF ENTRY - Entered 2000 or later	0.540869	0.753291	0.451578
HC03_VC152	Percent; YEAR OF ENTRY - Entered before 2000	0.471338	0.674386	0.500332

From the table above, we could see it clearly that:

(1) Generally, the OSH index is negatively correlated with education. The coefficients before these education variables are all negative, which means education can reduce the opioid use. Hence, **hypothesis 1** can be proved.

(2) Elder people living alone are more likely to be absorbed in the opioid use, which is significant at the 5% significance level. From the table above, the coefficient before

elder people living alone is positive, which shows the positive correlation between elder people living alone and the OSH index. Hence, Hypothesis 2 can be proved.
(3) Africa-born people are more likely to be absorbed in the opioid use, which is significant at the 5% significance level. The coefficients before Africa-born people are all positive, while other countries are negative. This means Africa-born people are more likely to be absorbed in the opioid use. Hence, **hypothesis 3** can be proved.

3.3.3 Modified SIR Model II

We modified the previous SIR Model to include important socio-economic factors.

From regression results, we can see that opioids abuse is related to education and household conditions. The higher one's education is, the less one live alone, the lower the possibility of getting opioids abuse. Therefore, we include education and household factors in our model. That is to say, the susceptibility rate *a* is not only related to the interaction between regions, but also to the education and living alone or not. Therefore, *a* can be expressed as follow:

$$a=a(G, Edu, S)$$

The susceptibility rate is a function of interregional influence, education, and household condition of living alone or not. This proves hypothesis 1 and 2 correct. Opioid use got to its current level due to relatively low education level in those areas, and people with low education level and those who live alone is using/abusing opioids and contribute to its growth. Despite knowing its danger, people continue to use it for three reasons: (1) some use it for medical purpose while other medical pain-relief substances (such as marijuana) are not legalized and available or are not effective in those states according to our background research; (2) people in those areas do not care about the danger.

To express this association of between opioid abuse and geo-socio-economic factors, we use exponential function. The susceptibility rate *a* can be expressed as follow:

$$a = G^{\gamma} Edu^{\theta} S^{\alpha}$$

Where γ, θ, α represents the coefficient of *G*, *Edu*, *S* respectively. Cause the negative relations between education, social status and infectiousness, the coefficient θ, α are correspondingly negative.

The Modified SIR Model II, which is also the Opioid geo-socio-economical spreading Model, is below:

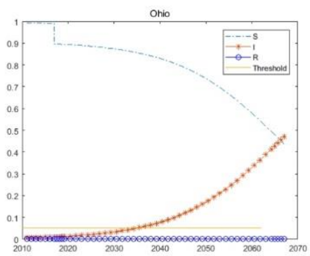
$$\begin{cases} \dfrac{dS}{dt} = -aS(t)I(t) \\ \dfrac{dI}{dt} = aS(t)I(t) - bI(t) \\ \dfrac{dR}{dt} = bI(t) \\ a = a(G, Edu, S), b = b(P) \end{cases}$$

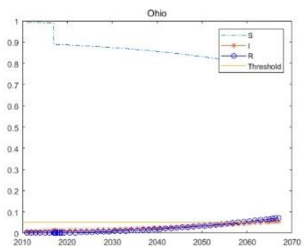
4. Sensitivity Analysis

Take Ohio State as an example, considering the effect of different infection rate (a) and different recovery rate *b* on results. The sensitivity here means the impacts of the changes of infection rate and recovery rate on the spread of opioid use.

(1) Establishing stricter policies to help addicts

In this case, addicts will be more likely to escape from the addition to opioids. As the figure shown below, the number of addicts and the increase rate will be delayed dramatically. The two graphs are made with the assumption that all people will possibly be affected.

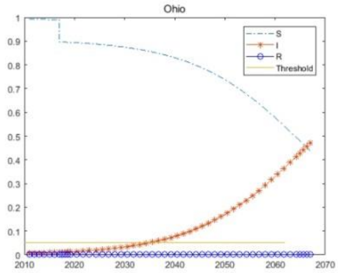


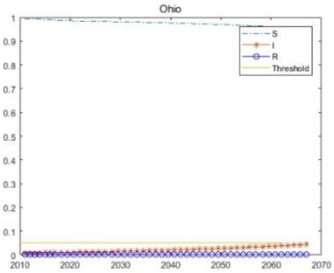


No policy situation with policy situation

From the graph above, we can observe that thanks to the stricter policies, people's addiction to opioids dropped obviously, thus this model is sensitive to policy.

(2) Improved education, or social interaction



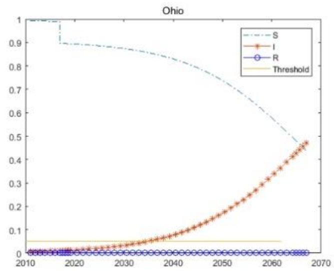


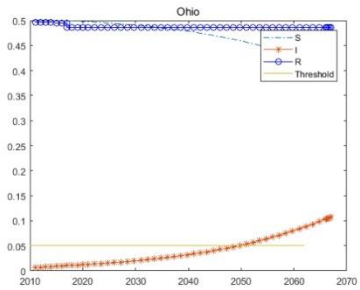
Because of the improvement of education level or personal social life, the rate of addiction decreased from 0.1 to 0.003. The chart on the right reflects the result of this change.

As shown in the figure above, due to the slight change of addiction rate a, the possibility of future opium crisis in Ohio State has been greatly reduced, and the occurrence time has been greatly delayed; the degree decreased dramatically.

(3) Consider that some people are not affected by opioids

In fact, many people tend to avoid opioid drugs because of their different levels of knowledge and education. Therefore, in terms of the contagiousness of the Opium crisis, these people are unaffected. Now, if we ignore this, as shown in the right of the following picture:





Because of the emergence of groups that are not affected by opioids in the population, the number of infected people will also be greatly reduced, and the occurrence time will be delayed.

5. Strategies and Effectiveness

5.1 Strategies

1. In our research in literature, our application of Analytic Hierarchy Process (AHP), and our clustering towards all kinds of drugs, we discover that heroin not only spreads breadthwise across the region measured by the total amount of drug report, but also contributes the largest proportion in the Opioid-induced Social Harm index. Therefore, the U.S. government should spend most effort in combatting the illegal activities related to heroin.
2. The U.S. government should arrange more budgets on public colleges, other graduate school, and elementary school, as well as subsidize the private

counterparts. The higher school enrollment in such time period means low Opioid-induced Social Harm index.

3. The U.S. government may encourage charitable societies to care more about the elder householders who are alone to alleviate their stress and save them from the negative psychological state, which may result in their abuse in opioids and the consequent spread of such abuse.
4. The U.S. government can legalize the medical use of some pain-relieving substances, so that less opioids will be used for medical purpose. The less exposure to the opioid may reduce the amount of people who are more susceptible to opioid abuse (reduce the S).

5.2 Effectiveness

The effectiveness of those strategies may be evaluated by observing Opioid-induced Social Harm Index, the respective drug reports of four types of most influential drug (which we obtain by Hierarchical Clustering method), as well as the total amount of the drug reports in local area.

6. Strengths and weaknesses

6.1 Strengths

1. Reasonable data processing. We process data while considering breadth and depth, and select representative counties via reasonable method discussed previously.

2. Direct visualization of Models via exhibition of graphs. We construct maps to visualize the spread.

3. Valid modeling of the dynamic process of conversion between different groups by comparing the abuse to the disease, such as people who are vulnerable to opioid abuse, the people who are abusing, and people who cease to abuse

4. Describing spread and characteristic via Microscope and Macroscopic Perspective

6.2 Weaknesses

1. Simplifying assumptions. To simplify real life situations, in our work, we make some assumptions which may affect the result of our model.
2. Lack of data. We select representative data, but do not apply not all of the data. Therefore, accuracy may be affected.

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