Measuring Opioid-Related Stigma using NLP - Capstone Project Report

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Definition

Project Overview

In 2016, 42,249 Americans died as a result of an opioid overdose [1]. To put that in perspective, that is more than the number of deaths in 2016 caused by firearms (38,658) or motor vehicle crashes (38,748) [2]. The epidemic has struck small towns and big cities; families struggling to make ends meet and families that seem like they're living the American dream. Certain parts of the country have been hit especially hard, including my native Kentucky.

The most effective known method for reducing overdose deaths is providing medication for addiction treatment (MAT) which has been shown in clinical studies to cut overdose deaths by 70 percent [3]. However, the persistence of stigmatized views of addiction as a moral failing rather than a medical condition among policymakers and the general public has fueled resistance to efforts to expand access to MAT and discouraged individuals struggling with addiction from seeking treatment [4].

Despite its importance, very little data is currently available on opioid-related stigma. In particular, although there have been nationally representative surveys that asked about opioid related stigma [5], there is no data on how stigma varies across the United States—an important gap given the significant geographic variation of the epidemic. To fill this gap, I have gathered data on opioid-related conversations using Twitter's Streaming API and analyzed these conversations for stigmatizing language using natural language processing tools.

Problem Statement

The goal of this project is to measure how opioid-related stigma varies across the United States. To do so, I have tracked and analyze opioid-related conversations on Twitter. Analyzing tweets to determine whether they perpetuate a stigmatized view of opioid-use disorder represents a sentiment analysis problem, which is a subset of natural language processing problems. Although many sentiment analysis tools have been created in recent years, most of these tools focus on analyzing the positivity/negativity of text data. In this project, I develop a supervised method for coding the text of tweets for opioid-related stigma. Since my target variable is whether or not a particular tweet contains stigmatizing language, this is specifically a binary classification task.

Measuring geographic variation in opioid-related stigma required completing the following tasks:

1. Build a dataset using Twitter's Streaming API
2. Clean data to exclude duplicates, replies that do not contain opioid-related keywords, and tweets from users without an identifiable location within the U.S.
3. Manually code a sample of tweets to be used as training data
4. Prepare text for natural language processing by normalizing and vectorizing
5. Train and evaluate classifiers
6. Select a classifier and use it to automatically code the remaining tweets

As part of task 5, I will evaluate the following supervised learning classifiers: Logistic Regression, Linear Support Vector Machine, Naïve Bayes, AdaBoost, and a Convolutional Neural Network. I will select a classifier to use for task 6 based on the evaluation metrics discussed in the next section. The final classifier is expected to be able to predict with a high-degree of accuracy whether a tweet contains language that perpetuates opioid-related stigma.

Evaluation Metrics

To quantify the performance of the benchmark model and the solution model, I will use two metrics: accuracy and F-1 score.

- **Accuracy formula:** `(TP + TN)/(TP + TN + FP + FN)`
- Accuracy measures the proportion of hand-coded values that are correctly predicted. In the formula above, TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives.
- **F-1 score formula:** `(2 * precision * recall)/(precision + recall)`
- F-1 score takes the harmonic mean of precision and recall.
  - Precision tells us what proportion of tweets we classified as stigmatizing actually were stigmatizing. It is defined as `TP/(TP + FP)`.
  - Recall tells us what proportion of messages that actually were stigmatizing were classified by us as stigmatizing. It is defined as `TP/(TP + FN)`.

Accuracy is an appropriate initial metric for this binary classification task since the goal is to correctly predict which tweets contain stigmatizing language (true positives) and which tweets do not contain stigmatizing language (true negatives) Ultimately, however, I will give less weight to accuracy and than to F-1 score since I expect my data to by highly imbalanced. To see why F-1 score is a more robust measure than accuracy when text data is highly imbalanced, consider the case of a classifier for junk email when less than 10% of email is junk. In this case just predicting that no email is junk would lead to a more than 90% accuracy but a F-1 score of zero since both precision and recall will be equal to zero because no true positives were identified.

Analysis

Data Exploration

Using Twitter's Streaming API, I have built a dataset of of 713,256 tweets that contain opioid-related keywords (Table 1) which were tweeted between March 25, 2018 and September 22, 2018. Many tweets relate to opioid-related news articles such as in Figure 1. However, some tweets clearly contain language that perpetuates stigma by arguing that addiction is an individual choice and that programs to reduce addiction are not good uses of public resources (Figure 2).

Table 1: Opioid-Related Keywords Tracked via Twitter

General	Harm-Reduction	Overdose	Medication	Prescription	Synthetic
heroin	injection site	overdose	burprenorphine	codine	carfentanil
narcotic	needle exchange	naloxone	methadone	hydrocodone	fentanyl
opiate	safe injection	narcan	naltrexone	morphine	
opioid	supervised injection		suboxone	opana	
opium			vivitrol	oxycodone	
				oxycontin	
				percocet	
				vicodin	

Figure 1: Example Tweet Sharing Opioid-Related News Article

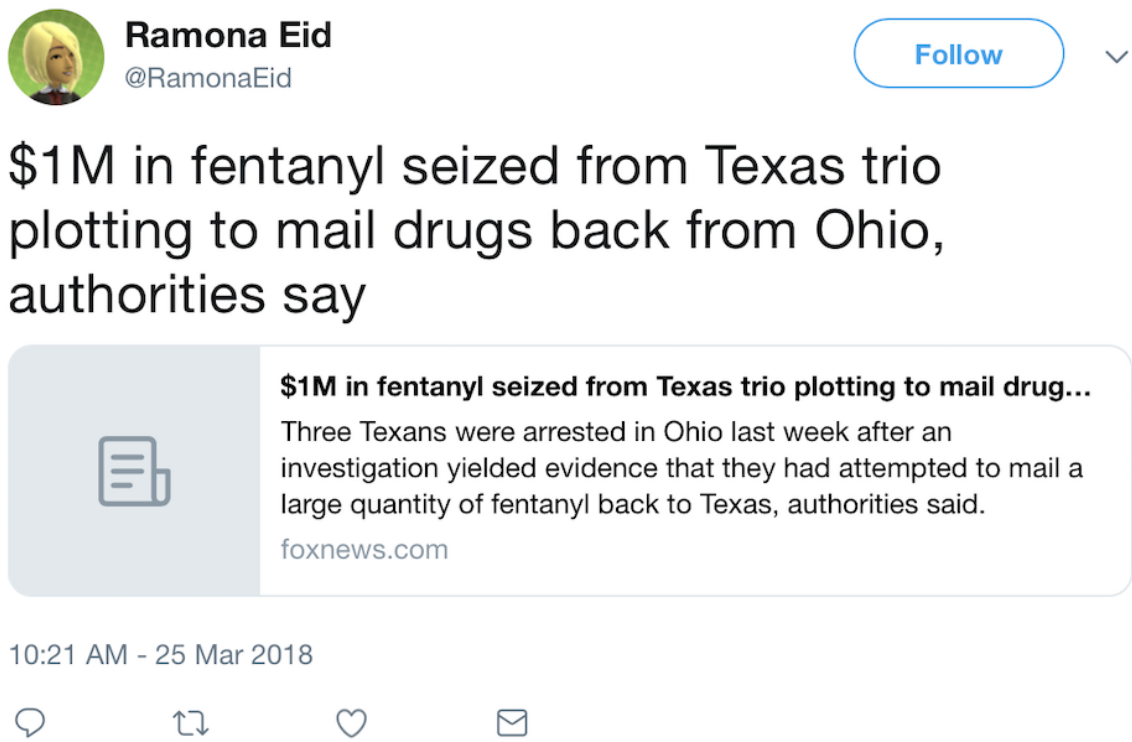
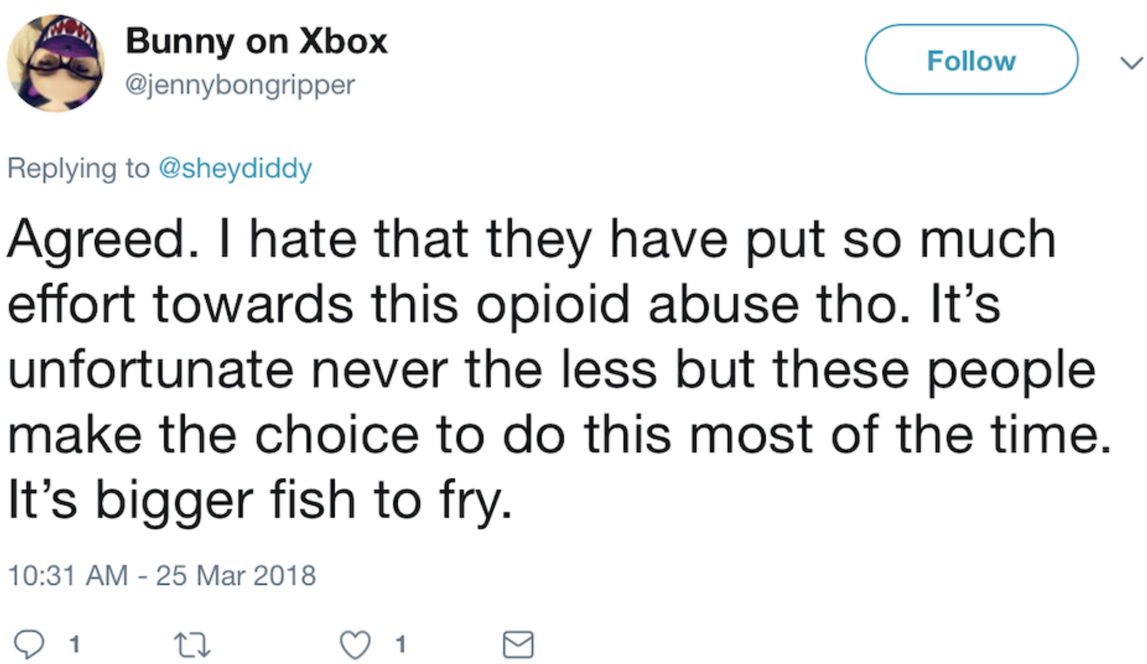


Figure 2: Example Tweet Perpetuating Opioid-Related Stigma



To select the final sample and prepare the data for manual coding, a number of cleaning steps were required. First, 324,776 tweets that did not contain opioid-related keywords were dropped. These tweets were only captured by the stream listener because they *quoted* a tweet that included an opioid-related keyword (Figure 3). Since the stream listener only captured the URL of the quoted tweet but not its text, the tweet_text field for these quote tweets does not contain any opioid-related keywords.

Figure 3: Quote Tweet Missing Opioid-Related Keywords

Second, 17,596 tweets were dropped whose text was identical to the text of an earlier tweet in the data *from the same user*. Duplicate tweets *across users* were kept because if the same news story with a stigmatizing headline is shared via tweet by multiple users, I wanted to count each tweet in my analysis.

Third, since the ultimate goal is to measure how stigma varies within the United States, 221,828 tweets were dropped if the user's self-entered location could not be mapped to a U.S. state. In order to capture as many tweets as possible, the user location field was examined to see if it ended in a postal abbreviation, contained a state name, or contained the name of city with a population over 100,000.

At the end of this cleaning, 149,056 unique tweets with opioid keywords and user location mapped to a U.S. state remained. As can be seen in Table 2 below, these tweets average 141 characters in length. This is exactly half of the maximum character length allowed by Twitter of 280.

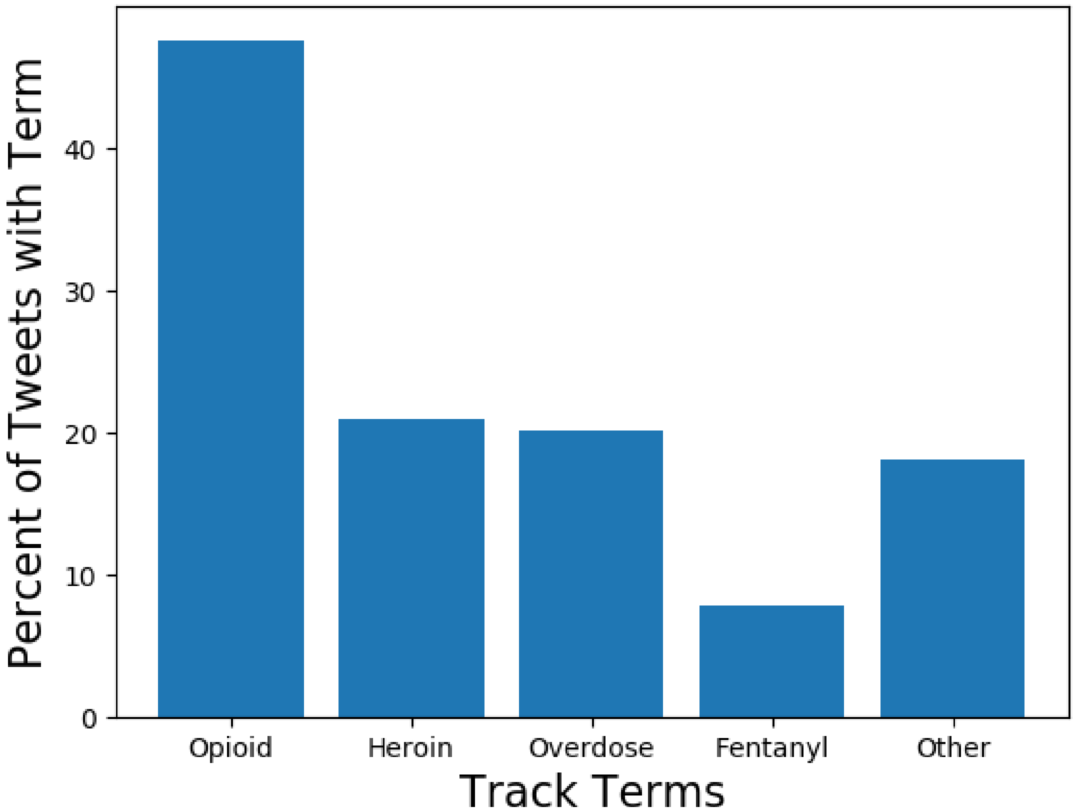
Table 2: Analysis of Tweet Character Length

Statistic	
Mean	141.30
Median	130.00
Standard Deviation	71.37
Minimum	8
Max	281

Exploratory Visualization

Before selecting a sample of these tweets for manual coding, it is useful to analyze which keywords that were used to filter tweets via the streaming API appear most frequently in the data. Although the list of keywords to track included 27 opioid-related terms, a large majority of tweets contain one of just four keywords: opioid, heroin, overdose, and fentanyl. This breakdown is visualized in Figure 4. Note that percentages sum to more than 100 because tweets can contain multiple keywords.

Figure 4: Most Popular Track Terms



Algorithms and Techniques

In order to create a custom classifier capable of automatically coding a large dataset, I followed the examples of Baum et al. 2018 and Oscar et al. 2017 and manually coded a small sample to use as training data for supervised machine learning algorithms [6,7]. The qualitative coding instrument was developed with reference to the academic literature and in consultation with two practitioners with significant experience addressing opioid-related stigma. (See Appendix: Qualitative Coding Instrument.)

Five supervised learning algorithms were trained and evaluated on the manually coded data: Logistic Regression, Linear Support Vector Machine, Naïve Bayes, AdaBoost, and a Convolutional Neural Network (CNN).

1. Logistics Regression or Logit, will be used as a second benchmark algorithm in addition to the Simple Majority Classifier discussed in the **Benchmark Model** section below. Logit is one of the most efficient algorithms, requires little tuning, and performs relatively well on binary classification tasks [8]. Additionally, since Logit returns the probability that an observation is in a given class, it is a good choice in settings where you want to be able to customize the threshold (for example if there is a need

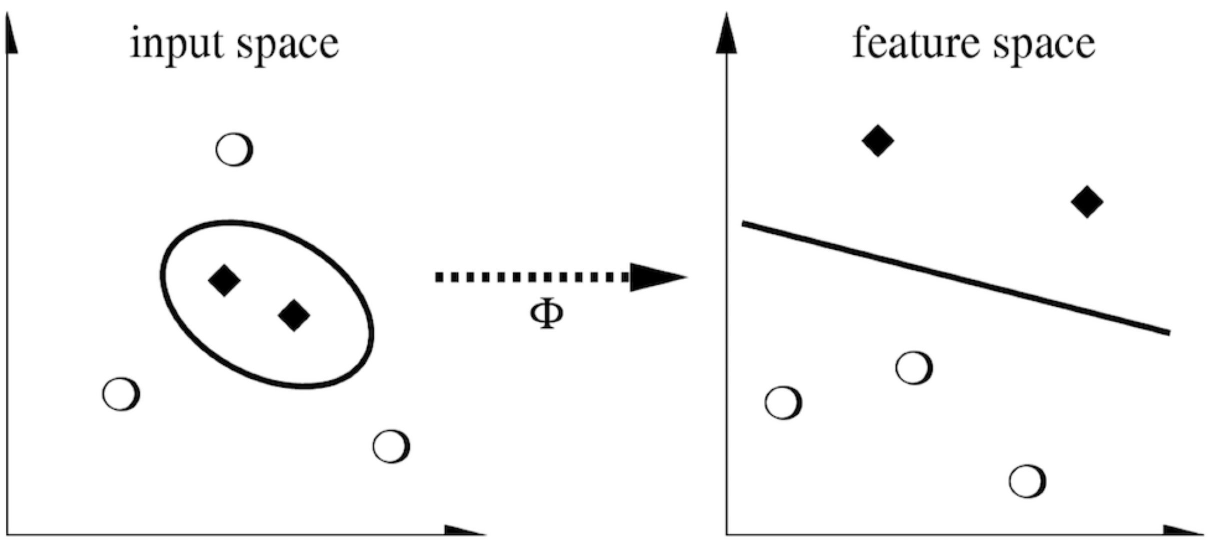
for high precision or high recall) [8]. Logistic regression works by finding the parameters β that fit the following equation:

$$y = \begin{cases} 1 & \beta_0 + \beta_1 x + \varepsilon > 0 \\ 0 & \text{else} \end{cases}$$

In this equation, ε represents an error term with a distribution matching the standard logistic distribution [9]. Although there is only one β and one x in the equation above, in our case it will actually be a vector of weights and a vector of features.

2. Prior to the resurgence of deep learning, Support Vector Machines (SVMs) were considered state-of-the-art for text classification [10]. They are well suited to text classification because of their ability to deal with lots of features [8]. I will be using linear kernel since, for text classification, it has been shown to perform as well as non-linear kernels [11]. Support Vector Machines work in classification tasks by trying to find the combinations of features that do the best job of creating separate categories. Mathematically, this is done by fitting a maximally-separating hyperplane to the feature space [6]. This is illustrated conceptually in Figure 5 which shows a mapping from the input space to a (higher-dimensional) feature space where the hyperplane that maximizes the margin between the two classes is calculated.

Figure 5: Conceptual Illustration of SVMs from from Schölkopf and Smola (2002) [12]



3. Naïve Bayes is popular as a baseline model for text classification since it trains quickly, requires little tuning, and is less of a black box than other algorithms. With additional pre-processing of text data, such as the TF-IDF weighting process discussed in the **Data Preprocessing** section below, Naïve Bayes achieve results competitive with SVMs [10]. The specific implementation of Naïve Bayes used is the multinomial Naïve Bayes classifier, which is well suited to text classification based on word counts. There is only a single hyperparameter to tune, alpha, which is an additive smoothing parameter. The algorithm works by looks at the different words present in a tweet and "naïvely" assuming that they *independently* contribute to the probability that the tweet contains stigmatizing language. Mathematically, this is calculated as:

$$p(C_k|x_1, \ldots, x_n) = p(C_k) \prod_{i=1}^{n} p(x_i|C_k)$$

In our case, this is interpreted as the probability a tweet contains stigmatizing language (that is, belongs to class C), given the vector of text features x_1 through x_n, is equal to the probability a tweet contains stigmatizing language (the prior probability) times the joint probability of a tweet containing these features given that it is stigmatizing.

4. AdaBoost is an example of a boosting model, one that combines a number of rough "rules of thumb" to create a highly accurate overall rule [13]. It has been shown to frequently outperform other non-deep learning algorithms, including on text classification tasks[14]. Adaboost trains by first generating a rough rule of thumb and then assigning it a weight based on how much better than random guessing it is [13]. Adaboost then adjusts the raw data, placing more emphasis on the exceptions to the first rule and looks for another rule of thumb that can explain those [13] This is a key difference compared to bagging models which generate rough rules of thumb by training on repeated random bootstrap samples of the data. This process is then repeated for a number of rounds. After training has been completed, AbaBoost generates predictions by looking at new data, considering all the rough rules of thumb that have been generated, and taking a "majority vote", with more emphasis given to those rules that were assigned a higher weight during training. The pseudo code for this is shown in Figure 6.

Figure 6: AdaBoost algorithm from Schapire 2013 [15]

Given: $(x_1, y_1), \ldots, (x_m, y_m)$ where $x_i \in \mathscr{X}$, $y_i \in \{-1, +1\}$.
Initialize: $D_1(i) = 1/m$ for $i = 1, \ldots, m$.
For $t = 1, \ldots, T$:

- Train weak learner using distribution D_t.
- Get weak hypothesis $h_t : \mathscr{X} \to \{-1, +1\}$.
- Aim: select h_t with low weighted error:

$$\varepsilon_t = \Pr_{i \sim D_t}\left[h_t(x_i) \neq y_i\right].$$

- Choose $\alpha_t = \frac{1}{2} \ln\left(\frac{1 - \varepsilon_t}{\varepsilon_t}\right)$.
- Update, for $i = 1, \ldots, m$:

$$D_{t+1}(i) = \frac{D_t(i)\exp(-\alpha_t y_i h_t(x_i))}{Z_t}$$

where Z_t is a normalization factor (chosen so that D_{t+1} will be a distribution).

Output the final hypothesis:

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right).$$

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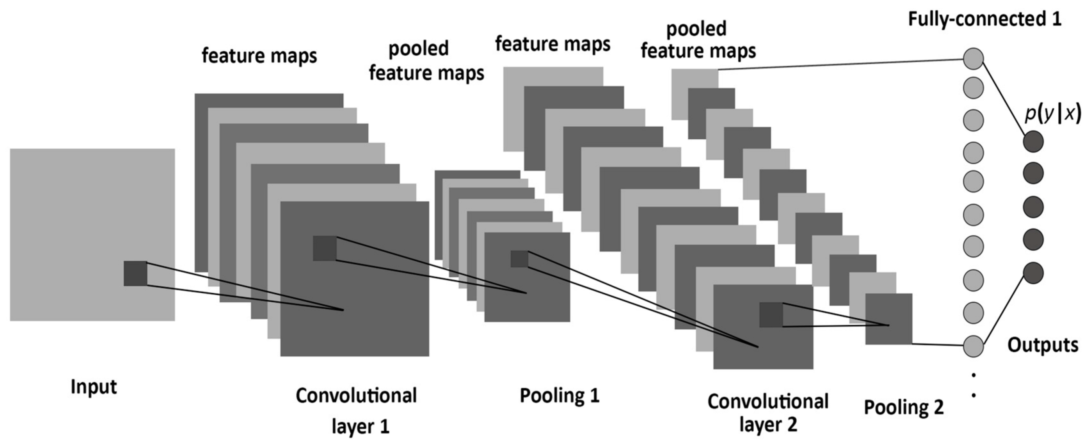
5. CNNs are now considered state-of-the-art for classification tasks, although they require large amounts of training data, which was not possible in this case due to the manual coding requirement. With sufficient data, CNNs can learn complex features that allow them to excel at natural language processing tasks [16, 17]. Like all deep neural networks, CNNs take input in the form of vectors, apply operations and feed results forward through a series of hidden layers, before connecting to a final layer that outputs predictions, in this case, text classifications. The hidden layers in a CNN typically alternate between convolutional layers and pooling layers, as can be seen in the example architecture in Figure 7. Within each convolutional layer, a filter slides over the input to extract a feature map. The dimensionality of this feature map is then reduced by the pooling layer. Finally, a fully connected layer uses the pooled feature maps to output classification predictions.

Figure 7: CNN Architecture from Albelwi & Mahmood 2017 [18]



Benchmark Model

One of the challenges in creating a custom classifier is the lack of a benchmark model. Following the example of Oscar et al. 2017, I initially compare the results of my classifier with the predictions of a simple majority classifier (also known as the Zero Rule or ZeroR classifier) [6]. Since a majority of tweets do not contain stigmatizing content, the simple majority classifier predicts that all tweets do not contain stigmatizing content.

Only 7.2% of the manually coded test examples contained stigmatizing language, meaning that the simple majority classifier achieved 92.8% accuracy. However, since the simple majority classifier did not predict any true values, its F-1 score was zero, as explained in the **Evaluation Metrics** section above.

As an additional benchmark, I use the relatively simple Logistic Regression algorithm with L1 regularization since the features are sparse. Its performance is discussed in the **Results** section below.

Methodology

Data Preprocessing

After filtering the data as described in **Data Exploration**, the following additional preprocessing steps were implemented:

1. Remove links, @mentions, and HTML to improve readability for manual coding.
2. Manually code training data sample and resolve inter-coder disagreements.
3. Normalize text by stripping special characters, expanding contractions, changing case to lowercase, removing stopwords, tokenizing (converting sentence to a list of individual words), and lemmatizing (converting each word to its root form to reduce dimensionality).
4. For the non-neural network algorithms, transform the normalized data to a matrix of word counts using a term-frequency times inverse document-frequency (tf-idf) weighting. This weighting re-balances to give more influence to rare words and less influence to common words. It has been shown to improve the performance of Naïve Bayes in particular [8].
5. For the CNN, transform the normalized data to arrays knowns as tensors (since CNNs require arrays rather than matrices).

During step 2, I coded all 1,000 training examples and then had a second coder independently code a random subsample of 100 training examples. On these 100 examples, we agreed on the classification in 94% of cases, which is a more than satisfactory level of inter-coder reliability by the standards of the literature. In order to reduce the risk of false positives, where coders disagreed about whether a tweet contains stigmatizing language, the final training set coded that tweet as not containing stigmatizing language.

Implementation

Once the preprocessing had been implemented, a training and testing pipeline was developed. The manually coded data was randomly shuffled and split into 750 training examples and a hold-out set of 250 examples for testing. Since the labels were highly imbalanced with only 7.2% of tweets coded as containing stigmatizing language, the data was split in a stratified fashion.

Each of the classifiers were trained on the training examples and then evaluated on the hold-out set. The following specifications were used for each classifier:

1. Logistic Regression with L1 penalty, tolerance for stopping criteria of 0.001, and liblinear solver
2. Linear Support Vector Classifier with L1 penalty, tolerance for stopping criteria of 0.001, and primal optimization solver
3. Multinomial Naïve Bayes with additive smoothing parameter of 0.01
4. AdaBoost Classifier with scikit-learn default parameters
5. spaCy Text Categorizer Neural Network trained over 20 iterations using minibatches starting at 4 examples and increasing by a factor of 1.001. The only parameter different from the defaults in spaCy's documentation was the use of a decaying, rather than fixed, dropout rate that started at 0.25 and decayed by a factor of 0.01 to 0.20. Although spaCy's architecture has not been published yet, details of the model are described in their API documentation [19] and the implementation can be replicated by following their guide to training a text classification model [20].

Thanks to guides from scikit-learn [21] and spaCy [20], implementation was relatively straightforward. The biggest complications involved figuring out how to adapt example code to the specifics of my custom data set.

The initial performance of each classifier is listed in Table 3 below. As predicted, the Simple Majority Classifier achieves a high level of accuracy but receives an F-1 score of zero. The classifier that performs best in terms of both accuracy and F-1 score was the Multinomial Naïve Bayes classifier.

Table 3: Initial Implementation Performance

Classifier	Accuracy	F-1 score
Simple Majority Classifier	0.928	0.000
Logistic Regression	0.924	0.240
Linear Support Vector Machine	0.924	0.296
Multinomial Naïve Bayes	0.944	0.364
AdaBoost	0.924	0.345
spaCy Text Classifier CNN	0.924	0.240

Refinement

After the initial implementation, the Naïve Bayes classifier was chosen for further refinement since, in addition to achieving the best performance, it is fast to train and relatively simple to understand compared to next highest performing algorithm, AdaBoost, which is more of "black box."

This classifier was further refined by using a grid search with five-fold cross validation to confirm the optimal level of the additive smoothing parameter alpha. The values of alpha considered included 1.0, 0.1, 0.01, and 0.001. Compared the the unoptimized model (alpha = 1) which has an F-1 score of 0, the optimized model (alpha = 0.01) has an F-1 score of 0.36.

Results

Model Evaluation and Validation

As mentioned above, the refined version of the final model is a Multinominal Naïve Bayes Classifier with an adaptive smoothing parameter of 0.01. The robustness of the model was validated by looking at a sample of predictions made when auto-coding the data that was not selected for manual coding. As can be seen in Figures 8 and 9, these predictions have a high degree of accuracy.

Figure 8: Tweets Coded as Non-Stigmatizing

	user	tweet_text_full	stigma_any
45351	qballjeff	How about taking care of the children and families that have been separated due to opioid epidemic in Ohio your doing nothing to help them oh that's right your on the stump for 2020 Democratic ticket	False
42396	MarziayW	I wish I had gone one step further then telling thebheroin addict to leave me alone I wish I had said to myself in going to hide from the heroin addicts.	False
134205	DonnaYoungDC	On #opioidcrisis, says change is coming for monitoring/reporting/communication; going to accelerate communication.This year, #CDC will be correcting contracting issues.#RAForum18 #Overdose #OpioidEpidemic	False
112790	rishi_b_Eshita	He was not prescribed fentanyl. Where did you get this info. Is Paisley Park telling folks this?	False
56261	OpioidHelpNow	Comparison of buprenorphine and methadone in the treatment of opioid dependence | American Journal of Psychiatry	False
114941	yonidanyell	Becuz, I asked pharmacists how they felt, AND why this INSANE response. They stated becuz the argument is "oh, opiods lead to worse drugs, like heroin." WELL, when you deny them legal meds, they RUN to the DRUG lord. Coun	False
143316	quexieqbal7	Obviously she did not know the whole story tapi tetap nak limelight konon heroin Melayu...	False
52667	vicejunky	literally a drug in mexico or somewhere that helped people kick heroin pretty easily, and they banned it in the US	False
127629	smol_angel	My grandma gave me some cough syrup to take before bed and I didn't realize it had codeine in it so I smoked a bowl first and....guuuuurl	False
95468	NuckChorris16	Whoa there. Take it easy. Be careful. You may be making the painkilling power of the fentanyl less effective too.	False

Figure 9: Tweets Coded as Stigmatizing

	user	tweet_text_full	stigma_any
123167	AnyssaVela	You can snort heroin	True
59820	charkszn7	Imagine doing heroin in 2018🤪	True
124871	KevinGutzman	Hmm, what would a suicidal heroin junkie say?	True
42527	Fuctupmind	Could you imagine a California heroin Christmas tree?	True
125490	33DoubleD1	I guess the plastic used in the free heroin syringes gets a mulligan go figure	True
25493	johnathanalxndr	dope like fuckn heroin	True
38598	kcevans56	This is as stupid as giving heroin addicts needles for free in the Streets of San Francisco and LA	True
45837	MKehoe88	I think you're a little too stoned there Snoop. Never done heroin in my life, never been a junkie. If you're gonna come at someone maybe do your research so you dont come off like a clown.	True
6363	B_inShortsville	But if Homer & Jethro; the landlady's 1st-call opioid addicts, err... "handymen" don't work Easter weekend, Zombie Jesus probably doesn't either.	True
23478	BluSturmer81	I don't need to buy a $9 latte to shoot heroin in your bathroom? SWEET. Thanks #Starbucks	True

Of the 10 sample tweets coded as non-stigmatizing, there only appears to be one false negative. The tweet from user MarziayW, clearly uses language referring to individuals with substance use disorder as "addicts," however, the classifier might have been confused by a spelling error ("thebheroin" instead of "the heroin").

Of the 10 sample tweets coded as stigmatizing, there seem to potentially be four false positives (from users AnyssaVela, charkszn7, Fuctupmind, and johnathanalxndr). Yet, considering the sparsity of positives in the training data, the fact that the classifier was able to pick out so many clear examples of stigmatizing language is impressive.

Justification

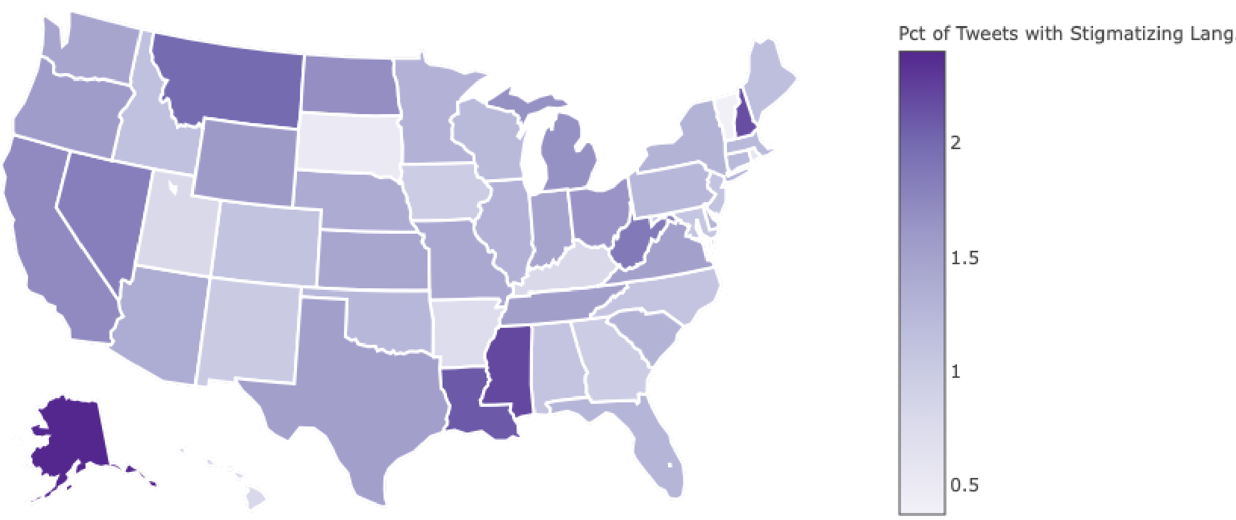
The final model achieves slightly higher accuracy (94.4%) and a significantly higher F-1 score (0.36) than the simple majority classifier (accuracy: 92.8%, F-1 score: 0.00) or the logistic regression (accuracy: 92.4%, F-1 score: 0.24). Additionally, inspection of a small sample of predictions made by the classifier indicates that it is generally able to distinguish stigmatizing language, though in this small sample the level of precision left a little to be desired.

Conclusion

Free-Form Visualization

At the beginning, I set out to measure geographic variation in opioid-related stigma. Figure 10 below presents one proxy measure based on tweets classified by the algorithm trained in this project. States with a greater percentage of tweets classified as stigmatizing are shaded darker.

Figure 10: Percent of Tweets Containing Stigmatizing Language by State



Although visualizing how stigma varies geographically answers an interesting descriptive question, the questions that are most important for policy are causal questions. Of particular importance is the question of whether increased opioid-related stigma *causes* increased overdose deaths. Unfortunately, these more important questions are also more difficult to answer. However, the new descriptive data generated by this project allows at least an initial exploration of whether stigma is *correlated* with overdose deaths.

Figures 11 and 12 analyze the relationship between the prevalence of stigma measured in tweets and the rate of overdose deaths due to opioids in 2016 (the most recent year for which data is available). States in the bottom three quartiles in terms of overdose rates (Figure 11) are examined separately from states in the top quartile (Figure 12). While Figure 11 indicates there is no relationship between stigma and overdose deaths for states in the bottom three quartiles in terms of overdose deaths, Figure 12 suggests that there is a relatively strong positive relationship between stigma and overdose deaths for the states with the highest level of overdose deaths.

Figure 11: Opioid Overdoses (2016) vs Tweet Stigma: Bottom 75%

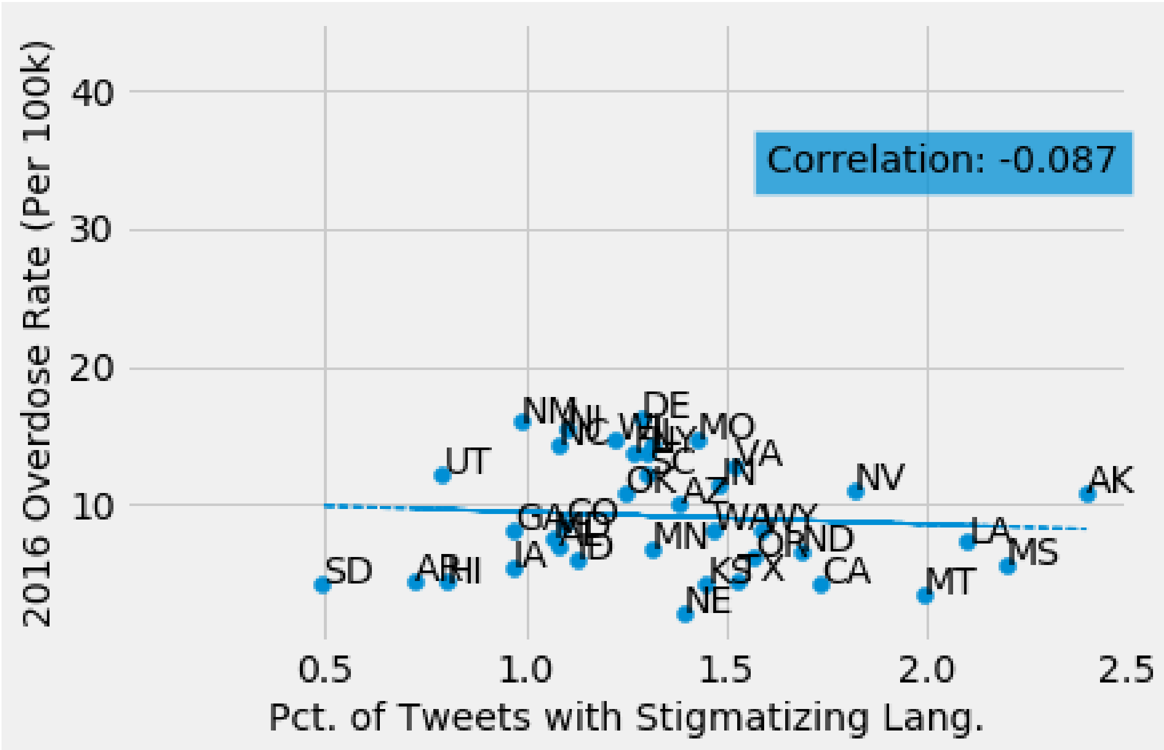
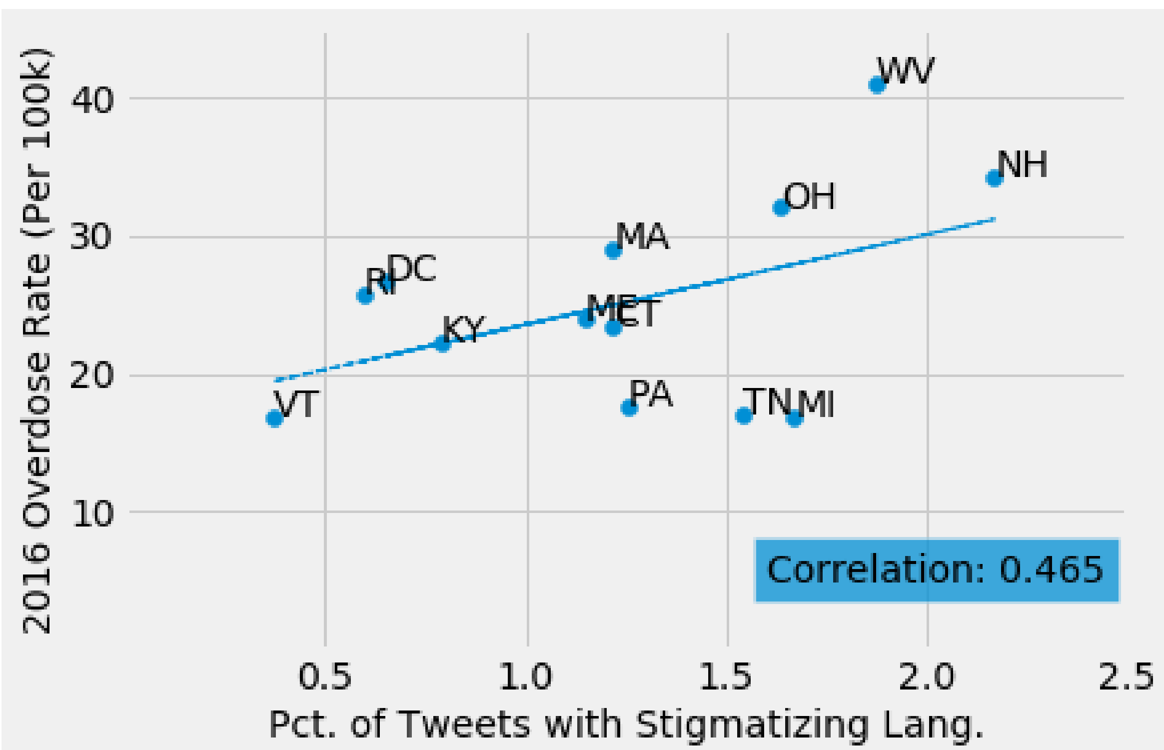


Figure 12: Opioid Overdoses (2016) vs Tweet Stigma: Top 25%



There are a number of caveats to emphasize here:

1. The relationship in Figure 12 is just a correlation. Instead of stigma causing more overdose deaths, it could be that more overdose deaths lead to more stigmatized views of individuals with opioid-use disorder.
2. The relationship is sensitive to the choice of criteria for which states to include. If only states above the 80th percentile in terms of overdose deaths are included, the correlation rises to 0.51. However, if all states above the 60th percentile in terms of overdose deaths are included, the correlation coefficient drops to 0.36. And if all states above the 50th percentile in terms of overdose deaths are included, it drops further to 0.28.
3. Overdose data from the summer of 2018, once available, might show a different relationship. There have been elements of continuity in the epidemic but it has also been fast-moving with some areas seeing rapid increases in overdose deaths, especially with the arrival of fentanyl.
4. As a result of the low prevalence of stigmatizing tweets, many states have very few tweets coded as containing stigmatizing language. Although the median number of total tweets per state is 1,612, the median number of tweets coded as stigmatizing is 22. This may mean that there is not enough data to detect significant differences in stigma between smaller states.
5. Correctly coding tweets for stigmatizing language is a hard NLP problem and, partially as a result of the relatively small size of the training data, the classifier ultimately used to auto-code the vast majority of the data had lots of room for improvement in terms of precision and recall.
6. Stigma as measured through Twitter conversations may not be reflective of stigma either among the general population or among the populations that interact most with individuals with substance use disorder.

Yet, even with all these caveats, Figure 12 provides enough evidence to at least justify gathering more data and conducting additional research to better understand the relationship between stigma and overdose deaths. 4,123 lives could have been saved in 2016 if all the states in the top quartile in terms of overdose death rates were able to reduce their overdose rates to the level of Vermont, the state with the lowest measured levels of stigma not only among the top quartile but among all states. Although we cannot be sure whether reducing stigma to Vermont levels would also reduce overdose rates to Vermont levels (or if it is even possible to reduce stigma on a statewide level), the scale of the potential benefits from doing so suggests that these are questions worth exploring further.

Reflection

The process for this project can be summarized in the following steps:

1. Gather data from non-traditional source in order to fill gap
2. Clean and preprocess data
3. Develop a qualitative coding instrument and manually code training set
4. Train and evaluate classifiers
5. Refine best performing classifier and auto-code remaining data
6. Analyze results

This process reinforced for me the lesson that getting data that is ready to go into machine learning algorithms is 99% of the work. In the first two steps, I learned a significant amount about how to deal with messy, real-world, relatively large data sets. And unrelated to machine learning and data science per se, I also learned a great deal about the opioid epidemic and stigma towards individuals with substance use disorder. Although the classifier I developed is admittedly imperfect, the problem of the opioid epidemic is too significant to let perfect be the enemy of good when it comes to gathering data that could inform evidence-based policies.

Improvement

In future, I would like to continue to collect data so that I can eventually compare historical tweets with contemporary data on overdose deaths. I would also like to crowd-source help with manual coding in order to build a larger training dataset that could be used to take advantage of deep learning techniques. Finally, I am eager to receive feedback from individuals working on the front lines of the epidemic about how my coding instrument could be improved and, most importantly, what other data could be collected that may help save lives.

References

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Appendix: Qualitative Coding Instrument

Based on a review of the literature about opioid-related stigma, the following instrument was developed to code tweets for language that perpetuates stigmatized views of individuals with substance use disorder and medications for addiction treatment.

Stigmatized views of individuals with substance use disorder (SUD)

Does the tweet make reference to any of the following? Check as many as apply.

- Addiction as a choice or result of character flaw (such as immorality, stupidity, weakness)
- Addiction as a sign of poor parenting
- "Clean" to refer to people in recovery
- Individuals with SUD are abusers, addicts, druggies, or junkies (include self-labeling)
- Individuals with SUD are not desirable as neighbors or community members
- Individuals with SUD are not worth saving or deserve to die (e.g. "natural selection")
- Individuals with SUD are not worth spending money on
- Individuals with SUD are violent/dangerous
- Opioid epidemic is not a problem, is exaggerated, or is something to joke about
- Other: [...]

Stigmatized view of medications for addiction treatment (MAT)

Does the tweet make reference to any of the following? Check as many as apply.

- Abstinence as more admirable than maintenance with medication
- Advocating criminal justice approach over public health approach
- "Clean/dirty" to refer to negative/positive toxicology results (exclude references to dirty needles)
- "Detoxification" from medication (buprenorphine/Suboxone or methadone)
- Individuals receiving MAT should not be pregnant or parents
- Injection sites as "drug dens"
- Providers of MAT as drug dealers
- MAT as an addiction or substitution
- MAT as harmful
- Treatment as hopeless
- Other: [...]