Visualization of the Opioid Crisis in the USA
Team Big Data (114)
Final Report

Introduction and Motivation

The American opioid crisis has reached alarming proportions and is taking a severe toll on public health. This reality motivated us to develop a multidimensional analysis to understand the degree of this crisis and the factors which may explain opioid usage and mortality.

Problem Definition

While prior research has attempted to measure the extent of the crisis, a holistic study that includes socioeconomic factors across multiple data sources, advanced prediction techniques, and informative visualizations is lacking. Our project creates such a study. Two-thirds of deaths from drug overdoses are caused by opioids, and opioid abuse has doubled in prevalence since 2004 [1]. The most common explanation is over-prescription [2] [3]. Nonetheless, some authors have found that prescription rates have steadily decreased while opioid deaths have increased in the same states [4], suggesting that the issue is more complex than just excessive prescription. Indeed, several major questions are still unanswered: Which demographics are most affected? What are the characteristic factors in these populations? Which opioids are most prevalent – and most deadly? Several publications call for increased access to such analysis, including some that have raised questions around potential bias in CDC data upon which much previous work was based [5]. Data reaching across multiple secondary sources are especially lacking [8]. No study but one [19] provides a freely available visualization tool. While existing socioeconomic status indices have been shown to help predict adverse outcomes [6] [7], these indices have not been widely used in prior studies due to limited availability. Previous studies also tend to be single- or dual-factor and cover effects at the aggregate level, rather than incorporating a wide array of concurrent factors and analyzing individual geographic localities [9] [11] [12] [14].

Proposed Method

<u>Intuition</u>

Our team noticed that existing work had several limitations that could be expanded upon in our project. First, data stitched together from a wide variety of secondary sources is noted by the literature as lacking [8], an opportunity that extends both to modeling and visualization. Further, the most widely-available visualization provides only pills per county [19]: there exists an opportunity to provide users with important or correlated sociodemographic data that helps them understand the opioid crisis much more deeply. Finally, for complex, multidimensional problems, nonparametric machine learning methods have been shown to improve tangibly upon linear regression, providing an opportunity to advance the state of the field in terms of modeling opioid consumption and opioid-related mortality.

<u>Description of Approach</u>

Data synthesis

We synthesized the 88GB ARCOS-Washington Post database of opioid transactions from 2006-2012 into groups by year, state, county, and drug type, based upon a star schema. The main dataset was 88 gigabytes in size with 179 million transaction records. We used Dask and pandas to perform grouping on each dimension which we then insert into a SQLite database using Python Jupyter notebooks; Dask was also used to reduce the transaction details with the four unique keys to a pandas dataframe with all data and keys marshalled into usable formats. We next queried Census Bureau APIs for 1-, 3-, and 5-year ACS data to acquire data for the following sociodemographic factors by county and year: median household income, number of individuals in poverty, degree holders, number of individuals in school, non-white population, number of veterans, population with disabilities, number of housing units, median home value, number of homes with mortgages, median monthly housing costs, estimated number of bedrooms, people in labor-sector jobs. We acquired mortality data from the CDC's website and used Python to extract the deaths caused from opioids, reducing a total of 25 million rows into 55k rows. Unemployment data, workplace fatalities, and crime data were acquired from the Bureau of Labor Statistics (BLS), Occupational Safety and Health Administration (OSHA), and state governments respectively. Finally, we merged all datasets into the SQLite database based upon county FIPS code and year as a primary key. At this stage we also ran correlation analyses between each of the above variables and opioid transactions, and hosted the website framework, server code, D3 scripts, data CSV files, and SQLite database on GitHub Pages.

Prediction tasks

We built three predictive models (log-log linear regression, log-linear LASSO regression, random forests) for each of two consumption-related prediction tasks (grams of hydrocodone, grams of oxycodone). We also built two predictive models (linear regression, random forest) for each of two mortality-related prediction tasks: mortality *without* drugs as input, and mortality *with* drugs as input. For each model, we assessed features of importance using standardized coefficients (regression) and feature importances (RF) (see Experiments 1 and 2). We compared the accuracy of RF models with regression models by using RMSE on a held-out test set (see Experiment 3).

Visualization

We built a web application using d3.js and the above-listed technologies that includes the following features: pills per person, grams per person, inlaid graphs of trends in the top 3 correlated factors for the selected county. It also contains a "click-to-analyze" feature: clicking on a county generates RF model projections for future opioid transactions, projected mortality in the county, trends in each input feature, ranking of county relative to rest of country. To evaluate the effectiveness of our product compared to the existing visualization [19], we contacted a panel of [???] health professionals and solicited their evaluations by using a simple anonymous survey (see Experiment 4).

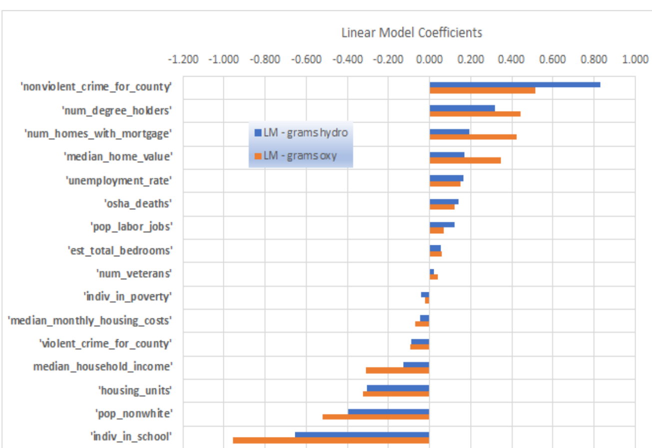
Experiments and Evaluation

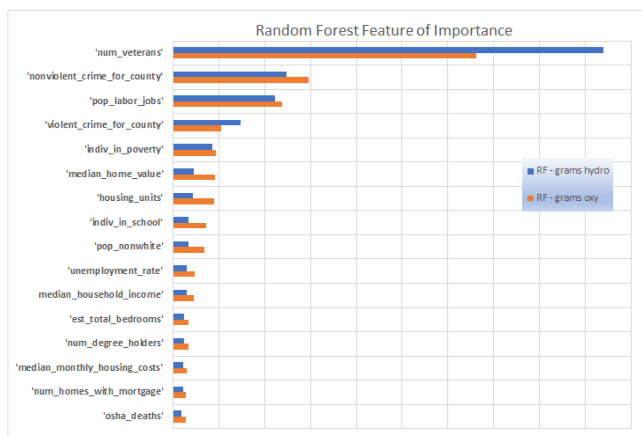
Key Questions

Key Question 1. What sociodemographic factors tend to correlate with, or explain the variance in, opioid transactions in the United States? What factors are most important? Do these factors indicate where governments could increase social services? Key Question 2. To what extent are opioids correlated with mortality rates? Put differently, does the data support the common narrative that excessive opioid prescription is the key factor in mortality rates among patients who have taken opioids? Testbed. We employed linear regression, LASSO regression, and random forests for two prediction tasks on a per-county basis: (1) prediction of grams of opioids transacted (hydrocodone and oxycodone), and (2) prediction of deaths related to opioids (both with and without opioids included in the model). Each prediction task was conducted on our synthesized, county-level dataset spanning 2006-2012 with the variables listed previously. We evaluated each model's performance by using root mean squared error (RMSE) on a held-out test set. We employed standardized coefficients (LR, LASSO) and feature importances (RF) to indicate variables of importance.

<u>**Experiment 1**: What factors tend to correlate with opioid consumption?</u>

Hypothesis 1: Among socioeconomic and sociodemographic variables, variance in opioid consumption is most explained by the state of the economy. Experiment 1: We trained six models in total: a log-log linear regression model, a log-linear LASSO regression model, and a random forest model to predict grams transacted of each of hydrocodone and oxycodone respectively. In each model, we follow accepted practice in the literature by controlling for each county's population. Findings 1: The following figures show standardized coefficients and feature importances for each prediction task. None of the methods prioritized economic factors in predicting opioid consumption, bucking the conventional narrative that economics explains the opioid crisis. Our results find that school systems (indiv_in_school, num_degree_holders), crime rates, veteran status, and housing availability/affordability (median_monthly_housing_costs, num_homes_with_mortgage) are *far more important than economic factors* in explaining opioid consumption. Median household income and unemployment rate, which our team expected to find as top factors, were comparatively unimportant. Conclusions 1: Our data suggest that it would be wrongheaded to insist on financial remedies to the opioid crisis. School systems, controlling the crime rate, and housing availability seem to be much more impactful areas for possible local government investment.

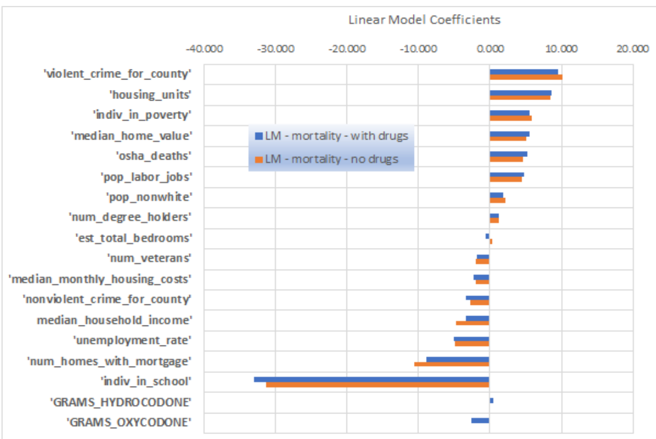


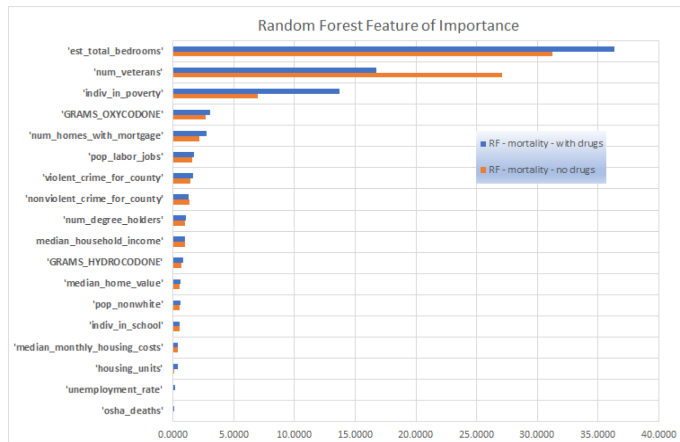


<u>**Experiment 2**: What tends to correlate with mortality among patients who have taken opioids?</u>

Hypothesis 2: Sociodemographic factors are of greater importance than opioid consumption statistics for predicting mortality among patients who have previously taken opioids. Experiment 2: In addition to the models trained in Experiment 1, we trained a linear regression model and random forest model to predict opioid-related mortality both *with* grams of drugs transacted and without it (four additional models). This task specifically allowed us to check whether (1) adding opioids to a model based upon sociodemographic factors

improved prediction accuracy, and (2) grams of hydrocodone and oxycodone proved to be the most important factors for forecasting mortality. Findings 2: Results of this experiment are shown in Table 1. Including grams of opioids transacted for each county showed *no benefit to predictive accuracy* in LR or RF models alike. Further, neither method prioritized hydrocodone or oxycodone consumption above key sociodemographic factors (e.g. crime, housing, veteran status) in explaining mortality for each county. Conclusions 2: Our results suggest that sociodemographic factors, including the availability of housing and education, are paradoxically more important than opioid volume for explaining opioid-related deaths. Put simply, pillcount is not the whole story -- our findings therefore contradict the "overprescription hypothesis", which holds that an increase in prescriptions has driven the opioid crisis. These sociodemographic factors require deeper scrutiny.





Experiment 3: Can machine learning methods offer a benefit to studies of population health?

Hypothesis 3: Advanced prediction techniques can offer an improvement in opioid-related forecasts as compared to regression. Experiment 3: As described above, we built three predictive models (LR, LASSO, RF) for each of two prediction tasks (grams transacted, mortality). We compared the performance of each model by evaluating its RMSE on a held-out test set unseen by the models during training. Findings 3: Results from modeling experiments are shown in Table 1. LASSO models provided little-to-no improvement to baseline linear regression. Meanwhile, RF methods provide a significant benefit to hold-out set RMSE, sometimes reaching 50% or more improvement over the baseline linear regression. This benefit held in forecasting opioid consumption and mortality alike. Conclusions 3: Health services researchers must incorporate advanced ML methods -- such as RF -- into population health forecasting if their goal is to improve accuracy.

Prediction task	Method	R^2 / OOB score	Hold-out set RMSE	Improvement over LR
Grams hydrocodone	LR	72%	1,081,923	-
	LASSO	73%	1,173,710	-8%
	RF	88%	598,310	45%
Grams oxycodone	LR	71%	2,953,543	-

	LASSO	74%	2,413,001	18%
	RF	82%	1,342,637	55%
Mortality *without* drugs in model	LR	41%	1,222	-
	RF	93%	620	49%
Mortality *with* drugs in model	LR	40%	1,516	-
	RF	93%	503	67%

Experiment 4: Can we offer a more informative, broadly-available visualization tool?
Hypothesis 4: A visualization application that provides correlations, local trends, and other data exploration offers significantly more benefit to policymakers than existing visualizations. Experiment 4: We built an openly-accessible website ([???] link here) that uses our six-source dataset to provide background information about top correlations between opioid consumption and sociodemographic factors, model predictions for future years, and local trends. We contacted a panel of [???] x and solicited their anonymous feedback via a survey (participants and survey questions listed in Appendix B). In particular, we sought to compare our offering to the most-available existing tool, provided by the El Paso Times. Findings 4: [???]. Conclusions 4: [???].

Conclusions and Discussion

While our experiments uncover several interesting findings, more work is needed. Our opioids dataset ranges from 2006-2012, and further data collection efforts are needed in order for research to continue. Further, visualization tools that map opioids and demographic features require further work, as our sample of participants is small and could be validated by broader public use, which we plan to continue pursuing. Much health data is restricted (e.g. comorbid conditions) due to privacy laws, so health systems must work directly with government entities to continue exploring the opioid crisis and its correlated factors. Finally, it is plausible that much opioid consumption is driven by illegal markets. *Very little data exists* about the illegal market, and much more research effort is needed to further clarify the picture.

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Appendix A: Sociodemographic factors

- Economy and employment
  - Unemployment rate
  - Median household income
  - Individuals in poverty
  - Population in labor-sector jobs
- Housing affordability and availability
  - Number of housing units
  - Median monthly housing costs
  - Median home value
  - Number of homes with mortgage(s)
  - Estimated total bedrooms in county
- Education system
  - Individuals enrolled in school
  - Number of degree holders
- Other demographics
  - Non-white race
  - Number of veterans
  - Nonviolent crime rate
  - Violent crime rate
  - Number of OSHA-reportable workplace fatalities

Appendix B: Survey participants and questions

Participants

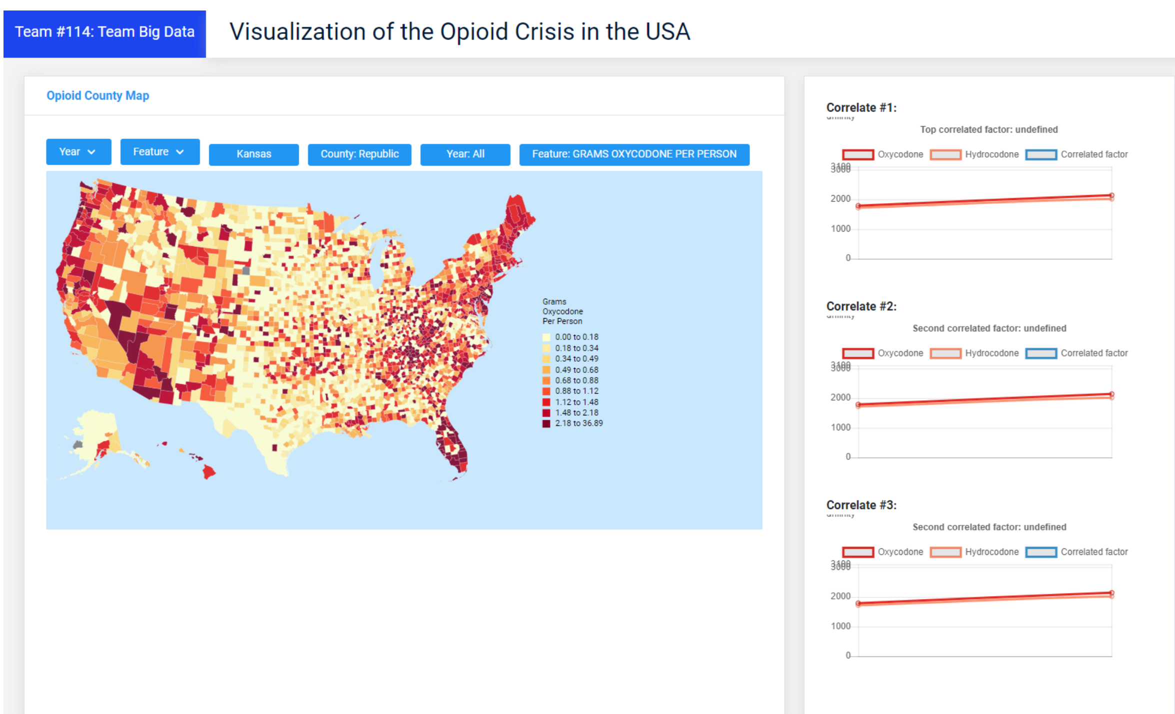
- Physician, internal medicine
- Chief of Research & Innovation, Nursing Department
- Strategy consultant for nonprofit organizations

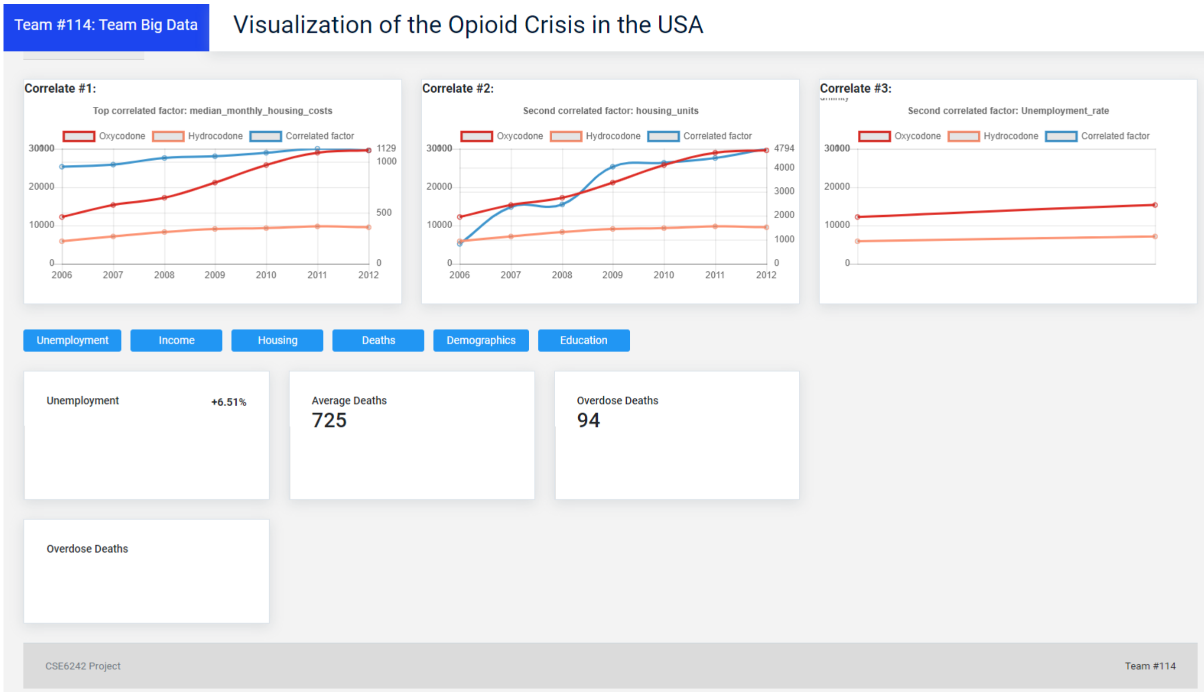
- Former OMSCS & CSE 6242 student
- Resident physician
- Medical student

Questions

- To what extent does our tool help you understand the sociodemographic factors that correlate with the opioid crisis? (1-5)
- To what extent does our tool *improve upon* the existing visualization tool? (1 = no improvement, 5 = complete improvement)
- To what extent do the visual layout, features, and graphs embedded in the product help you to improve your understanding of the American opioid crisis? (1 = I understood nothing new, 5 = I learned lots of new information)
- If you hoped to understand more about opioids in the course of your work, how likely are you to reference our tool? (1 = will not reference, 5 = will reference every time)
- Which feature was most important to improving your understanding (if at all)? (text entry)

Website screenshots:




Team #114: Team Big Data
Visualization of the Opioid Crisis in the USA
Correlate #1:
Top correlated factor: median_monthly_housing_costs
Oxycodone
Hydrocodone
Correlated factor
Correlate #2:
Second correlated factor: housing_units
Oxycodone
Hydrocodone
Correlated factor
Correlate #3:
Second correlated factor: Unemployment_rate
Oxycodone
Hydrocodone
Correlated factor
Unemployment
Income
Housing
Deaths
Demographics
Education
Unemployment
+6.51%
Average Deaths
725
Overdose Deaths
94
Overdose Deaths
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