Comparative Analysis of Data Inputs to Predictive Policing Models

Team 004

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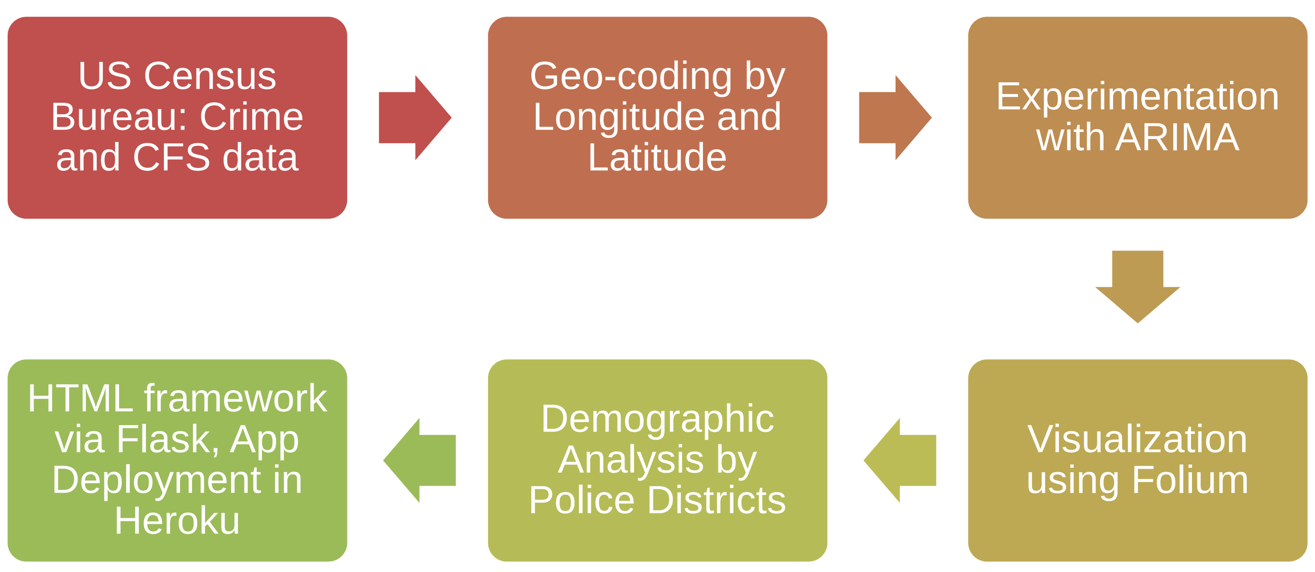
Summary

We generate different predictions where crime will occur in Baltimore using different police department data inputs from the year 2018. We evaluate which model inputs are more likely to concentrate police activity in communities of color.

Methodology



Geo-coding Requests

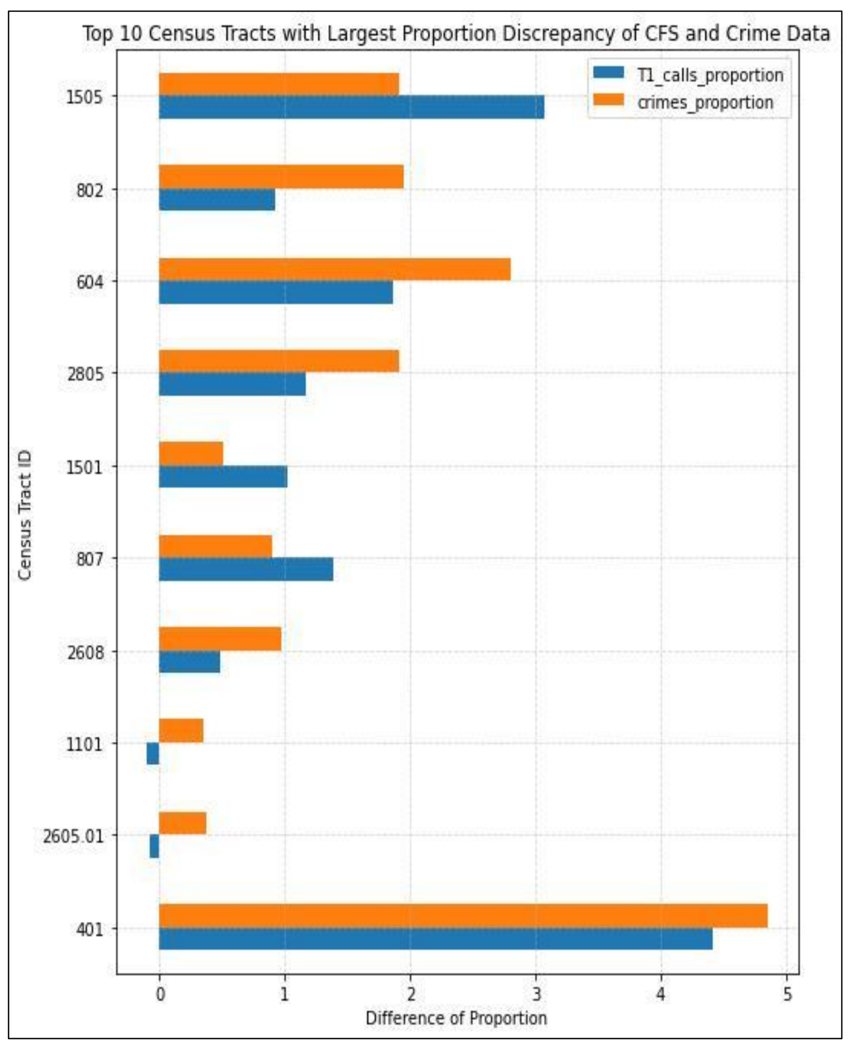
The Geocoding API is utilized to convert calls for service addresses to geographic coordinates. Due to the large number of observations in this dataset, the team each ran a subset within their API budget. This smaller division is randomly sampled data, stratified by census tract and month. Through this process, exact longitude and latitude coordinates were produced for roughly 400,000 calls for service locations.

Racial Bias in Predictive Policing

Crime hot spot prediction is a common tactic in law enforcement. However, racial bias is an inextricable feature of any historical data used to predict criminal activity. For many categories of crime, crime or arrest data is as much an artefact of where police look for crime as where actual crimes occur. But serious crimes like murder, or alternative data like 'calls for service' may be less subject to such bias.

Calls for Service and Crimes

A call for service is generated when a resident calls 911 or police internally request the assistance of additional officers for public safety issues, representing a broad range of potential police activity. Official crime data is generated when police choose to formally file a report of a crime that has occurred. This graph illustrates the differences in the extent to which a given census tract is over- or under-represented by different data inputs, relative to its population. This raises the question of how differences in representation by data input translate to differences in where crime is predicted.



Predictive Modeling Experiments

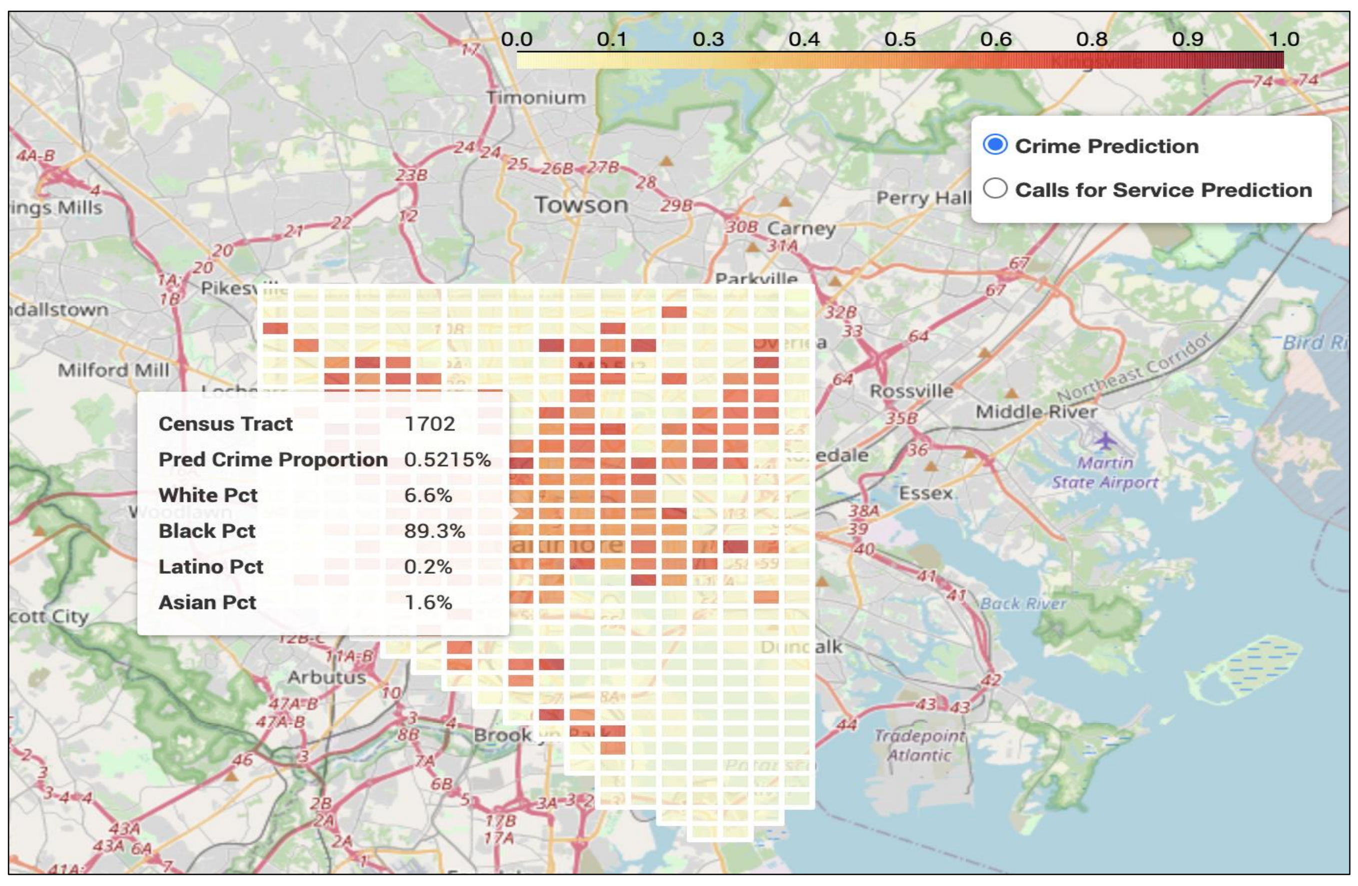
ARIMA is a commonly used time-series forecasting model, underpinned by verifiable statistical assumptions. A series of experiments generated ARIMA(3,0,1) as the best fit model for both the crime and calls for service data. To validate the model, an ARIMA library titled *pmdarima* is used. We took advantage of the stepwise grid-search that minimizes the AIC. For a 30-day prediction timeframe, the crime model has an MSE of 562.99 and the calls for service model generates an MSE of 19,041.24.

Parameters	Crime Model AIC	CFS Model AIC
ARIMA(1,0,1)	3095.037	4582.802
ARIMA(0,0,0)	4625.196	6274.308
ARIMA(1,0,0)	3260.674	inf
ARIMA(0,0,1)	4209.413	inf
ARIMA(2,0,1)	3091.008	4553.091
ARIMA(2,0,0)	inf	inf
ARIMA(3,0,1)	3089.782	4547.913
ARIMA(3,0,0)	inf	inf
ARIMA(4,0,1)	3091.081	4548.769
ARIMA(3,0,2)	3094.048	4626.752
ARIMA(2,0,2)	3089.944	inf
ARIMA(4,0,0)	inf	inf
ARIMA(4,0,2)	3093.586	inf
ARIMA(3,0,1)	3107.905	4571.641
Best Fit Model		
ARIMA(3,0,1)	**3089.782**	**4547.913**

Geo-mapping and Interactivity

Our visualization displays the forecasted crimes and calls for service for geographic regions in the city of Baltimore, coloring each region according to the proportion of the total amount of predicted crimes or calls for service for single day. Users can choose to display forecasts based on historical crime or calls for service data.

When hovering over a geographic region, users are presented with a tooltip that displays the predicted proportion of crimes or calls for service for that region and its demographic composition. This allows users to explore how different data inputs for predictive policing models may over or underrepresent certain neighborhoods.



Results and Evaluation

Crime predictions are an input to patrol pattern decisions made at the district level. We evaluate the predicted crimes and calls for service for all geohashes that reside within a single police district boundary and classify the geohash with the highest predicted criminal activity as that police district's hot spot.

Police District	Pct. White		Pct. People of Color		Pct. Below Poverty Level	
Hot Spot	*CFS*	*Crime*	*CFS*	*Crime*	*CFS*	*Crime*
Central	49.2	72.3	50.8	27.7	19.8	8.1
Eastern	3.0	36.0	97.0	64.0	40.7	25.9
Northeastern	18.3	30.1	81.7	69.9	7.9	7.7
Northern	36.7	79.3	63.3	20.7	26.1	5.0
Northwestern	0.6	4.2	99.4	95.8	36.2	20.0
Southeastern	63.7	61.6	36.3	38.4	29.9	11.9
Southern	24.5	57.9	75.5	42.1	41.9	25.9
Southwestern	57.4	6.1	42.6	93.9	20.4	16.1
Western	0.7	1.4	99.3	98.6	21.4	47.2
Average	**28.2**	**38.8**	**71.8**	**61.2**	**27.1**	**18.6**

Hot spots predicted based on calls for service data are consistently less white (10.6 pp on average) and poorer (8.5 pp on average) than hot spots predicted based on crime data. In 7 out of 9 police districts call for service hot spots are less white, and in 8 out of 9 police districts they are poorer.