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Summary Sheet

Reduce drug Crisis: Based on condition-weighted neural network and decision tree

Summary

According to statistics given by government, the number of people who abused opioids and result in death reaches 0.35 million, approximately 87% of death toll of the second world war. Besides, abused opioids problem occupies 66% of problem about death accident of person who is under 50 years old. In this research, we faced following problem about attributes of heroin and opioids accident, where is origin place of heroin and opioids accident, which kinds of reason or condition causes such serious problem and strategy of solving heroin and opioids problem. In order to solve problem, our team made assumption about condition-weighted network model. The first process we studied specific location, then we focused on the recursive rule of geographical location which means other county will influence drug accidents of local counties. The reason why our team constructed weighted-edge network model is network model can greatly describe relation between different county and each county will exert influence to other nodes. Additionally, decision tree model and k-fold cross validation method were used in this research. We assumed that education, married status and family property would influence drug accident of county and the reason why decision tree model was used is that decision tree can conclude or summarize formula of feature and make prediction about instance according to its feature. In this research, we constructed decision tree based on education, married status and family property. In order to prevent overfitting problem, k-fold cross validation method was used in process of constructing decision tree model.

Keywords: Neural network; Decision tree; Graph theory; K-fold cross validation

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1 Introduction

1.1 Background

A critical crisis is threatening the public health of the United States of America these years, according to the National Institutes of Health, opioid overdosing kills more than 130 Americans every day. There is a 900% increase in persons looking for treatments for addiction to opioids from 1997 to 2011 [1]. Moreover, it was estimated that there were approximately 19,000 deaths with respect to Opioid addiction in America in 2014 [2]. Apart from that, it can be damaged to American's society if it spreads to all classes, precise labor in industry may lose, college students may not attend lectures, government's health care costs within the elderly will also increase.

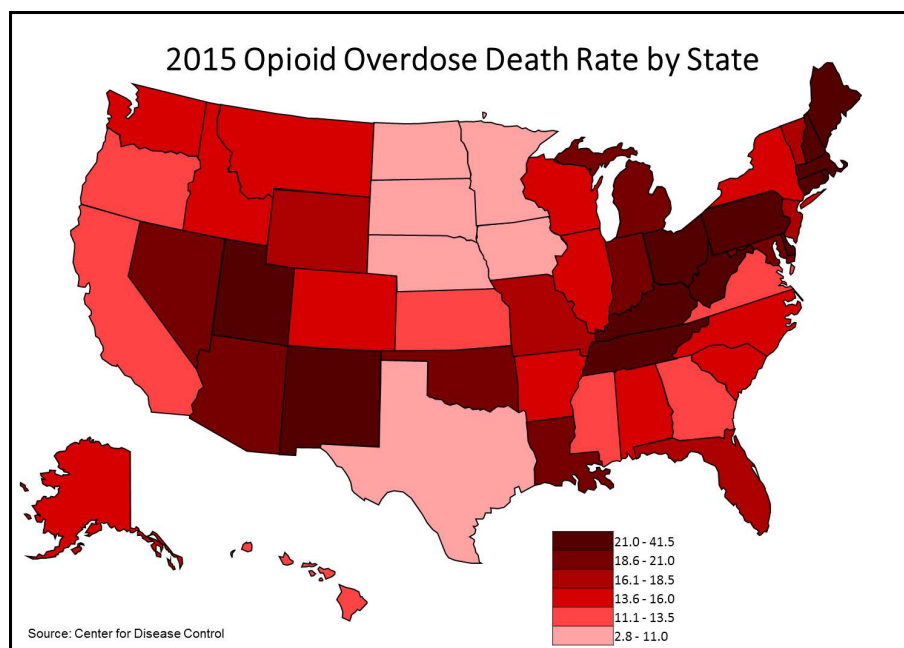


Figure 1: 2015 opioid overdue death rate by state

The US Food and Drug Administration (FDA) has taken a series of responses against Opioid crisis, including balancing personal need social pressure and making clear regulations for Opioid use [3]. However, it has received a large amount of resistance during the implementation and due to the ill budget of FDA these years, US government is seeking for methods of preventing opioid overdose among specific areas, which was often overlooked previously [4]. In this experiment, we examine Opioid addiction in five States: Ohio, Kentucky, West Virginia, Virginia and Tennessee, which can be seen as above-mean States among the whole federation. A prediction model is built to recognize possible locations where specific opioid use might have started. The model integrates factors including relative distance and economy between two counties among different Opioid based substances, it can be used for the comparison of various explanations regarding to the growth of Opioid addiction.

1.2 Restatement of the problems

We are supposed to build the mathematics model to describe non-synthetic and synthetic opioids diffusion. Taking five states and their counties reported samples, the discrete dynamical systems with initial condition are the suitable method. In order to retrospect and forecast the specific opioid growth, we need to use location data and Time-Series drugs reported data to develop model. Furthermore, these characters of output functions also need to be explained and applied in the real world, such as some stationary points and thresholds behavior reflected. In Part2, we need to check abusers distribution in the various industry with the U.S. Census socio-economic survey. To construct the relationship between model and social policy helps government to avoid extreme adverse scenarios. In Part3 and proposal memorandum for DEA/NFIS, we also design the strategy to counteract America current opioid crisis.

1.3 Justification of our approach

Considering about aspect of model, our team constructs condition-weighted network model which is inspired by neural network model of machine learning. Neural network is a collection of connected nodes which are called artificial neurons and neurons are connected with weighted edge. In condition-weighted network model, node represents each city and weight of edges depends on distance between two connected cities and ratio of economic income of two connected cities. Our team consider that distance between two cities is one of important factor which will influence spread speed of same drug. The shorter distance between two cities is, the faster spread speed will become. Therefore, the linked edge whose distance is short will assign high weight. Moreover, ratio of economic income of two near cities will influence weight of linked edges. Economic income of A is divided by economic income of B will represent ratio of economic income of city A and city B. The higher ratio of economic income of two cities is, the higher weight link edge will have.

1.4 Assumptions and Notations

1.4.1 Assumptions

- All of the counties are distributed evenly
We choose same distances threshold adding as data of neighbour counties.
- All of the Opioid-based drugs behave negative influence on the amount of drugs report.
We choose all of the Opioid-based drugs to analyse.
- The other factors, excluding distance and economic ratio can be omitted
In the condition-weighted convolutional neural network model, the influence of outer nodes is only decided by distance and economic ratio between two nodes.
- The Opioid-based drugs propagation status can be represented by the amount of drug reports
- The impact factor of different opioid-based drugs can be represented by the concentration of Opioids in those drugs.

- The difference of influence of drugs administration policy in different States can be omitted.
Our model is built inter-State and transmission speed is not influenced by the difference of drugs administration policy.
- The physical distance between two counties can be represented by earth surface distance between two nodes
Due to the large amount of data, this model does not consider the actual transmission distance on human available roads and only calculate the distance by longitude and latitude
- Drug report amounts in one year could be selected as the indivisible unit
- The economy and population scale among all the counties are approximate

1.4.2 Notations

- $n(t)$ The number of drug reports in a county at time t
- d_0 Toxicity coefficient
- t Time
- n_{inner} The number of drug reports in a county at last year
- $n(t + 1)$ The number of drug reports in a county at this year
- μ Distance efficiency: the influence of distance and economic development of the i th county to the researched county
- f_i Diffusion efficiency: the influence of the number of drug reports of the i th county last year to the researched county
- G GDP of a county
- g Piecewise function at any time

2 Nodes Analysis and Neural-network dynamical system

In order to avert the opioid abuse in the United states, it is necessary to construct a dynamic functions covered finite district. The task list provided by COMAP is clear that the dynamic system is in strong relation to the different area and opioid category. Thus our model contains such impact factors and will explain the influence in the real world.

2.1 Single-Node and Neural-network dynamical system

2.1.1 Formula derivation

Actually, it is a complex diffusion model. And the social influence of drugs abusers is tougher than general fluctuation condition in physicisim. Obviously, classic diffusion

situation satisfies partial differential form with position elements of $u(x, y)$ and time elements of t . Furthermore, the methods are more similar to the Euler description rather than the Lagrange description in the Method of Mathematical Physics field[5]. In order to avoid much enormous trajectory description, our team simplify the model. In the initial condition, we focus on the specific position to study how the count of all substances identified changes. According to the previous academic report, we believe that $n(t)$ is proportional to the product of the power term of toxicity coefficient d_0 and time t . Thus, it gives the formula:

$$n(t) = \lambda \cdot d_0^A \cdot t + C \quad (1)$$

where λ , A and $C \in \mathbf{R}$

2.1.2 Algorithm and parameter determination

The algorithm we use to predict parameter of formula is non-linear regression whose principle is least square and convergence theory. In non-linear regression, we imitate parameter of formula given training data which minimizes sum of loss of predicted value and actual value. We calculate gradient of loss function and let gradient become zero in order to make loss function convergence. The formula of regression is

$$n(t) = 2.254 \cdot d^{0.03961} \cdot t - 3770 \quad (2)$$

which d represents toxicity coefficient and t represents number of year. Our team convert t into 8x1 vector whose different row represents different year, convert d into 11x1 vector whose different row represents different kinds of drug and convert z into 8x11 matrix whose $z(i, j)$ represents number of incident of specified drug i in year j . In figure xx, non-linear regression method projects high-dimensional data into low dimension manifold in order to get parameter of non-linear regression equation. We use root mean square error metrics to evaluate accuracy of non-linear regression and result of root mean square error is 2.9149366358445313 which has high accuracy.

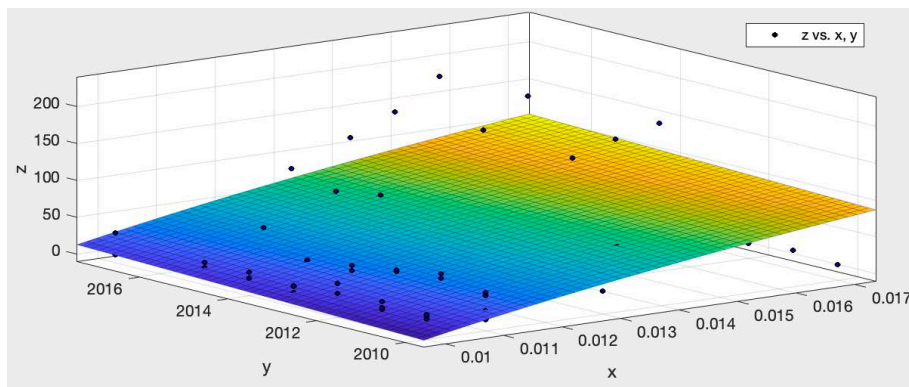


Figure 2: scatterplot figure

2.2 Multi-Nodes and Neural-network dynamical system

2.2.1 Formula derivation

Since we are supposed to explore the abuse reports identified behavior, cities around the center one play a crucial role. According to the superposition theorem in electric circuit analysis, it is easy to get the formula[6]:

$$n(t) = n_{inner}(t) + n_{outer}(t) \quad (3)$$

where $n_{inner}(t) = \lambda \cdot d_0^A \cdot t + C$. So we can build a new difference model that Drug crimes in the new year are equal to the sum of drug crimes and the influence of other cities on the same county in the previous year. And the equation is that:

$$n(t+1) = \lambda \cdot d_0^A \cdot t + C + n_{outer}(t) \quad (4)$$

Thus, we focus on the external influence on specific county. The model simulates the opioids diffusion by the effect caused by its neighbor cities. To study the neighbor condition, the Node-Network methods are applied. Our team take cities as node and link as edge. Network analysis based on graph theory and topology are usually used to huge-dimension complex. We introduce two important classic characteristics of Complex network:

- The node space is too large to solve unless there exists some recurrence relations. That's, characteristics of the network can be only gained need to be numerical and statistical methods, but not explicitly calculated
- Generally, the network has space-time complexity. On the one hand, quantity of nodes in the network will keep increasing; on the other hand, the weight of nodes will iterate as the change of environment.

Multigraph can build the model from the abstract undirected or directed graphs to the concrete map in the graph theory. As well Topological mapping is the measurement of mathematical tools in the real world. According to the definition from graph theory[Ref], we can see:

Theorem: An multigraph is an ordered triple $(V(G), E(G), G)$ consisting of

- a finite non-empty set $V(G) = v_1, v_2, \dots, v_n$ of vertices
- a finite set of edges $E(G) = e_1, e_2, \dots, e_r$
- an incidence function G that associates with each edge of $E(G)$ an (unordered) pair of vertices of $V(G)$.

Significantly, the direction properties in graph theory are helpful to analysis Direction of drug transmission and judgment of initial value. We also introduce the criterion that: $G = (V, E)$ undirected if for all $v, w \in V$: *suchthat* $(v, w) \in E \Leftrightarrow (w, v) \in E$, *Otherwisedirected*.

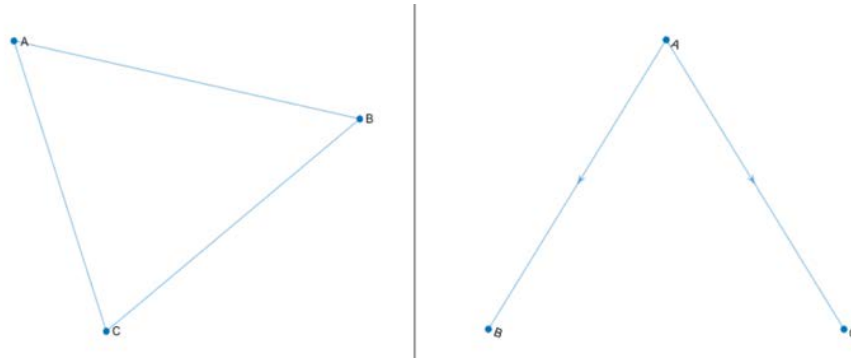


Figure 3: directionl or unidirectional graph

Therefore, we construct directionl or unidirectional graph based on real maps of place in the report. the relationship could be described like these graph:

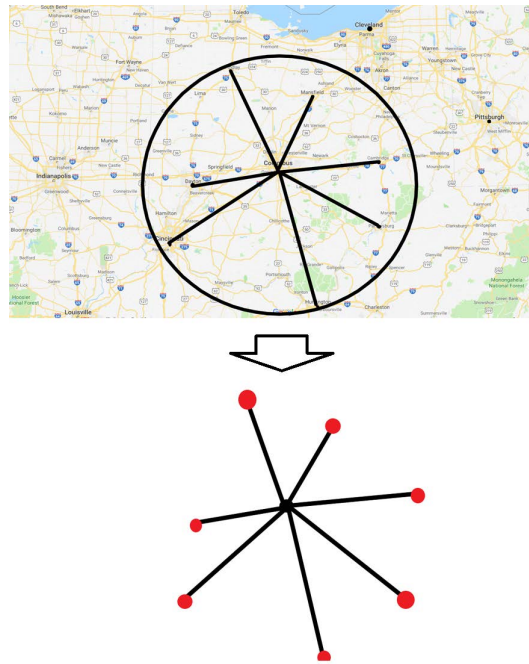


Figure 4: From map to Network

In the macroscopic dimension, we can consider that the central city and the local city follow the property of multigraph mapping. In the microscopic dimension, the neighbourhood can be regarded as the dendrites and axons in biological neuron system. The Neural network is combined with bunch of nodes. In almost cases, the Perceptrons are adaptive. The artificial Intelligence algorithm can exchange internal data structure by training by generous external data sets. These nodes are responsible for information transmission and delivery. Furthermore, Neurons could also be strengthened to develop a fixed ideology nerve in the back-propagation process. So the extrinsic influence is a linear combination of the central cities where the weight is assumed by the initial value. The model will become sensitive to the real important information as the training level of data sets enhances.

$$n(t)_{outer} = \sum_{i=1}^{\infty} \mu_i \cdot f_i(n(t)) \quad (5)$$

Where $f(x)$ represents the crime propagation transformation function. According to classic diffusion equation which simplifies the influence on position, we can get the equation: $\frac{dn}{dt} = p \frac{d^2n}{dt^2}$, $p \in R$. so we believe that $n(t)$ follows Exponential function form. Thus, This model integrates the network and the two-layer perceptron model to explore the recursive relationship between the city and the surrounding cities of drug-abusers diffusion. Among the whole process, the network is the topology structure of the influence of the central city with its neighborhood, and AI algorithm is the best modification method for parameters optimization.

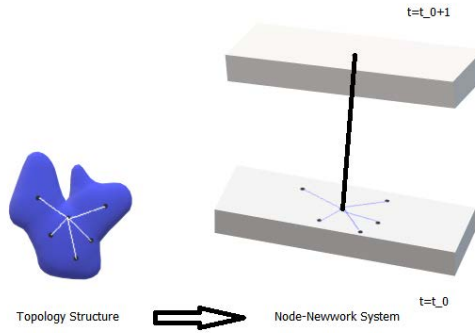


Figure 5: directionl or unidirectional graph

2.2.2 Algorithm and parameter determination

As previously stated, the drug report amount in a county is not only related to the drug amount in-county, but also drugs out of state, which in the state that can show an influence on this county by their specific distance and GDP. Thus the model $n(t+1) = \lambda \cdot d_0^A \cdot t + C + \sum_{i=1}^{\infty} \mu_i \cdot f_i(n(t))$, where $N(t+1)$ and $N(t)$ refer to the drug report amount in a county in different neighbour years, $n(t) = \lambda \cdot d_0^A \cdot t + C$, d_0 is the concentration of Opioid in different substances, t is the time each year, and C are constants, referring to the influence factor from neighbour counties, $f(t) = e^N(t)$, μ is a constant referring to $\frac{G_1}{G_2}$, where G are GDP in those two counties, and D is the distance between two counties. also stands the direction form County 1 to county 2. Even though there are many factors that affect efficiency, we think the important factors are distance and economic development:

- distance: the drugs crime diffusion efficiency will decrease as the distance grows;
- economic development: the drugs crime diffusion efficiency will increase as the economic development level grows;

The algorithm used to train this model is Convolutional Neural Network, two layers of neural network are built with Leaky Relu as activation function since it could have better response area and efficient for calculation, also max-pooling method is adopted to avoid over-fitting and improve the generalization ability, also our team use softmax loss function to increase the updating speed. When training the model, we first separate our data sets into 10 sectors, 8 for training sets, 2 for test sets, after training, we get the model with parameter:

$$n(t)_{t+1} = 2.7 \cdot d_0^{0.06} t - 3760 + \sum_{i=1}^{\infty} \mu_i \cdot f_i(n(t)) \quad (6)$$

Validation method name [⌘]	expected value range or status [⌘]	model value or status [⌘]
Goodness of fit [⌘]	>0.5 [⌘]	0.760 [⌘]
Residual distribution [⌘]	residual is consistent with random error [⌘]	the fitting values are [⌘] scattered around actual values [⌘]
Residual independency [⌘]	Durbin-Watson is 2 [⌘]	1.910 [⌘]
The overall effect of regression [⌘]	Regression residual total [⌘]	model is statistical [⌘] significant at $\alpha=0.05$ [⌘]

Figure 6: Verification

2.2.3 Criterion of initial condition

In the following quation, we have the assumption that is the $n_{outer}(t)$ is always positive. However, it is not always consistent for every time. Therefore, we add another description to enhance the model adaptability. Let $\mu^0 = \mu \cdot g$ where g is a piecewise function at any time.

$$g > 0, n(t+1) > n(t) \quad (7)$$

$$g < 0, n(t+1) < n(t) \quad (8)$$

For $n(t+1) > n(t)$, then $g > 0$. So other neighbors drug diffusion will make the center city increase opioid abusers. For $n(t+1) < n(t)$, then $g < 0$. So the center city drug diffusion will make other neighbors increase opioid abusers. Therefore, it is a directed graph in the 2.2.1 Theorem as a topological structure.

Furthermore, We can study the initial condition for specific county burst into drugs popular mode. we can define the criterion standard.

initial criterion: If a city is studied in its neighborhood, when $t < t_0$ and g is never negative at any time; then we can consider the city at the burst initial condition.

The initial criterion is the most important solutions in the report. Both the prediction of future conditions and the examination of past data, the criterion always shows good practicality.

3 Decision tree model and k-fold cross validation method

3.1 Construct the Model

Our team constructs decision tree model in order to make predict for county of state about whether drug crisis will become serious and which attributes or features of county will let county be classified as equipped with serious drug problem.

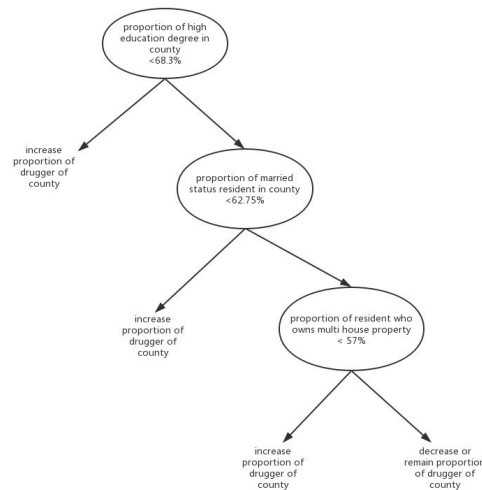


Figure 7: Decision Tree Flowchart

First, our team need to construct label for each instance. The criterion of making label is contrasted between proportion of number of druggers of local county and average proportion of number of druggers of country. According to statistics of drug facts[7], the proportion of druggers of country was 9.4%. If proportion of druggers of local county is smaller or equal than 9.4%, we consider this county has non-drug crisis and label is 0. Otherwise, we consider county as drug crisis county and label is 1. For different feature, our team instantiate features by representing percentage of feature as feature number and convert instance into high dimension points.

After we successfully constructed data sets, we divide data set into proportion of eight and two. Eighty percent of data sets will be used for training model and twenty percent of data sets will be used for testing model. In order to prevent overfitting problem, our team used K-fold cross validation method which splits data set into k partition, randomly select data of datasets as test data and change selection of test data for different rounds. For evaluating model, we use accuracy method. The definition of accuracy method is value of number of sample whose predicted values are equal to actual value

divided by total number of sample. We set threshold of accuracy to 95% which means if accuracy of model equals more than 95%, we consider model as appropriate.

```
Epoch 5/10
60000/60000 [=====] - 74s 1ms/step - loss: 0.1155 -
acc: 0.9661
Epoch 6/10
60000/60000 [=====] - 74s 1ms/step - loss: 0.0996 -
acc: 0.9702
Epoch 7/10
60000/60000 [=====] - 74s 1ms/step - loss: 0.0882 -
acc: 0.9740
Epoch 8/10
60000/60000 [=====] - 74s 1ms/step - loss: 0.0791 -
acc: 0.9758
Epoch 9/10
60000/60000 [=====] - 75s 1ms/step - loss: 0.0727 -
acc: 0.9778
Epoch 10/10
60000/60000 [=====] - 75s 1ms/step - loss: 0.0667 -
acc: 0.9802
[INFO] evaluating...
10000/10000 [=====] - 7s 663us/step
[INFO] accuracy: 98.06%
```

Figure 8: Training Process

After training decision tree model, we reach conclusion that high percentage of resident who owns higher education degree, married status and multi house property in county will be classified as non-drug crisis. Therefore, we consider these vectors could stand for the drug abusers factors in the human group behaviors.

$$\langle educationdegree, marriedstatus, multihouseproperty \rangle \quad (9)$$

To prove that our hypothesis is correct, our team tested trained decision tree model and found that accuracy reached 98% which means our conclusion was correct as the figure 4. Then we tried to find boundary of percentage of features involved. After testing many times, it is obvious that boundary between drug crisis and non-drug crisis is 68.3% of higher education degree resident, 62.75% of married status resident and 57% of resident who owns multi house property.

3.2 Case Study and Government Strategy

In the United States society, we suggest the government to consider the change rule of thress key vectors in 3.2. The boundary of model means proportion of drugger of country will not increase or decrease. The method of decreasing proportion of drugger of county is to increase percentage of highincrer education degree, married status and multi house property. However, if any of three factors, percentage of higher education degree, percentage of married status or percentage of multi house property decreases, proportion of drugger of county will increase.

In conclusion, it is necessary for government to control proportion of drugger of county based on three perspectives which are education, married status and family property. For improving proportion of higher education degree, it is necessary to increase investment about foundation education such as improving salary of teacher and enforcing criteria of assessing teacher. On the other hand, increasing expenditure of universities'

research at meantime is also important. Considering about married status, government needs to provide married family with welfare benefit in terms of decreasing tax fee and giving subsidy to married family. Besides this method, it cannot deny that influence of company. Government is suggested to publish relevant law for company which involves supplying holiday and bonus to pregnant. From perspective of improving families' property, decreasing tax fee and providing work opportunity are utility method.

4 Conclusions

In conclusion, weighted edge network model aims to describe spread and characteristic of reported synthetic opioid and heroin incidents among five states and their countries. Apart from influence of other county, the development of synthetic and opioids satisfies power function $n(t) = 2.254 \cdot d^{0.03961} t - 3770$ in every county which d is toxicity coefficient of every drugs and t represents number of year. Government can predict common drug development of following years in each county to certain degree. To find origin county, we defined function g which satisfies condition that if $g > 0$, $n(t + 1) > n(t)$, if $g < 0$, $n(t + 1) < n(t)$. The criteria of origin county is if $t < t_0$ and $g \geq 0$ for random time, the county can be considered as origin county. Combining with statistics data of social economy, we convert different features of data into numeric form and construct decision tree model. After training decision tree model successfully, it is obvious that three main features, percentage of higher degree resident, married status resident and resident who owns multi house property influence proportion of druggers of local county. It satisfies formula that specified percentage value of three features will remain proportion of druggers of local county. The proportion of druggers of local county can be improved by means of increasing value of three features. In the end, our team gave suggestion about how to decrease proportion of druggers of local country based on education, married status and family property.

5 Strengths and weaknesses

5.1 Strengths

- **Meaningful use of condition-weighted network model to represent node**
In condition-weighted network model, nodes are meaningful to represent distance and ratio of economic income between two cities, which are often overlooked as meaningless parameters in other neural network models. After extracting those parameters of nodes, it is easier to recognize the role of distance and economy in transmission between two cities, also which cities are highly dependent on distance and economy can be analysed.
- **Complex decision tree model to process high-dimension data**
Though the model might be prone to over-fitting in some degree, decision tree is used to process high-dimension data at part 2, which integrates more than 20 characteristics, and its special structure makes classification efficient and accurate.
- **Forecast mechanism for starting-growth locations of Opioid**
By means of decision tree method, this mechanism can be used to forecast drug

report amount in a long enough time even though some less important characteristics are omitted.

5.2 Weakness

- **Relative fewer data to train a perfect model**

Time span is not enough, only 8 years can make the trained model over-fitting, also for some counties, there are missing data in some specific drugs and some years and will make the model less reliable.

- **Complicated relation between noisy points and starting-growth points**

In scatter plot graph, noisy points mean the point that are abnormal to points nearby, however, there are many noisy points that correspond to starting-growth points, which sometimes show the similar properties, thus it is hard to clear out all the noisy points with starting-growth points left, and will make the model over-fitting in some degree.

- **Sensitive to abnormal points**

The structure of decision tree is highly sensitive to abnormal points, which can change the shape of the tree dramatically, thus will make the predicted model more over-fitting and unreliable.

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Appendices

Appendix A First appendix: Memo To the Chef Administrator

In this experiment, our team first build a mathematical prediction model to demonstrate the propagation of Opioid-based drugs, by this model, the starting-point of specific opioid use can be predicted. Then another decision tree model is built to analyse which characteristics in U.S. Census socio-economic data contribute drugs addiction the most.

We first study the diffusion at Single-Node and Neural-network dynamical system, which means that we do not consider the influence from nodes nearby. $n(t) = \lambda \cdot d_0^A \cdot t + C$ is proposed as the structure because of the product relation of the power term of drug concentration d_0 and time t . After training by non-linear regression convergence method, $n(t) = 2.254 \cdot d_0^{0.03961} \cdot t - 3770$ is concluded as the formula of regression. Then we further consider the problem in a Multi-Nodes and Neural-network dynamical system, $n(t) = n_{inner}(t) + n_{outer}$ is proposed according to the superposition theorem, where $n_{inner}(t)$ is the same as in the single-node dynamical system and n_{outer} refers to $\sum_{i=1}^{\infty} \mu_i \cdot f_i(n(t))$, μ is the constant regarding to economic ratio and $f(t)$ is impact amount of neighbour point. After the training by condition-weighted neural network, $n(t)_{t+1} = 2.7 \cdot d_0^{0.06} t - 3760 + \sum_{i=1}^{\infty} \mu_i \cdot f_i(n(t))$ is concluded. Then we build a decision tree model to analyse which attributes are more serious to the increase of Opioids. After training, we find that the boundary of our model is stable when the number of drug reports does not change. Increasing the percentage of education background, married status and multi house property can decrease the number of drug reports.

We further introduce a function g as a criterion to describe the propagation direction between two cities, $g > 0$ if $n(t+1) > n(t)$, which means neighbour counties are spreading drugs to this county and vice versa. And we define a starting-propagation point when this point of a year t_0 contains the maximum drugs report amount and $g \geq 0$ when $t < t_0$.

After analyse of those three models above, we propose 6 strategies for decreasing negative impacts of the Opioid crisis according to three factors, education background, married status and family property. In order to improve the education background, the government can higher the salary of and the assessing criteria educational workers. Apart from that, increasing the funding of universities' research is another good approach. As for increasing proportional of married family, government can lower down the tax and subside married family, also it is important to make strict regulations for companies to extend holiday and bonus for the pregnant. Considering the family property factor, it will be useful to decrease housing tax and provide more opportunity of working.

To sum up, our team studies the relation including time, distance and economic ratio for propagation of Opioid crisis. We then analyse which features contribute the drugs overuse the most and propose 6 strategies based on 3 factors, education background,

married status and family property.