

Forecasting Opioid Incidents for Rapid Actionable Data for Opioid Response in Kentucky

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Abstract

We present efforts in the fields of machine learning and time series forecasting to accurately predict counts of future opioid overdose incidents recorded by Emergency Medical Services (EMS) in the state of Kentucky. Forecasts are useful to state government agencies to properly prepare and distribute resources related to opioid overdoses effectively. Our approach uses county and district level aggregations of EMS opioid overdose encounters and forecasts future counts for each month. A variety of additional covariates were tested to determine their impact on the model's performance. Models with different levels of complexity were evaluated to optimize training time and accuracy. Our results show that when special precautions are taken to address data sparsity, useful predictions can be generated with limited error by utilizing yearly trends and covariance with additional data sources.

1. Introduction

Opioid use disorder (OUD) remains a persistent public health crisis and epidemic. In 2023, Kentucky had the fifth-largest drug overdose fatality rate in the United States, and 79% of those deaths involved opioid substances¹. Community-level heterogeneity in OUD and overdose trends complicates state-level responses and suggests community-driven interventions guided by local data are needed. Efforts to reduce opioid overdoses and support opioid overdose control and prevention are limited by delays in data availability and fragmented data systems. In the context of the dynamically changing opioid epidemic, agencies and organizations responsible for monitoring and improving the health of the population need timely (state and local) data to make critical decisions on resource allocation and targeted responses.

Time series forecasting can have multiple applications in addressing the opioid epidemic. By creating accurate forecasts for specific areas, it is possible to determine both when and where increases or decreases in overdoses are expected to happen. With this knowledge, interventions such as naloxone can be distributed to these areas effectively. Law enforcement and EMS agencies could have advance knowledge of expected spikes and prepare accordingly, making treatment quicker for overdose victims in those areas. Additionally, time series forecasting can help provide more insight into the data and its trends. Analyzing the relationship between overdose trends and other variables can illuminate other factors that correlate with those counts. These factors could be monitored to track future overdose incidents to hopefully reduce either the frequency or the lethality of these events.

The techniques used to forecast opioid overdoses can vary depending on the scale, speed, and data availability. Some existing work focuses on individual risk for overdose using statistical or basic machine learning models^{3,4}, while other work takes a national scale to forecast weekly counts⁵. There is a variety of existing work focused on forecasting overdose counts at different scales^{6,7}, but the work proposed here differs in key areas. First, we examine combinations of different geographical and temporal scales, as well as surveying different architectures of statistical and machine learning models to determine the optimal data setup and forecasting models to achieve the highest accuracy. Additionally, we discuss the usage of novel data sources as covariates to determine their impact on forecasting accuracy.

This article will present a survey of approaches taken to forecast opioid incidents around the state of Kentucky, using different model architectures and covariate data to improve prediction performance. The work is to support the Rapid Actionable Data for Opioid Response in Kentucky (RADOR-KY) project (NIDA R01-DA057605) to provide state agencies and local stakeholders with actionable timely information to support opioid overdose prevention, harm reduction, evidence-based treatment, and recovery. The results show that forecasting overdose counts with low error is possible using preprocessing, machine learning, and varied data collection.

2. Methods

Time series forecasting is the process of analyzing temporally structured data and creating future predictions on that data. This can be done with simpler, regression-type models that take a statistical approach to analyzing the trends and changes in the data⁸, or it can be performed with more complex machine learning models⁹. These models are less interpretable and more complicated to build, but they can also outperform statistical approaches, especially with larger sample sizes, increased complexity of data trends, and higher counts of covariates to interpret¹⁰. These models can identify components of the time series such as the overall trend as well as seasonality, or repeating cycles seen throughout the data. Through the identification of these components, more can be learned about the series.

To support our forecasting efforts, we collected data from a variety of sources. We aggregated these data into appropriate temporal and geographical levels, which supported the creation of statistical and machine learning models needed to perform the forecasting.

2.1. Data

The primary target variable for forecasting is the count of opioid related incidents recorded by EMS agencies in Kentucky between January 2017 and July 2024. This data source consists of individual records of every suspected opioid overdose encounter recorded by the EMS agencies, which includes diagnosis information and dates and address information about where the incident took place; we geocoded these addresses to assign each incident to a county. We receive this data weekly in partnership with the Kentucky Board of Emergency Medical Services. The timeliness of the data enables us to rapidly update and adjust our forecasting efforts.

Additionally, several other data sources were used to create covariates that could aid the model in generating predictions. The most basic covariates are categorical variables representing the month and season at each timestamp, but others required external data sources.

The OpenMeteo weather API was used to gather weather data from around the state¹¹. Data containing temperature, precipitation, and sunshine measurements, among others, was gathered from central locations in each of Kentucky's fifteen Area Development Districts (ADDs), which are groupings of counties based on similar geographic and demographic characteristics. These weather variables were summarized for each geographical grouping and time frame for use as covariates with the models.

Social determinants of health (SDOH) for each Kentucky county were also gathered¹². These are key variables that indicate for different geographical regions the levels of socioeconomic status, ethnic and age distributions, and household/transportation characteristics. Some key variables utilized include unemployment rate, proportion of cost-burdened housing, vehicle access, and municipal housing rates. These variables describe each county's SDOH environment. Since these variables do not change over the near term they act as static covariates, rather than dynamic covariates. They are used to improve model performance by distinguishing between different areas with variance in key SDOH characteristics.

Medicaid data is provided by the Kentucky Department for Medicaid Services and contains information from Medicaid claims for each Kentucky county. These measures include the number of individuals in each area diagnosed with OUD, receiving treatment for OUD, screened for substance use, connected with an opioid-related ED visit, and more. This data is provided at a quarterly aggregation.

Drug seizure data was used in partnership with the Kentucky State Police and includes where drugs were seized and what substances tested positive in the seizure. For this work, the data is combined into monthly counts for each area and limited only to opioid substances.

The Kentucky Department of Corrections provided information on inmate intake and release data for those individuals with substance risk. This includes the number of prison intakes and releases for each month, and the substance use risk level for each person, on a scale of 1 to 5. These counts are utilized here as a weighted average of risk levels to determine a single value for each county and timestamp.

Finally, overdose data for other related counties, lagged by one month, was included for each county as a covariate. Time series forecasting models naturally use lagged values of the target series to aid in predictions, i.e. previous values of the target series are used to determine what the current value could be. In addition to this, a covariate was created to represent lagged overdose values for other counties. The idea is that the trends of some counties are likely to precede the trends of other counties. For example, a spike in overdoses in a particular area of Kentucky may be followed by spikes in overdoses in other areas of the state, due to the movement of drugs throughout these areas. Therefore,

correlation analysis, a technique to determine linear relationships between variables, was used for each county to determine what other counties best matched in previous months, and averages of those counties were used to create this covariate.

2.2. Geography/Time

The first implementation choice we addressed was the geographical and temporal units that would be used for aggregation. The EMS data for opioid overdoses allowed for aggregation at the state, county, zip code, census tract, block group, or block levels. For forecasting overdose incidents, the state level was too broad and not useful for helping determine allocation of resources. While potentially useful, groupings smaller than counties were too sparse, lacking the data needed to interpret trends. As the geographical level for aggregation decreases in size, the overdose counts become more and more sparse, as smaller areas will have more zero values for their measurements. Preliminary experiments showed that forecasting did not work well for very sparse data, as it is difficult to analyze any trends when there are so few positive counts. To balance usefulness and sparseness, the county was the smallest level of aggregation that could still be used effectively for this work.

However, the counties in Kentucky vary widely in size, so even then, not every county should necessarily be treated equally. For example, Jefferson County and Fayette County are the two largest counties in Kentucky, containing the cities of Louisville and Lexington respectively, so these counties have significantly higher populations and higher counts of overdose incidents. The trends of these counties are easier to analyze because as the number of overdoses increases, changes over time become more predictable. Overarching trends and external influences become apparent, significantly mitigating the uncertainty of random chance. Many of the smaller, more rural counties in Kentucky have records of very few incidents. This complicates the ability to discern if these changes are incidental or due to external factors. Therefore, the fifteen Kentucky ADD groupings, each containing several counties, were evaluated to determine if the larger scale led to better results.

At the temporal scale, monthly forecasting proved to be the best option, compared to yearly or weekly. Similarly to the tradeoffs with the geographical units, yearly is too broad, but weekly is too specific and sparse. Many covariates are already collected at the monthly level, so monthly forecasting was a natural choice. However, the weekly scale may have other advantages. Covariates such as drug seizures or lagged spikes in other counties may be more impactful at a smaller temporal scale. For example, a big police drug seizure may be expected to influence overdoses in that area, but those effects may have subsided after a month. More work will be done in the future to analyze the effectiveness of this scale for certain areas of the state.

2.3. Models

A variety of different models and architectures were evaluated to determine the optimal choice for forecasting performance. However, there were some limitations on which models could be used, the most significant of which is the usage of past covariates. The two primary types of dynamic covariates are future and past: future covariates are known beforehand at the time of prediction, while past covariates are not. A future covariate would be the month or season, as those values are known into the future at prediction time. Weather can also be considered a future covariate, as realistic estimates of average temperatures or precipitation can be determined beforehand. However, most of the covariates considered specified to opioids would be past covariates. This includes drug seizures or prison releases as those values are not known into the future at the time of prediction. Future covariates can be more helpful to the model, as it can use current covariate values to adjust predictions, but past covariates can still be used to pick up on new trends or correlations throughout the data.

With these limitations in mind, three primary models were evaluated, each with individual structures and complexities: Histogram-based Gradient Boosting Regressor¹³, the N-Linear LSTF model¹⁴, and the Temporal Fusion Transformer (TFT)¹⁵. Histogram-based Gradient Boosting is the simplest of these models, building an ensemble of decision trees to perform regression on the target variable. While gradient boosting is technically a machine learning technique, it also has strong elements of statistical analysis. This is mainly through the gradient descent technique used to optimize decision trees. It is also a general approach, able to be applied to many domains outside of time series forecasting. This model was chosen because of its simplicity, straightforward approach, and support of past covariates.

The N-Linear model is a simple, one-layer neural network that is built specifically for time series forecasting. It is more complex than gradient boosting, but still very simple compared to other neural network architectures.

The Temporal Fusion Transformer is the most complex model chosen. The TFT is a deep learning architecture explicitly designed to work with time series data. To best capture long-range dependencies, transformer models consist of multiple layers and use a self-attention mechanism to weigh the importance of data at different time steps relative to each other.

All three of these models perform well with time series data and possess multivariate capabilities, allowing for multiple distinct time series to be trained at the same time. This is important for this use case, as each county or geographical grouping has its own time series, and all of them need to be evaluated separately. Using all series at once rather than training individual models for each allows the models to capture common trends across the board, while training individual models for each series lacks this collectiveness. Additionally, these three models all have support for past, future, and static covariates, allowing for a variety of additional data to be utilized.

2.4. Preprocessing

Before model creation, we preprocessed our data to normalize groupings and to address missing data. The target series contains data for each timestep, but many of the covariates do not. Each external data source covers different time frames; for example, the prison intake/release data only begins in 2022, but the Medicaid data is only available until 2023 due to lags in data processing. The time series itself cannot be limited only to time periods where all data is present, as this would eliminate a large quantity of good data for training and would prevent modern predictions from being generated until historical data catches up. However, of the three models tested, only the gradient boosting model has native support for missing values in covariates. To address the missing value problem for the other two models, the approach was taken where missing values are encoded with a constant fill value, and an additional flag variable is created to indicate whether the original data was missing. This technique was chosen rather than, for example, an imputing method. The missing data tends to be in large blocks at the beginning or end of the time series, due to mismatched data time frame availability. Imputing works well for filling individual missing values spread throughout a series, but not for completely filling a missing years' worth of data with any realism. Therefore, we simply encode missing data with constant values and introduce a flag variable. In testing, this was significantly more effective than simply dropping timesteps with missing values.

Each time series is individually normalized for each grouping. This is done because different counties or ADDs can have very different scales, with some having orders of magnitude more overdose events than others. Each grouping was individually normalized between 0 and 1, with 1 representing the maximum number of monthly overdoses recorded for that county/ADD. This allows each grouping to be treated at its own scale, which is useful for analysis to determine when counts are more or less than that area's usual average.

2.5. Training

After aggregating data into the proper format and groupings in preprocessing, data was grouped at the monthly level for time, and either the county or ADD level for geography. Then, the necessary covariates would be included. The data was split into a training and testing set, with the last three months used for testing. This is a relatively small test set compared to the standard 20% split, but it was chosen for realism and accuracy. In real use cases, predictions for opioid overdoses beyond three months are less useful and limit the relevance of past covariates. Limiting the forecasting horizon allows the model to train on as much data as possible.

3. Results

Table 1 shows results for each of the three forecasting models using Root Mean Squared Error (RMSE) to measure differences between predicted and actual values. Each model contains data for both the county grouping level and the ADD grouping level. Also, errors are provided for each covariate. For this testing, the only 'base' covariates included in all models are the categorical variables representing the month and season at each timestep. These covariates are included in both the base model and all iterations with other covariates. Aside from the month and season, each covariate was included individually and independently in testing. This process is used to decide which covariates had the greatest impact on model performance. The best error achieved in testing with any combination of multiple covariates is included at the bottom of Table 1.

Table 1. RMSE forecasting results (best scores per row are bolded, best scores per column are underlined)

Covariate	Gradient Boosting Regression		N-Linear		Temporal Fusion Transformer	
	County	ADD	County	ADD	County	ADD
Base	0.1832	0.1431	0.1886	0.1395	0.2199	0.1490
Seizures	<u>0.1780</u>	<u>0.1307</u>	0.1787	<u>0.1158</u>	0.2075	0.1536
Weather	0.1925	0.1596	0.1839	0.1447	0.2111	<u>0.1462</u>
SDOH	0.1845	0.1431	0.1865	0.2484	0.2271	0.1651
Medicaid	0.1818	0.1418	<u>0.1779</u>	0.1204	0.2199	0.1590
Intake	0.1887	0.1518	0.1869	0.1379	<u>0.2071</u>	0.1568
Related Groupings	0.1813	0.1373	0.1804	0.1343	0.2361	0.1559
Best	0.1711 (Medicaid, related groupings)	0.1272 (seizures, related groupings)	0.1709 (seizures and Medicaid)	0.1158 (seizures)	0.2071 (intake)	0.1462 (seizures)

These results show that the N-Linear model performs best in almost all cases. Additionally, the errors for ADD groupings are consistently lower than when county-level groupings are used. In some cases, combinations of multiple covariates perform better than any individual covariate, but not always. At times, covariates can decrease performance when they are irrelevant to the trends of opioid overdoses or involve too many individual data streams.

Each of the error metrics provided in the table are averages across all groupings. The individual errors across groupings can vary widely. For the best performing model and covariates (N-Linear, with seizure covariate), which achieved a combined RMSE of 0.1158, the individual RMSEs for three-month predictions for each ADD are given in Table 2.

Table 2. Individual RMSE scores for three-month predictions for each ADD grouping.

ADD Grouping	RMSE
KIPDA	0.0435
Northern Kentucky	0.0435
Lake Cumberland	0.0516
FIVCO	0.0749
Cumberland Valley	0.0829
Lincoln Trail	0.0948
Buffalo Trace	0.0967
Big Sandy	0.1141
Gateway	0.1197
Green River	0.1255
Kentucky River	0.1329
Purchase	0.1440
Barren River	0.1597
Bluegrass	0.1720
Pennyrile	0.2768

Almost half of the ADD groupings have error less than 0.1, and all but one grouping has error less than 0.2. This proves the efficacy of this method. Below are charts for two ADDs, showing the historical trends and predictions.

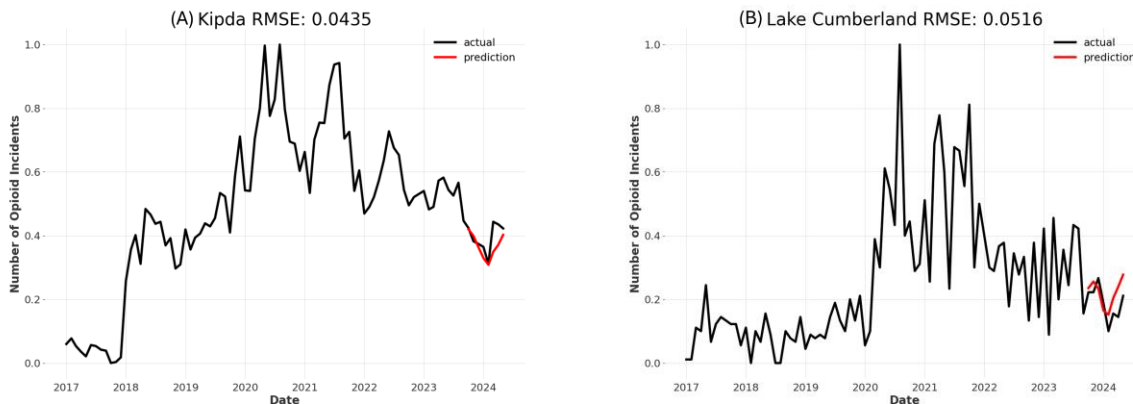


Figure 1. Historical data and predictions for two ADDs: (A) Kipda and (B) Lake Cumberland.

These two graphs highlight how the model can learn the trends that all groupings have in common, while adjusting for each individual time series. Between these two graphs, both forecasts show a decrease of overdoses at the beginning of 2024, but an increase again afterwards. However, the exact shape of each forecast and their positions on the y-axis differ between the two series. It should be noted that the y-axis ranges only from 0 to 1 because each series is normalized before training and evaluation.

Similarly, individual errors at the county level also vary significantly. For the best-performing model with an average RMSE of 0.1709, individual errors range from 0.0277 to 0.4614 across all 120 Kentucky counties.

4. Discussion

The biggest factor in prediction accuracy is the choice of geographical aggregation method which influences preprocessing strategy. Every model has consistently lower errors at the ADD level than the county level. This is due to the sparsity of incidents in many smaller and less populated counties, which may only have a few opioid overdose incidents every year. It is difficult to accurately predict overdose counts in those cases because smaller scales are more affected by random or unpredictable factors. By combining these areas into ADDs, the number of incidents increases at each timestep. This allows the models to better understand the trends of the data, as the larger scale will be more predictable and less random. In practice, this result shows that the ADD aggregation level should be used for smaller counties across Kentucky, while the county level aggregation may be used for larger counties to provide more resolution for urban populations.

We also note that RMSE is not a perfect error metric, especially when determining how useful the predictions are. Some of the smallest counties have the lowest errors because overdose events are so rare; this causes the model to predict 0 for the entire forecast window, which is highly likely to be right. However, a model that predicts no overdose incidents will ever occur in a county is not useful because rare events do eventually occur. Grouping into ADDs helps resolve this problem by ensuring each time series is active enough to produce valuable forecasts.

Some of the covariates have bigger impacts at the ADD level compared to the county level. For example, when drug seizures are included as a covariate at the county level, the RMSE decreases by 5% for the N-Linear model. At the ADD level, this change increases to a 17% drop in error. Similarly to the target series, this is likely because these covariates are very sparse at the county level, and aggregating into ADDs improves their usefulness.

Across models and groupings, the most effective covariates were drug seizures and Medicaid measures. Prison intake/release data is less effective but still useful in many cases. Weather is not as effective for most models, even though analysis of the data finds a strong seasonal component to opioid overdoses. In the summer opioid overdoses increase, while in the winter the counts decrease. It is likely that this seasonality is already accounted for with the month and season covariates, so inclusion of weather only provides redundant and unnecessary data. The social

determinants of health also seemingly do not improve the model. Because these covariates are static and do not change over time, it is likely that their impact is limited and their aggregations at the ADD scale may be irrelevant. Finally, the covariate for lagged trends of related counties occasionally will improve and other times worsen the model. Some groupings have stronger related trends than others; it is possible that the error on some counties' predictions is being improved, while others are being worsened.

The best performance achieved in testing was with the N-Linear model, which achieved the lowest error in nearly all cases. This model was simple enough to prevent overfitting on the target series, while in-depth enough to learn trends across multiple series. The gradient boosting regression model performed similarly, and the temporal fusion transformer was moderately worse than both. This is potentially because the TFT is too large and complex for this use case. With monthly data beginning in 2017, each time series only has around 80 timesteps, which is a relatively small amount of data for time series analysis. The inclusion of multiple different series helps to offset this, but large transformer models are generally best suited for large datasets which limits their utility for our use case.

5. Conclusion

We found that opioid overdose incidents can be forecasted within a reasonable degree of error across the state of Kentucky. It is best to aggregate this data at the ADD level; smaller groupings, such as county level, are frequently very sparse except for the large urban areas. Two of the best performing covariates tested in this process were counts of police drug seizures and Medicaid measures detailing diagnoses and treatment for opioid use disorder. Multiple models were tested and the N-Linear model, which uses a simple one-layer architecture, had the best performance with these covariates. These results could be used by state agencies to determine when and where opioid overdoses can be expected to increase or decrease. This information will allow resources and personnel to be distributed effectively. The goal is the reduction of overdoses while providing more efficient treatment when they do occur. In the future, more data sources, methods, models, and covariates will continue to be tested to improve performance.

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