Socioeconomic and Racial Factors Influencing Larceny Rates in U.S. Regions

Kenny Shibu, Jonathan Hutteman, Lidya Mehari, Mahader Zeru

School of Data Science, University of North Carolina at Charlotte

DTSC 3601/3602: Predictive Analytics and Their Implications

Dr. Nadia Najjar & Dr. Shannon Reid

December 10, 2024

Abstract

Keywords: social disorganization, larceny, socioeconomic indicators, resource allocation, demographics, predictive modeling, Crime prevention.

This study evaluates the impact of racial composition and socioeconomic factors such as median income, unemployment rates, and poverty on larceny rates across the West, Midwest, Northeast, Southwest, and Southeast areas of the United States. This study uses a large dataset to examine the socioeconomic variables that affect larceny rates, emphasizing the relationships between these variables in various geographic settings. According to the study, there is a significant correlation between economic instability, typified by high unemployment and poverty rates, and a rise in larceny events. People facing financial struggles may turn to criminal conduct to survive. The study also takes into account the social disorganization theory, which contends that low social cohesiveness in neighborhoods under economic hardship increases the risk of criminal conduct to address the underlying causes of larceny through focused interventions that take into account the socioeconomic environment and community dynamics, this study intends to offer insightful information to politicians and community organizations (Wickert, 2018). This research hopes to contribute to a more sophisticated understanding of crime prevention and community safety by linking the predictor and target variables between these factors.

Introduction

Larceny, one of the most prevalent property crimes in the United States, not only threatens community safety but also reflects deeper social and economic issues. In 2019, over 5.1 million larceny-theft incidents were reported, emphasizing the urgent need for effective, targeted crime prevention strategies (Bureau of Justice Statistics, 2019). Understanding the drivers behind these incidents is essential, especially in communities facing severe economic hardship. Communities suffering from poverty and unemployment are disproportionately affected, as property crimes destabilize neighborhoods, perpetuate economic disadvantage, and undermine trust in local institutions (Lee et al., 2021)

The relationship between socioeconomic factors and crime can be explored through several criminological theories. Strain Theory suggests that individuals facing significant economic stress may resort to illegal activities when legal means to meet basic needs are inaccessible (Agnew, 1992). Routine Activity Theory highlights that crime occurs when motivated offenders encounter suitable targets without adequate guardianship, particularly in environments shaped by unemployment and poverty (Cohen & Felson, 1979).Additionally, Social Disorganization Theory emphasizes that communities with high economic deprivation and weak social cohesion may experience increased crime due to diminished collective efficacy and structural inequalities (Shaw & McKay, 1942, Anderson, 1999).

This study will explore the intricate relationships between socioeconomic factors—especially poverty, unemployment, income levels, and community demographics—and larceny rates across different regions in the U.S. By analyzing these variables through established criminological theories, this research seeks to deepen our understanding of how social and economic instability contribute to property crime. Through statistical and machine learning techniques, predictive modeling can analyze historical data to uncover patterns and trends that may not be immediately apparent. Predictive modeling can also be used to assess the success of previous interventions, providing a data-driven approach to enhancing future attempts to reduce crime. The ultimate goal is to develop informed, targeted strategies for crime prevention that address the nuanced intersections of racial, social, and economic influences on criminal behavior.

Literature Review/Background

Shaw and McKay's Social Disorganization Theory provides a foundational framework for understanding how weaker social institutions in economically challenged areas contribute to increased criminal activity (Wickert, 2018). Communities with high rates of unemployment, poverty, and racial segregation often suffer from diminished social cohesion, which creates conditions conducive to crime (Tillyer & Tillyer, 2010). The theory underscores the structural challenges destabilizing neighborhoods and exacerbating crime rates, providing a critical lens for analyzing the interplay of socioeconomic and demographic factors in crime trends.

Several studies expand on this framework by connecting economic instability to property crime, highlighting structural vulnerabilities across different contexts. Mustaine and Tewksbury (1998) similarly identify higher rates of larceny and other property crimes in areas experiencing economic hardship. These findings collectively illustrate how economic instability functions as both a direct and indirect driver of criminal behavior, with impoverished neighborhoods lacking the social and institutional resources to prevent crime. Despite their contributions, these studies often focus broadly on urban environments without addressing regional variations or intersectional dynamics, such as race and economic inequality, which remain underexplored.

When paired with findings from Mustaine and Tewksbury (1998), the structural link between economic conditions and criminal behavior becomes clearer, yet significant gaps persist.

For instance, while these studies acknowledge racial disparities, they often stop short of analyzing how these disparities vary across regions or influence specific crime rates like larceny.

Reactive strategies to combat larceny—such as increased policing and harsher penalties—continue to dominate crime prevention efforts, often neglecting the underlying socioeconomic drivers of crime. Strain Theory, as articulated by Agnew (1992), provides valuable insight into this issue, suggesting that individuals facing societal pressures, such as unmet economic goals or limited access to legitimate opportunities, may turn to illegal activities out of necessity or frustration. Complementing this, Routine Activity Theory emphasizes how structural conditions, such as poverty and unemployment, reduce guardianship and increase the vulnerability of potential crime targets (Cohen & Felson, 1979). Together, these theories underscore the systemic nature of larceny, highlighting the need for preventative measures that address its root causes rather than its symptoms.

Synthesizing these theoretical perspectives and empirical findings, this study examines how socioeconomic and demographic factors influence larceny rates across U.S. regions. It also aims to fill gaps in the literature, particularly the limited focus on regional analyses and the interplay between race and economic inequality. The need for comprehensive research that integrates data from diverse contexts is evident, as existing studies often isolate factors rather than exploring their intersections. By bridging these gaps, this research can provide actionable insights for data-driven interventions that prioritize community safety and tackle the structural conditions facilitating larceny.

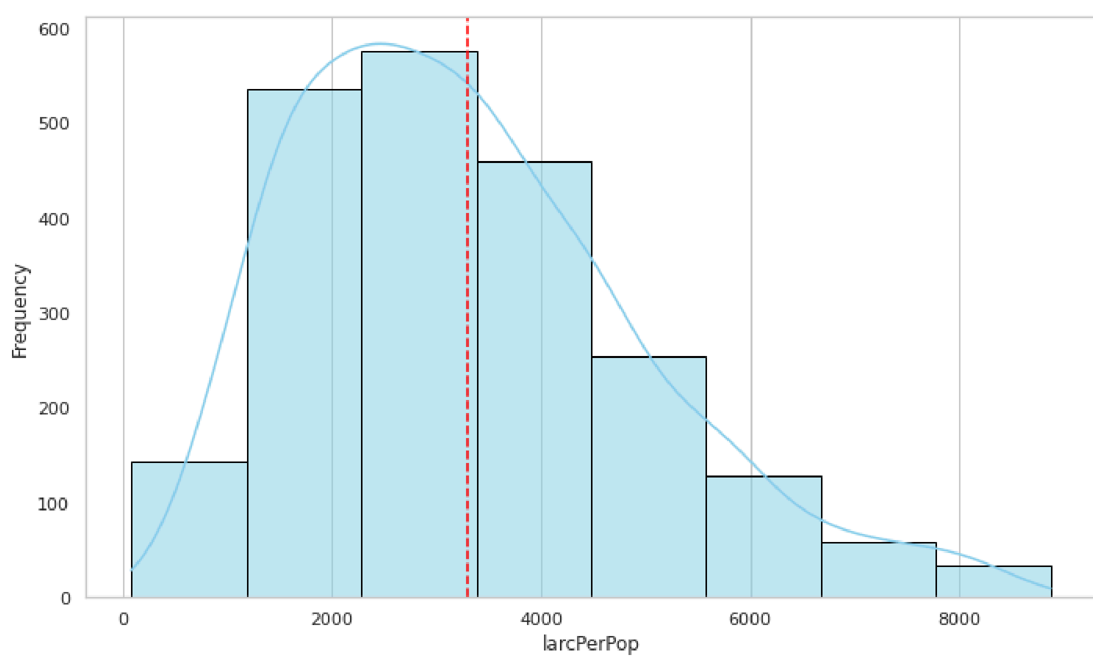
Dataset Description

The dataset used for this study is the Communities and Crime data, provided by the UCI Machine Learning Repository. The dataset is a combination of data from the 1990 US Census, several different law enforcement agencies via the 1990 US LEMAS (Law Enforcement Management and Administrative Statistics) survey, as well as additional crime data provided by the 1995 FBI Uniform Crime Reports. It contains information on crime in 1999 from 2,215 cities across the United States, originally containing 147 fields capturing various socioeconomic and demographic indicators. Some cities were excluded from the dataset as a result of missing rape data which influenced the values of violent crime per capita.

After a thorough evaluation, we reduced the dataset to 13 relevant fields, removing 134 unnecessary fields for our analysis. The target variable, represented by larcPerPop, gives us the amount of larcenies per capita in a given community. The average of larcPerPop is 3,293 offenses, and the overall distribution is right skewed.

Figure 1

Distribution of larcPerPop



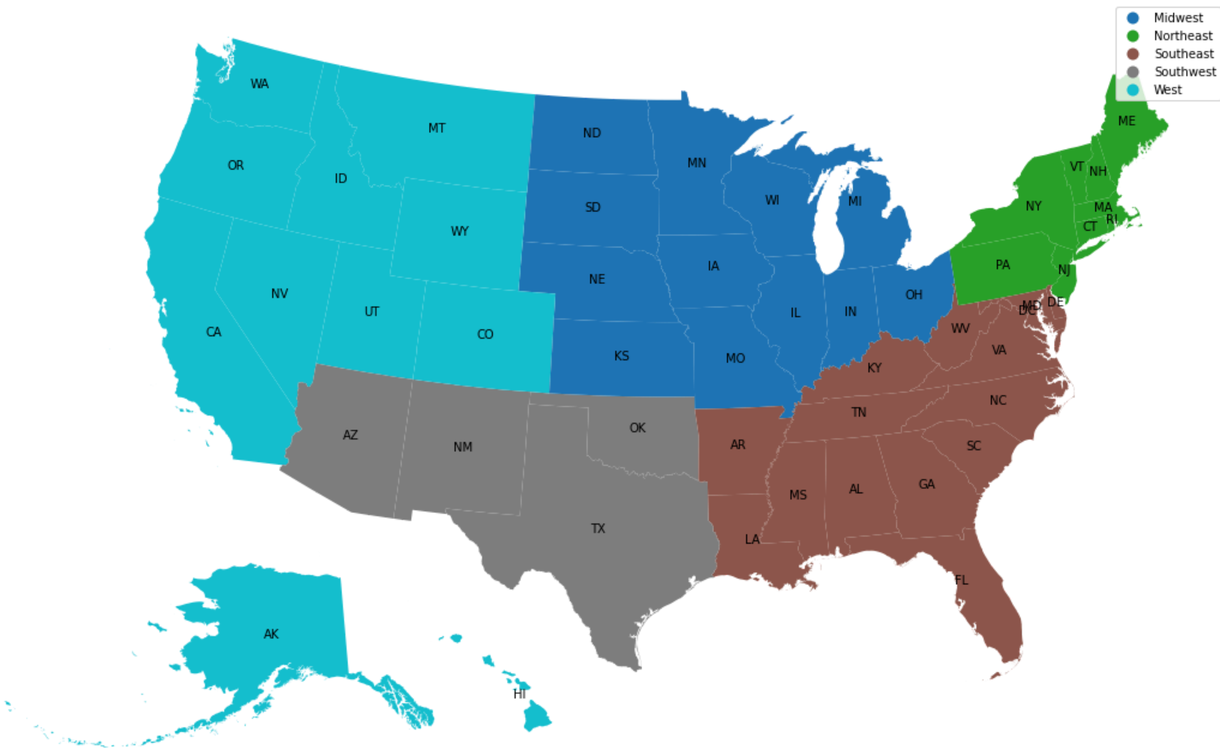
Made on Hex using Python

Eight of these features were chosen to be used in predictive models due to their relevance to Social Disorganization Theory and Strain Theory. Social Disorganization Theory suggests that factors such as segregated communities, access to employment, and poverty rates are directly connected to the racial demographics of a community (Anderson, 1999). These factors can weaken the social cohesion of a community, leading to an increased rate of larceny. To account for this theory, racial demographics, represented by racepctblack, racePctWhite, racePctAsian, and racePctHisp, as well as employment levels, represented by PctUnemployed and PctEmploy, were chosen. In addition to this, Strain Theory suggests that financial instability can lead to a higher risk of one committing crimes for economic gain (Agnew, 1992). To account for this, medIncome and NumUnderPov were also chosen to be used in predictive modeling to determine if a city's economy plays a role in the rate of larceny.

To facilitate regional comparisons, we added a *region* feature, categorizing cities into five geographic areas based on their state. This categorization allows for a comprehensive analysis of how socioeconomic factors influence larceny rates across distinct regions within the United States.

Figure 2

United States Separated by Region



Made on Hex using Python

Table 1

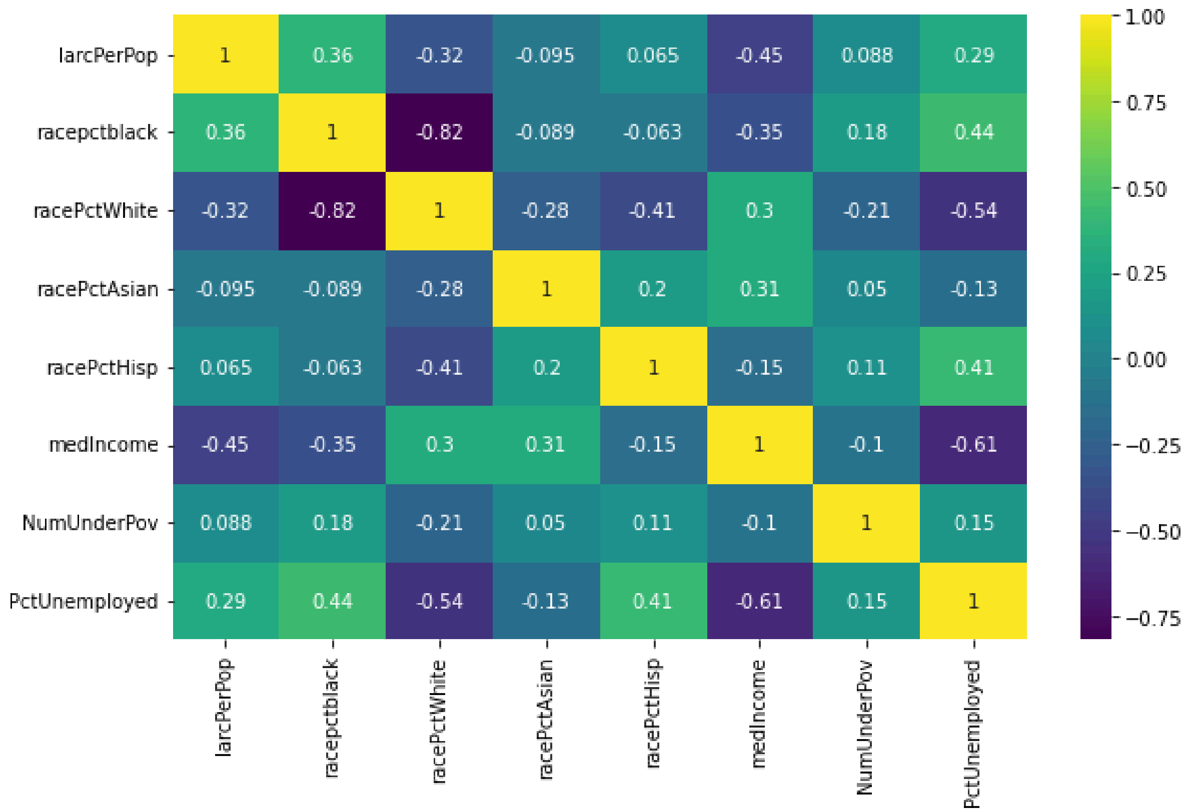
Variable Definitions

Variable	Description
Êcommunityname	The name of the city or town.
state	The state in which the city resides.
population	The population of the community.
region	The region of the United States in which the data originates (West, Midwest, Northeast, Southeast, or Southwest)
racepctblack	The percentage of individuals who identified as black.
racePctWhite	The percentage of individuals who identified as white.
racePctAsian	The percentage of individuals who identified as Asian.
racePctHisp	The percentage of individuals who identified as Hispanic.
medIncome	The median household income for a specific region.
NumUnderPov	The proportion of individuals living under the poverty line in a region.
PctUnemployed	The percentage of the population that is unemployed.
PctEmploy	The percentage of the population that is employed.
larcenies	The amount of larcenies occurring in a community.
larcPerPop	The amount of larcenies per capita.

This refined dataset, free of missing values and outliers, serves as the foundation for our analysis, enabling us to explore the connections between socioeconomic factors and larceny rates effectively. A correlation analysis heatmap was used to assess the relationships between the chosen predictive features and the target.

Figure 3

Correlation Heatmap of Larceny and Potential Factors

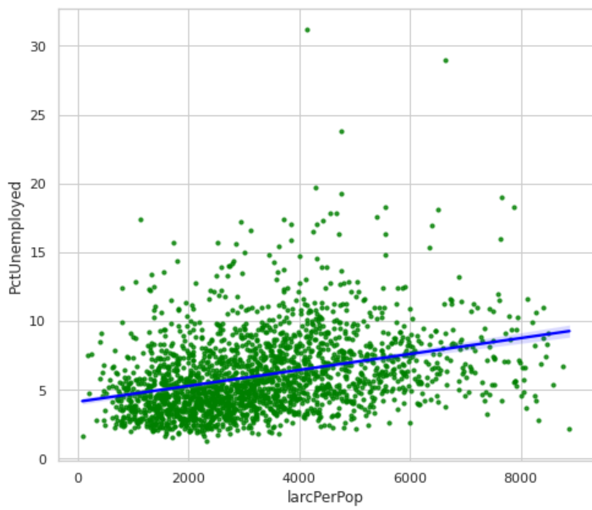


Made on Hex using Python

The heatmap reveals significant correlations between various features and the target, larcPerPop. PctUnemployed has a correlation of 0.29 with larcPerPop, the strongest correlation between the target and a socioeconomic feature. The strongest negative correlation with the target was medIncome, having a correlation of -0.45. These correlations showcase that cities with a higher rate of employment and a higher average income are less likely to have high amounts of larceny occurring. In addition to this, medIncome has a strong negative correlation coefficient of -0.61 with PctUnemployed, showcasing that the two features are both strongly correlated with one another as well as larcPerPop.

Figure 4

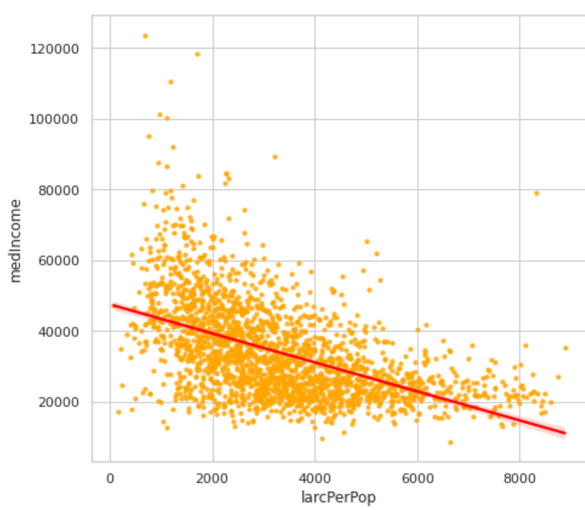
Correlation Between Larcenies per Capita and Unemployment Rates



Made on Hex using Python

Figure 5

Correlation Between Larcenies per Capita and Median Income



Made on Hex using Python

The strongest positive racial correlation with the target was racepctblack, having a correlation coefficient of 0.36, while the strongest negative racial correlation was racePctWhite, having a correlation coefficient of -0.32. These correlations suggest that there are underlying socioeconomic factors that disproportionately affect black populations, leading to a significant increase in larceny rates for cities with a large black population and a significant decrease in larceny rates in cities with a large white population. This is further shown through the correlations between these races with PctUnemployed. racepctblack and PctUnemployment have a correlation coefficient of 0.44, the strongest positive correlation between a socioeconomic feature and a racial feature, while racePctWhite and PctUnemployment have a correlation coefficient of -0.54, the strongest negative correlation between a socioeconomic feature and a racial feature. These relationships further showcase that unemployment is a key factor in predicting larceny rates.

Methodology

This study uses a quantitative approach to investigate the connection between various socioeconomic factors and larceny rates in different U.S. regions. The main objective of the project is to understand how different predictors such as unemployment, income, and racial composition influence larceny rates and to derive insights that could assist policymakers in implementing crime prevention strategies.

As outlined in this study, larceny comprises a large portion of the crime dataset, making up approximately 52.89% of the total crime incidents across 2,215 cities. This high percentage demonstrates the importance of focusing on larceny as the target crime for our analysis.

The data was first examined for missing values and outliers, with none identified. The dataset was divided into two parts: 75% for training and 25% for testing. This division ensures there is enough data to train the model while also allowing for a strong evaluation of its performance on new data. We used the train_test_split function from scikit-learn and set a fixed random state to ensure the results were consistent each time.

It was then decided which variables were irrelevant to the study, such as countyCode and fold, leading to their removal and leaving a total of 13 fields. The region field was then created, allowing for a stronger analysis of larcenies in different regions within the United States. While we found no immediate need to add new data fields, we acknowledged that incorporating additional socioeconomic variables, such as education levels or access to public services, could enhance the analysis in future iterations. Both categorical and continuous variables were prepared to improve the model's performance. We transformed categorical predictors like race and income using one-hot encoding. We scaled continuous predictors using StandardScaler. These steps made sure that all variables played their part in the model and prevented those with larger numbers from having too much influence on distance-based calculations. We selected eight predictor variables—racepctblack, racePctWhite, racePctAsian, racePctHisp, medIncome, NumUnderPov, PctUnemployed, PctEmploy—that were deemed most relevant based on their correlation with the target variable, larcPerPop.

Additionally, a histogram was generated to assess the distribution of larcPerPop after removing outliers using Z-scores (see Figure 1). The binning resulted in eight distinct categories of larceny rates, ranging from "Very Low" to "Severe." Most cities fell into the "Low Moderate" and "Low" categories, with fewer cities classified as "Severe". This distribution indicates a skew towards lower larceny rates across the dataset, with fewer extreme cases of high larceny rates.

We explored several machine learning models, each chosen based on their strengths for regression and classification tasks. The baseline Model l uses the mean value of the target variable (larcPerPop) to predict larceny rates. It is a comparison point for evaluating the performance of more complex models. The CART (Classification and Regression Trees) is straightforward and can effectively manage complex data. Its branching structure helps us identify non-linear relationships between predictor variables and larceny rates. We chose Random Forest to overcome issues like high variance and overfitting that often come with a single decision tree. By combining multiple trees, Random Forest minimizes overfitting and enhances generalization.

Analysis/Findings

Table 2

Baseline, CART, and Random Forest Model Summary

Model Type	Train MSE	Test MSE	Train MAE	Test MAE	Train R^2	Test R^2
Baseline	3,613,368.81	3,613,368.8144	1,404.1235	1,404.1235	0.0000	0.0000
CART	1,877,800.5130	2,215,277.72	994.21	1,090.92	0.4995	0.2756
Random Forest	1,778,526.9952	2,150,143.34	965.2696	1,060.2576	0.5260	0.2969

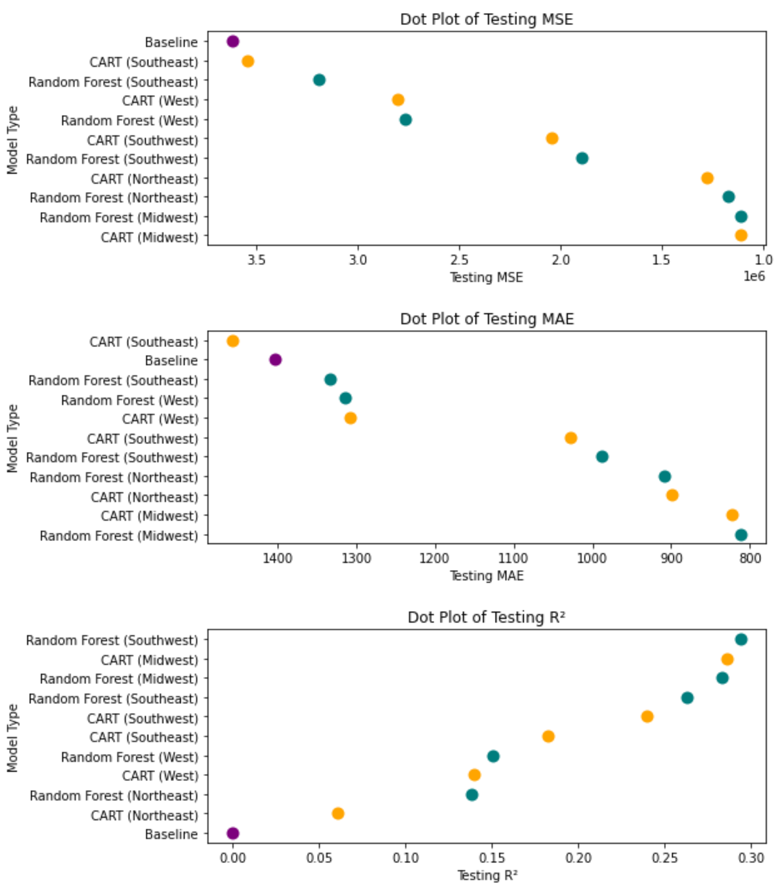
This table summarizes the performance of the three models we explored in terms of Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 on the training and test sets. During modeling, we decided to bin the target variable (larcPerPop) into three categories: Low, Medium, and High, using quantiles to ensure an even distribution of data across the bins.

We observed that deeper decision trees often overfit the data, which led us to apply pruning techniques to improve generalization. The Random Forest model consistently outperformed the Decision Tree model, showing a lower MAE of 38.28% compared to 53.81%

for the CART model. However, both models faced difficulties in predicting larceny rates, especially in areas with higher minority populations. This is a potential area for further research, as it suggests the need for models that better account for demographic diversity. Overall, the framework provides a solid foundation for analyzing the factors affecting larceny rates and can inform targeted crime prevention strategies.

Figure 6

Comparison of Performance Metrics of Models in Regions across the United States



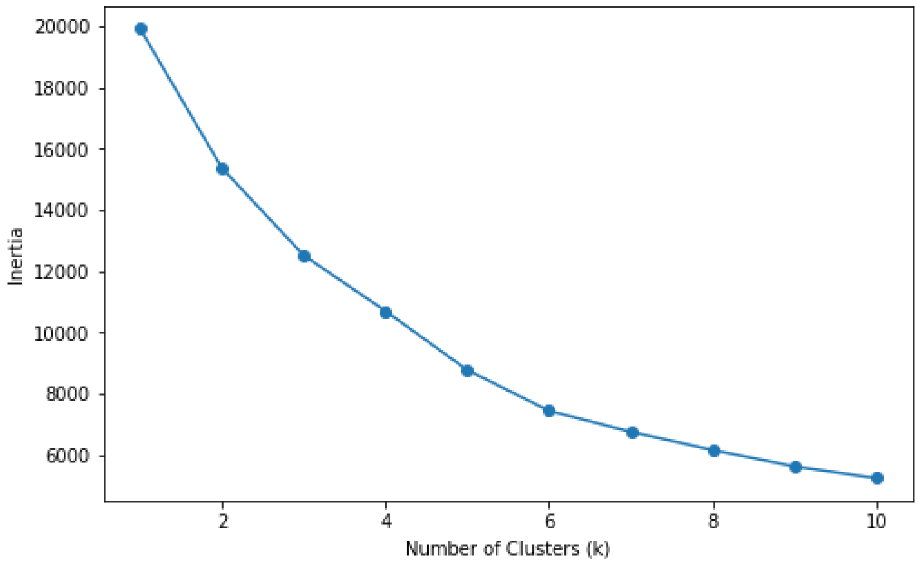
Made on Hex using Python

The performance of each model in different regions is shown in Figure 6. This includes a plot of the testing mean squared error (MSE), where lower values indicate better model performance. The Random Forest model performs particularly well in the Southwest region. Additionally, the testing mean absolute error (MAE) plot shows that models with lower MAE values closely match actual larceny rates, further proving that the Random Forest model is superior. The testing R^2 plot indicates that higher values suggest better explanatory power. Generally, the Random Forest model outperforms the CART model, although results vary by region. This regional analysis also highlights challenges in predicting larceny rates in areas with higher minority populations, suggesting it could be a topic for future research and model improvement. Overall, this framework provides a solid basis for examining the factors that influence larceny rates and can help in developing targeted crime prevention strategies.

We implemented a K-Means clustering algorithm to find hidden patterns in the dataset, adding to the supervised learning models used previously. The predictor variables included demographic, socioeconomic, and employment-related features such as population, median income, poverty levels, and racial composition. Before applying K-Means, the data underwent preprocessing, including scaling with StandardScaler to ensure comparability for the distance-based algorithm. We used the Elbow Method to plot inertia, which measures the sum of squared distances within clusters, for cluster values from 1 to 10.

Figure 7

Elbow method for optimal K value



Made on Hex using Python

The Elbow Method identified the optimal number of clusters as three. After clustering, we achieved a silhouette score of 0.53, confirming that the clusters were reasonably well-separated. The clustering analysis revealed the following group characteristics:

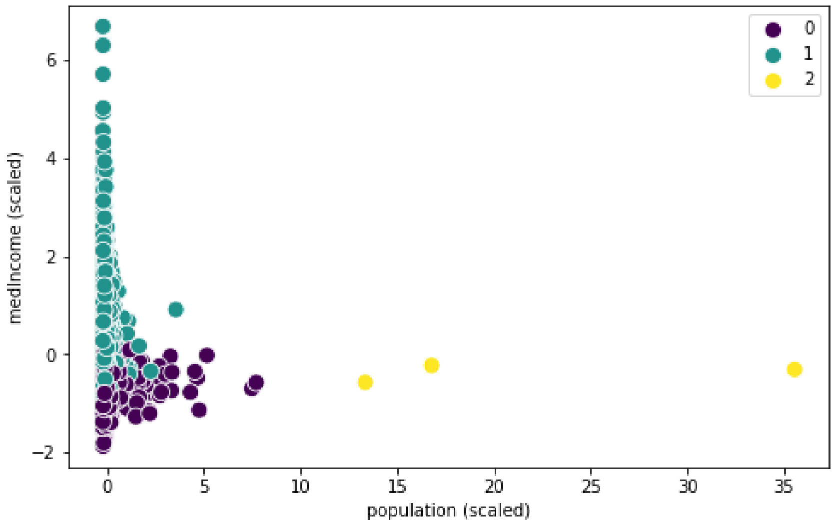
Cluster 0: Mid-sized populations with lower incomes and higher unemployment rates.

Cluster 1: Smaller populations with higher incomes and better job rates.

Cluster 2: Large metropolitan areas with diverse racial backgrounds.

Figure 8

Visualization of clusters



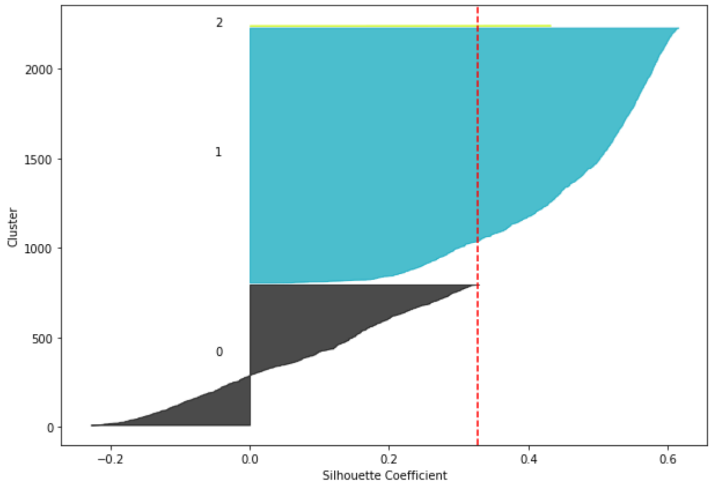
Made on Hex using Python

This scatter plot shows groupings based on the scaled dimensions of population and median income, highlighting economic disparities.

When compared to larceny rates, Cluster 1 predominantly had lower larceny rates, suggesting that economic stability correlates with reduced crime. Cluster 0 showed a mix of larceny rates, while Cluster 2 had very few cases, reflecting its sparse representation.

Figure 9

Silhouette plot



Made on Hex using Python

The silhouette plot further validates the robustness of the clustering process by illustrating the distinctiveness of the clusters.

We tested several supervised machine learning models to predict larceny rates based on various socio-economic factors, to evaluate their predictive performance using cross-validation. After applying the models and comparing their results, we chose the Random Forest Regressor as the most effective model for this dataset. Below is a detailed analysis of each model tested and the rationale behind our final choice.

Table 3

Summary of Tested Models

Model Type	Accuracy	R^2	MSE	Mean CV MSE/Accuracy	Significant Features
Logistic Regression	76.75	N/A	N/A	73.26% (Accuracy)	Precision: 0.77; Recall: 0.78; Balanced classification of binary larceny rates
Linear Regression	N/A	0.24	2,768,250.21	2,685,590.45 (MSE)	Struggles with non-linearity; useful baseline for interpretability
Naive Bayes	N/A	0.31	2,514,378.05	2,528,890.47 (MSE)	Performs well for categorical features; cross-validation highlights variability
Random Forest	81.93	0.31	2,514,378.05	2,528,890.47 (MSE)	Best overall performance; Cross-validation shows robust performance across folds

This table summarizes the performance metrics for the four models tested in this study: Logistic Regression, Linear Regression, Naive Bayes, and Random Forest. The models were evaluated based on Accuracy, R^2 (for applicable models), Mean Squared Error (MSE), and Mean Cross-validation MSE/Accuracy.

- Logistic Regression performed reasonably well with an accuracy of 76.75%, suitable for binary classification tasks. It showed a balanced classification of binary larceny rates, with precision and recall both around 0.77 and 0.78.
- Linear Regression, while useful as a baseline, struggled to capture complex non-linear relationships, achieving an R^2 of 0.24 and an MSE of 2,768,250.21.
- Naive Bayes performed well with categorical features, achieving an R^2 of 0.31 and MSE of 2,514,378.05, with cross-validation results showing variability across folds.

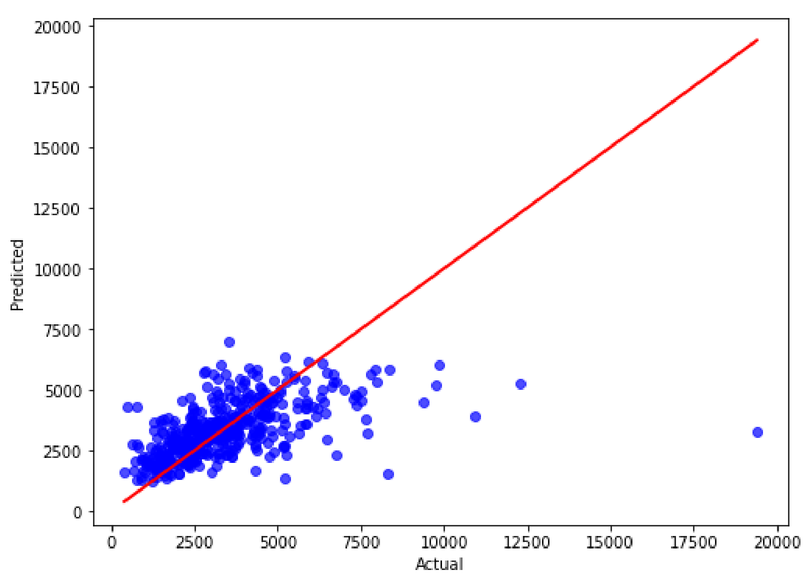
- Random Forest, the best-performing model, achieved an accuracy of 81.93% and an R^2 of 0.31, with consistent MSE and robust performance across cross-validation folds.

Based on these results, the Random Forest model emerged as the most effective for predicting larceny rates, outperforming both the Logistic Regression and Linear Regression models in terms of accuracy and predictive power.

After evaluating multiple models, we conducted a thorough visual analysis to gain deeper insights into the model's performance and feature relationships. The following visualizations offer key information regarding the Random Forest model's predictive abilities, feature importance rankings, and residual patterns, helping to validate our choice and highlight areas for improvement.

Figure 10

Comparison of Actual Values to Predictions Made by Random Forest Model



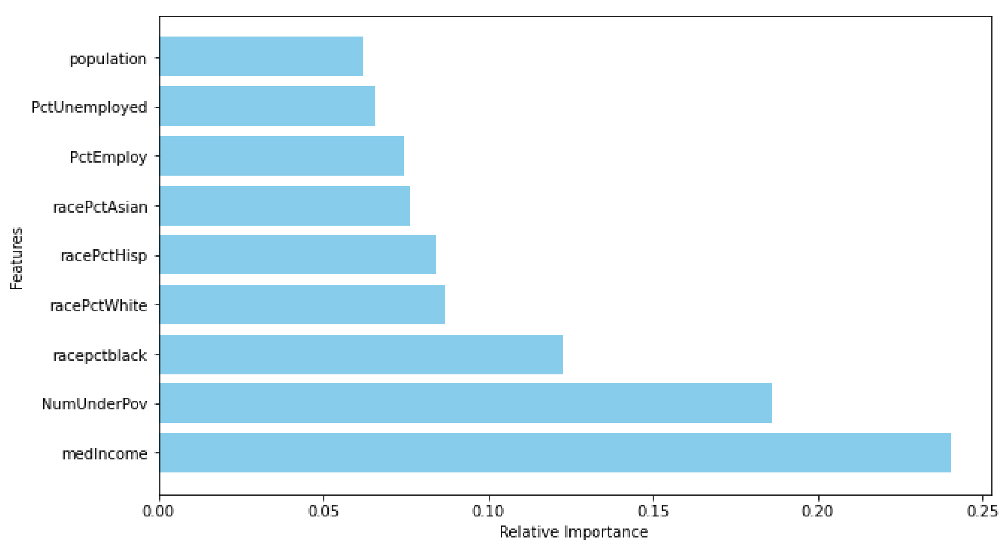
Made on Hex using Python

The scatter plot in Figure 10 compares actual values to predicted values from the Random Forest model. The red diagonal line represents the ideal situation where predicted values match actual values perfectly. The blue data points show a moderate positive correlation between predicted and actual values, but there is a lot of spread, particularly at higher values. This indicates potential accuracy issues when predicting extreme values.

The increasing spread of errors as actual values rise suggests that the model has heteroscedasticity, meaning the errors grow larger with higher predictions. This implies the model may be underestimating higher values and overestimating lower values. This likely happens because the model does not fully capture the non-linear relationships in the data. These findings show that there is a need for further improvement, such as trying more advanced techniques to handle non-linearity. After assessing the model's overall performance through a scatter plot (Figure 10), we further examined the contributions of individual features using a feature importance plot (Figure 11).

Figure 11

Feature Importance



Made on Hex using Python

The feature importance plot in Figure 11 shows which socioeconomic factors most affect the model's predictions. Median income is the most important factor, with an importance score of about 0.24. The number of people living under the poverty line (NumUnderPov) follows next. Demographic factors, like racial composition, have a moderate effect, while population size and unemployment rate have less influence on the model's predictions.

This ranking matches what we expect. Economic indicators, such as income and poverty levels, are more important in predicting larceny rates than demographic factors like race or population size. This supports the idea that economic stability, shown by income and poverty levels, plays a key role in crime rates. By understanding the model’s focus on these economic factors, policymakers can target economic development programs to reduce larceny rates.

Conclusion

After analyzing larceny rates and socioeconomic characteristics across U.S. areas, we concluded that the models successfully discovered important connections between unemployment, larceny rates, and income disparity. The Random Forest and Naive Bayes models both performed well, however, Random Forest's accuracy and precision were greater. Particularly high precision—a crucial criterion for assessing a model's ability to predict true positive cases—made it possible to identify significant predictors for larceny rates. These results are consistent with theoretical frameworks, stressing the situational and structural dynamics that underlie crime patterns, such as social disorganization, strain theory, and routine activity theory. These solutions fall into three main strategies:

Economy Empowerment

Economic empowerment strategies have been shown to effectively reduce crime rates. Youth workforce development programs, such as summer job initiatives, have reduced youth involvement in violent activities by up to 45% (Smith et al.2020). Similarly, universal basic income programs have demonstrated significant reductions in crime, along with promoting community well-being and economic stability (Brown & Davis, 2019; Johnson, 2021). Investments in education that enhance skills and career opportunities are also correlated with a decline in crime rates, as they alleviate financial stress in economically disadvantaged areas (Miller et al., 2021; Brown & Davis, 2019).

Interventions Based in the Community

Neighborhood improvement initiatives contribute significantly to crime reduction and enhanced social cohesion. For example, housing repairs in low-income neighborhoods of Philadelphia led to a 21.9% decrease in crime, and greening vacant lots reduced violent crime by

29% (Jones, 2020; Anderson, 2020). Urban greening projects, such as tree planting and improved lighting, were associated with a 76% reduction in homicide rates in certain areas (Anderson, 2020; Jones, 2020). These projects improve the physical environment while fostering community bonds and reducing criminal opportunities (Jones, 2020).

Population Affected and Policy Implications

The proposed strategies primarily benefit economically disadvantaged communities that are disproportionately affected by larceny and related crimes (Smith et al., 2020; Anderson, 2020). Policymakers should integrate these approaches into broader crime prevention strategies, such as allocating American Rescue Plan funds for youth employment and urban infrastructure improvements (US Department of Education, 2021). Future research should focus on localized dynamics and longitudinal studies to measure the sustained impacts of these interventions (Crews, 2009).

This study recognizes several limitations, even though these tactics offer a strong framework for lowering larceny rates. The analysis's reliance on aggregated regional data may have obscured local variances or dynamics at the individual level. Furthermore, results might have been impacted by biases in socioeconomic data collection and crime reporting. Longitudinal studies to assess the long-term efficacy of suggested tactics and investigate connections with other crime categories or cultural elements should be a part of future research. This study concludes by emphasizing the crucial part socioeconomic differences play in influencing larceny rates and offering research-based remedies for the problem. Policymakers and community leaders may significantly reduce larceny and improve public safety by boosting economic possibilities, building community resilience, and utilizing data-driven crime prevention. Exploring these findings in future studies will help enhance strategies, address limitations, and ensure inclusive and effective interventions.

References

Agnew, R. (1992). Foundation for a General Strain Theory of Crime and Delinquency. *Criminology, 30*(1), 47–87. https://doi.org/10.1111/j.1745-9125.1992.tb01093.x

Anderson, T. G. (1999). *Social disorganization theory: The effect of social and economic factors on crime and delinquency* (Master's thesis, Old Dominion University). https://doi.org/10.25777/c70p-6m15

Anderson, R. (2020). Urban greening projects and crime reduction. *Journal of Urban Policy Studies*. https://www.journalofurbanpolicystudies.com

Bureau of Justice Statistics. (2020). *Criminal Victimization, 2019: Selected Findings*. U.S. Department of Justice. https://www.bjs.gov/content/pub/pdf/cv19.pdf

Brown, T., & Davis, S. (2019). The impact of universal basic income on community well-being and crime. *Economic Research Review*. https://www.economicresearchreview.org

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*(4), 588–608. https://doi.org/10.2307/2094589

Crews, G. A. (2009). Education and crime. In J. M. Miller (Ed.), *21st century criminology: A reference handbook* (pp. 59–66). SAGE Publications, Inc. https://doi.org/10.4135/9781412971997.n8

Fowler, P. J., Hovmand, P. S., Marcal, K. E., & Das, S. (2019). Solving Economic Distress from a Complex Systems Perspective: Insights for Crime Prevention Responses. *Annual*

Review of Public Health, 40(1), 465–486. https://doi.org/10.1146/annurev-publhealth-040617-01355

Hanratty, M. (2017). Do Local Economic Conditions Affect Crime Rates? *Housing Policy Debate, 27*(4), 640–655. https://doi.org/10.1080/10511482.2017.1282885

Hannon, L., DeFronzo, J., & Hout, M. (2021). Relative deprivation and crime: A comparison of social theory and crime trends. *Criminology, 59*(3), 573–602. https://doi.org/10.1111/1745-9125.12305

Johnson, M. (2021). Summer job initiatives and youth violence prevention. *Youth Development Quarterly*. https://www.youthdevelopmentquarterly.org

Jones, A. (2020). Housing repairs and social cohesion in Philadelphia. *Community Development Journal*. https://www.communitydevelopmentjournal.com

Lee, M. R., Zhang, J., & Zhang, M. (2021). The relationship between poverty and property crime in urban areas: Evidence from a national sample. *Sociological Inquiry, 91*(2), 224–243. https://doi.org/10.1111/soin.12412

Mustaine, E. E., & Tewksbury, R. (1998). The Relationship Between Economic Conditions and Property Crime: A Cross-Sectional Analysis. *Criminology, 36*(4), 829-857. https://doi.org/10.1111/j.1745-9125.1998.tb01267.x

Sampson, R. J., Raudenbush, S. W., & Earls, J. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science, 277*(5328), 918-924. https://doi.org/10.1126/science.277.5328.918

Smith, L., et al. (2020). Economic disparities and crime prevention strategies. *Crime Prevention & Policy*. https://www.crimepreventionandpolicy.com

U.S. Department of Education. (2021). Frequently asked questions: American Rescue Plan Elementary and Secondary School Emergency Relief (ARP ESSER) program and the Governor's Emergency Education Relief (GEER) Fund [PDF]. Retrieved from https://www.ed.gov/sites/ed/files/2021/06/21-0130-ARP-Public-Safety-ED-FAQ-06-16-2021.pdf

Wickert, C. (2018). Social disorganization (Shaw & McKay). *SozTheo*. Retrieved from https://soztheo.de/theories-of-crime/social-disorganization/soziale-desorganisation-shaw-mckay/?lang=en

Zhao, E. (2022). The Key Factors Contributing to the Persistence of Economic Instability and Crime. *International Journal of Sustainable Development & World Ecology, 30*(1), 1-5. https://doi.org/10.1080/13504509.2022.2120109

Zhao, J. (2017). Economic Conditions and Crime: A Panel Data Analysis. *Journal of Experimental Criminology, 13*(4), 603–626. https://doi.org/10.1007/s11292-017-9320-4