Iowa Prison Population Forecasting for Potential Legislation Changes

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Final Report

Introduction/Motivation

Iowa prison populations are currently projected to rise over the next ten years, despite recent legislation changes. Additionally, today's Iowa prison population also exceeds the official capacity of their nine correctional institutions (Fineran, 4-10). The Iowa executive and legislative branches, along with the Iowa Department of Corrections, have a desire to quickly identify and understand how potential legislation changes could impact forecasted prison populations over the next ten years.

Problem Definition

Although existing prison population forecasts are generated by the Iowa Department of Corrections, they are manually generated once per year in Excel and require many weeks of effort to create (Fineran, 6). Since legislative bills are written on a more frequent basis, our project aims to create an interactive forecasting model and visualization tool that can be used to quickly identify how potential legislation changes could impact the forecasted populations. Additionally, our project highlights race and gender statistics to aid in the generation of racial impact statements created by the Iowa Department of Corrections when new legislative bills are introduced. There is a need to expand the use of analytics in crime analysis (Egbert, 14) which emphasizes the importance of this project.

We want to incorporate more explanatory variables in our forecasting methods than what currently exist, but are cautious not to impact minority race subpopulations within our forecasts. As noted in multiple sources, race is a complex issue when it comes to predicting crime (Egbert, chapter 9; Fogliato). In compliance with Iowa's requirements of racial impact statements that summarize the effects of potential legislation on minority groups (London, 212; Erikson 1426-1428) we will highlight the racial impacts in our forecasts as new parameters are selected, calling out trends and disparities as they exist in the data and respective predictions. Even though fighting bias and discrimination in machine learning is very complex (Kiemde; Kleinberg; Mehrabi), our proactive approach and potential use of metrics that can be calculated to highlight disparate impacts (Bellamy, 8) will mitigate biases built into our forecasts.

Proposed Method

Our proposed method is to forecast Iowa prison populations at the offense classification and type granularity and create an interactive visualization tool utilizing an interactive flexdashboard, as described and implemented in Rimal's book (Rimal). This will allow the Iowa Department of Corrections to quickly identify how potential legislation changes could impact forecasted prison populations over the ten-year forecasted period.

The method we are proposing leverages modern, open-source tools to rapidly advance the current state of the Iowa Department of Corrections prison forecasting process by automating manual steps, incorporating interactivity to enable adjustments of forecast values based on percent change and adjustment start date, and visualizations to see the immediate impacts of these changes. As mentioned in our proposal, the benefits of this method are two-fold. Not only will the team have the ability to better predict future prison population growth, but this will also save time and resources by migrating away from manual, time consuming processes to a more automated solution. This point is reinforced in the following sentence from chapter 5 of Criminal Futures, “a machine doesn’t get tired, it reduces complexity, and, if properly configured, it produces no errors.” (Egbert, 95). Our tools and forecasts will be doing all the heavy lifting unlike the current manual process, relieving responsibilities of the Iowa Department of Corrections (Fineran) and allowing for their time to be allocated elsewhere.

Initially, we planned on creating our forecasts at the offense code level since legislative bills are written at that granularity. However, upon further discovery and conversations with the Research Director at the Iowa Department of Corrections, we learned that the numeric offense codes are often modified numerous times throughout each year, and no mapping system exists to track how prior codes tie to the existing ones. Given this, we modified our approach to forecast population changes at the offense classification and offense type granularity.

The forecasting model development included testing and evaluating several different methods like ARIMA, exponential smoothing, and regression-based models, then utilizing the flexdashboard framework within R to implement and publish our best model as a shinyapps.io site for public use. Implementing and serving the model in this way enables contributing and sharing code to be seamless and efficient while working in a cross-organizational environment like the Iowa Department of Corrections. Once the first model is developed we plan to perform rigorous validation by backtesting over different periods of time and comparing model predictions to baseline models. Baseline models will include a simple model, like moving averages, and comparing to the existing model the Department of Corrections supports today. This process will be challenging as there are several layers of complexity we will need to consider along the way. In the following several paragraphs, we explain some of these complexities and how we plan to approach them.

Taking advantage of modern machine learning algorithms as well as statistical time series approaches, we expect our new solution will also perform accurately. Forecasting models are strong when it comes to picking up trends, cyclical and seasonal patterns, and detecting autocorrelations (Wan). These forecasting tools will help impact policy change specifically to non-violent crimes (Groff) even though the nature of our prison data makes predicting challenging because of the short-time dynamics and long-time seasonality in our data (Ding). While this is not within the scope of our project, there are additional methods to consider for future enhancements to this project. A policy based forecast model in itself is static but a survival model can take recidivism into account (Baker). In addition, considering prisoner type can also enhance the forecasting model. The composition of prisoners often broken down into violent and non-violent crimes impacts the population numbers (Farrington).

In performing our exploratory data analysis (EDA) and data preparation activities, we uncovered some data abnormalities and unusual trends which we believe to be due to recent historical events (namely, the outbreak of Covid-19). First, as our population metrics are being rolled up to the month, a decision had to be made as to what constitutes a month of incarceration. For instance, if a convicted individual is incarcerated from January 15th through March 15th, should we consider them a resident of the system for the months of January, February, and March? That seems a reasonable assumption, but would the answer change if their incarceration was from January 25th through March 5th (specifically, spending only very small portions of January and March as a resident in the system). Our final approach treated any amount of residency as a resident for that month (even if only for a day), as this approach was supported by our primary stakeholder, the Research Director for the Iowa Department of Corrections.

Additionally, our EDA activities revealed trends in the data that appear to line up with the onset of the US Covid-19 outbreak, starting in early 2020. As US Covid-19 cases continued to rise, many local governments and institutions began taking measures in an attempt to curb the outbreak - ranging from temporary shutdown of local businesses to remote learning for public school students. At this same time, data showed a large increase in incarcerated individuals released for probation, much more than observed previously (Fig 4, see Appendix). Other clear impacts from the Covid-19 outbreak (and from responses to it) include a very notable dip in admissions (Fig 3, see Appendix) and overall lower Iowa prison populations as a result of these decreased admissions and increased releases (Fig 5, see Appendix). We considered multiple approaches for how to handle the impact of Covid-19 on our model and projections, ranging from record removal (e.g., discarding records of individuals admitted during the rise and height of the outbreak), to imputation, to deriving features to feed into the model (e.g., an 'admitted during Covid-19' flag).

We also modeled admissions and releases in order to project future populations. There are multiple models currently in consideration and evaluation, including time series forecasting, survival models, and various regression ML models in order to predict months served (from which we could further derive a release date and forecasted population).

For the user interface, we initially planned to use the flexdashboard framework within R with the intent of publishing the tool through GitHub Pages. However, since we wanted to use input boxes and parameter toggles, the flexdashboard framework required the shiny runtime, which is not supported in GitHub Pages due to the requirement of having an R process/engine running to support it. As an alternative, we deployed our flexdashboard application to shinyapps.io under their free tier. While this isn't our ideal solution for long-term sustainability, it will be sufficient for our initial project development while still allowing us to share the tool with the Iowa Department of Corrections.

Experiments/Evaluation

In experimentation, we will be measuring success by benchmarking forecasts from each of our evaluated models against existing forecasts created by the Department of Corrections. Setting up the design of our method can take several forms. One method we will explore is a train test split to measure performance across different models.

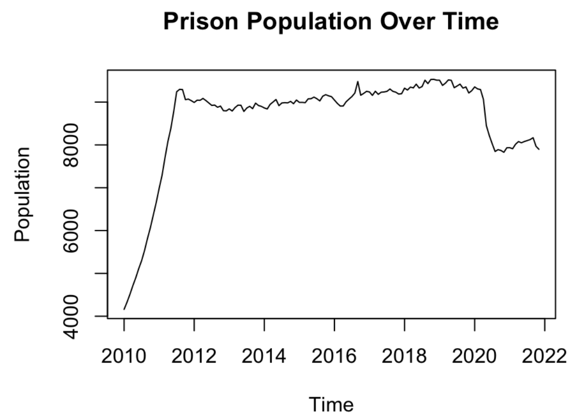
To identify our best model, we utilized metrics such as mean squared error, mean absolute error, root mean squared error, and AIC. As mentioned above, all models we generate will be compared against the baseline (existing) forecasting model developed by the Department of Corrections.

Model	**MAE**	**RMSE**	**MSE**	**AIC**
ARIMA	75.4	110.8	12296.8	1734.4
Exponential Smoothing	76.3	108.5	11775.1	2049.8
Regression	708.0	966.0	934044.0	2425.7

(Table 1. - Overall Performance Metrics)

The three methods of forecasting we decided to compare were ARIMA, Exponential Smoothing, and Regression. Due to the time sequenced nature of our data, our initial thoughts were that ARIMA and exponential smoothing would perform the strongest. However, regression would allow us to use other attributes in the data (growth of area, crime rates, etc.) to predict the prison population which is why we were interested in testing it.

In order to prepare our data for modeling and visualization, we needed to create an expanded dataset to include a record for each month where an individual was incarcerated. This “exploded” dataset was derived based on months between admission and release dates. This was then aggregated at a monthly level to derive monthly populations for each offense classification and offense type. Additionally, for months where categories didn’t have a population, we imputed populations of zero.



(Figure 1. - Prison Population)

Once our exploratory analysis and data restructuring was complete, our final training data was aggregated at the monthly level. From there we implemented the above modeling techniques. As you can see in Figure 1, due to the lag in prisoners being convicted to when data was first recorded, our data did not stabilize until 2012. To mitigate this false trend we started our training data at this 2012 mark.

As mentioned before, Covid-19 impacted our data heavily as shown by the drop in 2020 from Figure 1. This led us to create multiple training data sets where we started our projections at the current time and before Covid-19. Comparing these two approaches, we noticed that the forecasts had stronger downward trends while using the data that incorporated Covid-19, and because this trend was not too unreasonable and due to the continuation of Covid-19 even today we decided it was best to keep this data in our training set.

While building our ARIMA models, we noticed no obvious seasonality in our data. However, when we split our data into more granular levels such as by offense type (e.g., Drug, Property, Violent, Theft) small seasonal trends were observed. This led us to factor in seasonal differences into our models going forward. We also found that our data was mostly stationary, but due to the recent downward trend a regular difference was taken in our ARIMA models to account for this. These observations held true for our exponential smoothing model as well.

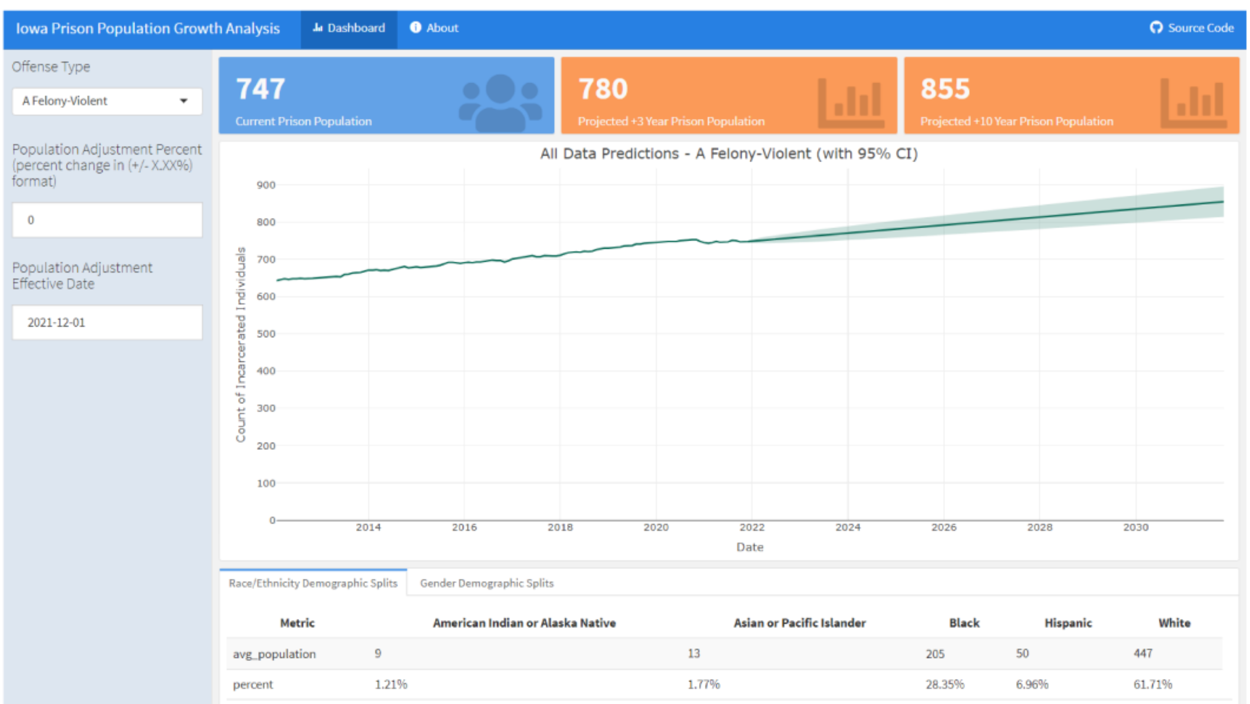
An observation we noticed from our regression modeling was that race and gender had large coefficients for certain offense types. Monitoring how different races are affected by our models was a huge priority for us. This is so important because certain groups are disproportionately represented by various crimes. For example, due to a myriad of social systemic issues, individuals who are African-American are convicted of Robbery offenses (and subsequently admitted to prison) more so than individuals of other racial/ethnic groups. Robbery 1 and Robbery 2 are two crimes which carry significant penalties and sentence lengths therefore, any legislation that would increase the penalties for Robbery (crime type:

violent; crime subtype: robbery) would disproportionately impact the African-American population. Conversely, sex offenses are largely committed by individuals who are white. Sexual offenses are actually one of the few crimes there is not racial overrepresentation. I.e. A law that would increase the sentence length of sex offenders, would likely not have a direct racial or ethnic impact due to this population largely being of a White race (Fineran).

Ultimately to compare models, we looked at overall performance (Table 1) as well as performance split across different offense classification and offense types. We also compared how the forecasts looked and compared the width of our confidence intervals. From Table 1, MSE, MAE, and RMSE were very similar for ARIMA and exponential smoothing, but both our time series approaches provided substantially better performance than regression. Comparing our two time series approaches, AIC was much lower for our ARIMA which also helped us decide to move forward with that modeling approach.

Once we decided to implement ARIMA models, the results were integrated in our visualization platform. The framework for our visualization is built in R and published as a shinypps.io flex dashboard. Within our dashboard, there is customization and interactive capabilities for the user. For example, they can select the offense type and the time frame they are interested in. Also in our dashboard, there is race/ethnicity demographic splits so we can see how a policy change could affect certain groups. This will allow our stakeholders to be able to experiment with hypothetical policies (e.g., ‘what would happen to our population projections if *x* sentence term increased by 20% 6-months from now?’).

Dashboard



https://iowa-prison-forecast.shinyapps.io/iowa-prison-pop-forecasting/

(Figure 2. - Dashboard)

The interactive dashboard allows a user to drill down to the offense classification and offense type granularity to visualize specific forecasts and various demographic breakdowns. A major feature within this tool is enabling the user to adjust forecasts based on expected impact of legislative decisions. Once adjusted, the user can infer the potential influence a decision may have on certain demographics (Fig 2, above).

The tool is built in R using the flexdashboard package with a shiny runtime. Using this framework allows for a high degree of interactivity for the user and enables us to dynamically control the visualizations based on user input. RStudio has a service, shinyapps.io, which gives us a place to host the dashboard. Once published to their server, the entire process can be automated on a scheduled job.

This will be adopted by the Iowa Department of Corrections in place of their current process, which takes weeks to build each time they need to reforecast. Not only will this save time, but it also reduces the risk of error by ensuring reproducibility each run without a decrease in performance.

Conclusions and Discussion

Throughout the semester, we periodically met with the Research Director at the Iowa Department of Corrections to gain feedback on the usefulness of our forecasts and dashboard, and incorporate suggested changes into our project. In the coming weeks, we plan to present our tool and findings to a larger group at the Iowa Department of Corrections following some recent departmental restructuring for their potential adoption. Our meeting will allow us to identify a long-term support plan for the tool if it proves successful by providing various suggested options for hosting and documentation detailing how to automate a pipeline to refresh the data on a more regular basis.

Additionally, all code is currently stored on GitHub and will be open-sourced for anyone who wishes to continue development on it pending additional suggestions by the larger Department of Corrections meeting. This project has been very fulfilling to work on knowing there is high potential for it to be adopted by the State of Iowa and will dramatically improve existing processes through technological innovations.

Team Member Effort

<u>William Ebert, Greyson Henderson, & Kristi Rasmussen</u>: Primarily focused on data processing and dashboard development. Specific responsibilities have included data cleansing, combination, and aggregation for modeling and visualization as well as identification of platform options this tool will be delivered through. William Ebert, Greyson Henderson, and Kristi Rasumussen each contributed 18% towards the overall project.

<u>Shivani Kharbanda, Grant Ruedy, & Husam Yassin</u>: Primarily focused on forecast development, evaluation, and implementation of appropriate methods for the forecasting model. Grant Ruedy and Husam Yassin contributed 18% towards the overall project. Shivani Kharbanda contributed 10% towards the overall project.

Appendix

Datasets:

[Iowa Prison Admissions]

[Offenders Released from Iowa Prisons]

[Current Iowa Correctional System Prison Population]

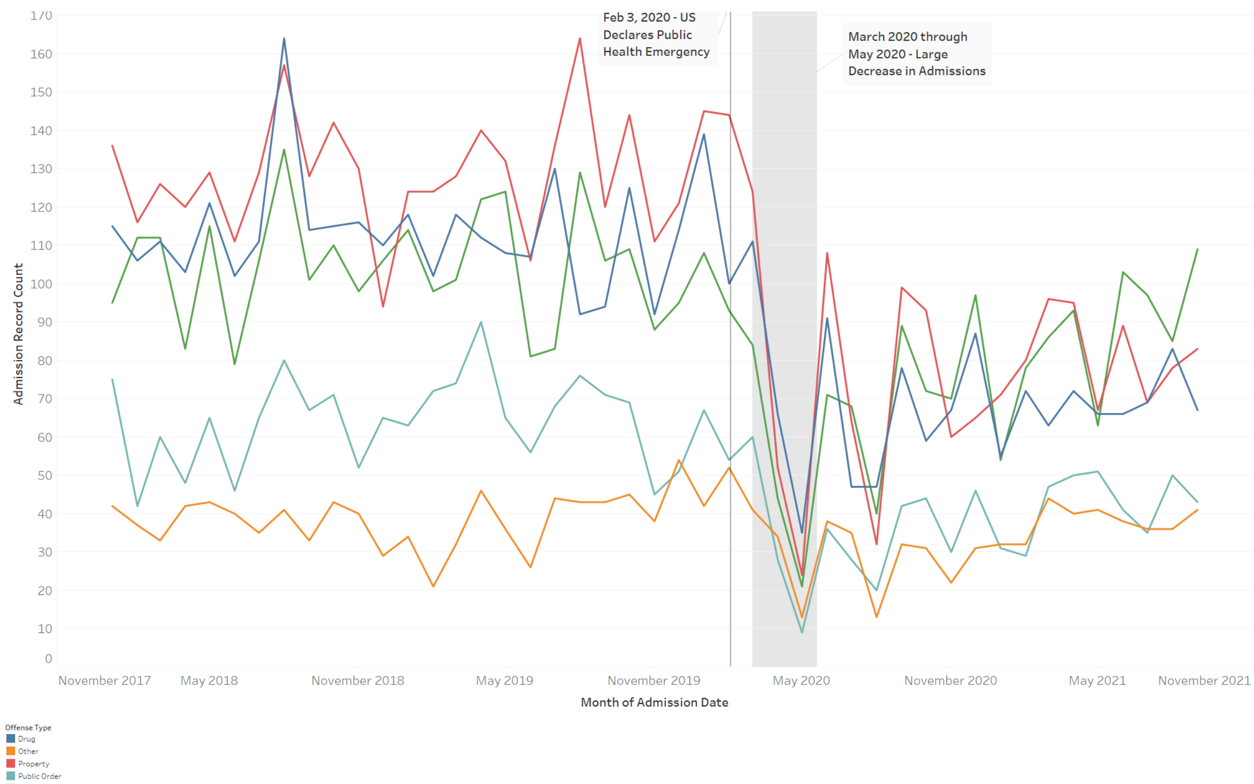
Github Code Repository:

https://github.com/kristirasmussen/iowa-prison-pop-forecasting

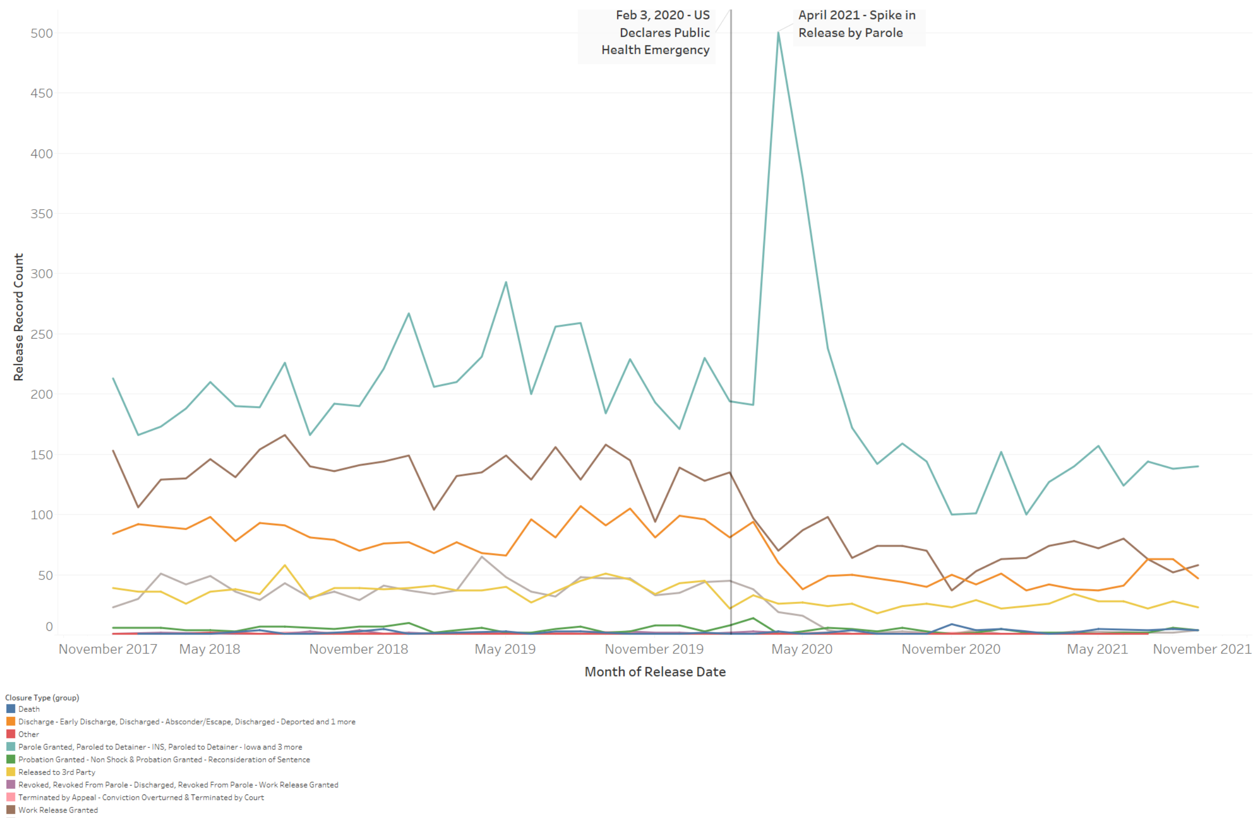
Published Dashboard:

https://iowa-prison-forecast.shinyapps.io/iowa-prison-pop-forecasting/

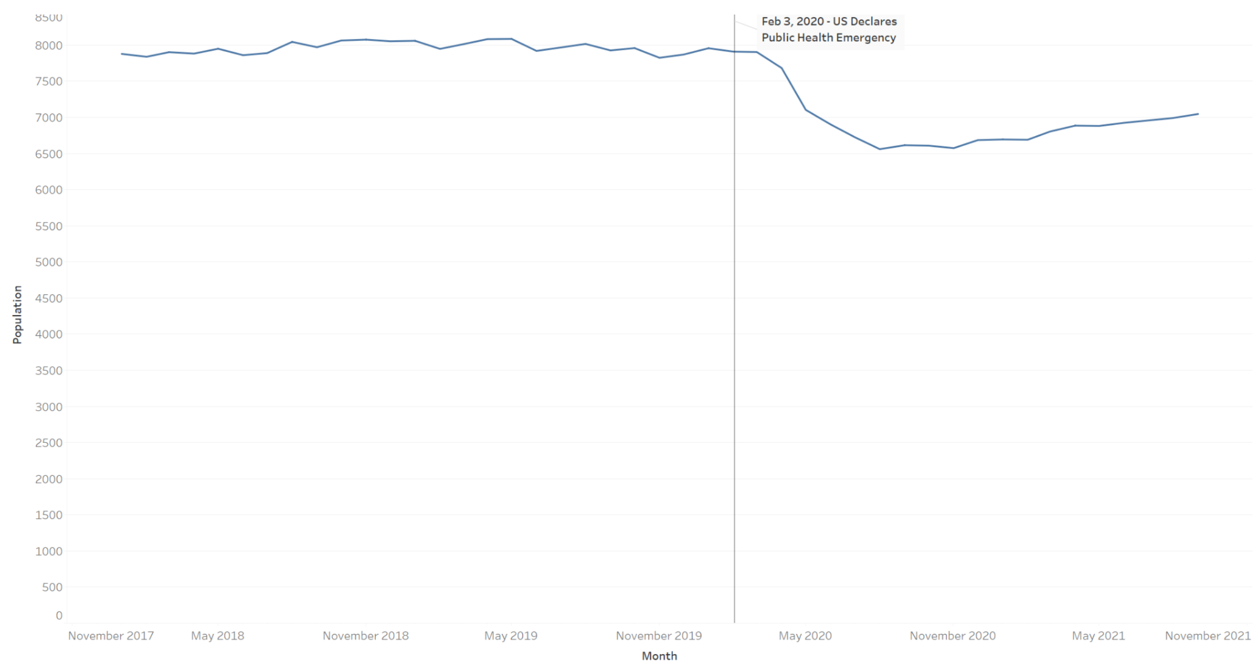
Figures:



(Fig 3. - Covid Impact on Admissions)



(Fig 4. - Covid Impact on Releases)



(Fig 5. - Covid Impact on Population)

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