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Predicting Countries with Low and High Robbery Rates Using Discriminant Analysis

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Abstract

Crime such as robbery has been identified as one of the socioeconomic problems across the world, which adverse social, economic, and family conditions have caused. Using discriminant analysis, this study proposed a model for classifying and predicting countries with low and high robbery rates. Robbery rates in 2018 of 42 countries across the world have been extracted from United Nations Office on Drugs and Crime as the dependent variable. Meanwhile, the independent variables included the unemployment rate, average household size, and poverty index. The study originally classified 32 countries with low and 10 with high robbery rates. Pretesting was employed, and the results showed that all the assumptions for discriminant analysis were fulfilled. Using standardized beta and Wilk's Lambda, the average household size is the best predictor variable, while the unemployment rate is the least predictor variable. The overall prediction function model is significant. The classification results by discriminant analysis algorithm for groups with low and high robbery rates show that the proposed model correctly predicts 78.6% of the robbery rates of countries based on the three characteristics, such as their unemployment rate, average household size, and poverty index.

Keywords: Robbery rates, discriminant analysis, unemployment rate, average household size, poverty index.

Introduction

Crime results from several ill-disposed social, economic, and family conditions. This is in accordance with Jose (2021) that criminality is the product of social and cultural causes, not biological factors. According to the Conflict Theory, the roots of crime and deviance can be attributed to various social and economic factors. Individuals who experience an unstable economy, limited education, or disadvantaged social backgrounds are more likely to engage in criminal activities.

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Additionally, exposure to violent family environments, gang involvement, childhood physical assaults, and other physical factors can impede an individual's moral and social development, ultimately leading to violent behavior and criminal conduct. Risk factors for violence at the community level include rising unemployment, poverty, and transience; declining economic opportunities and community involvement; substandard housing; gang activity; emotional anguish; and a lack of access to services (Chen et al., 2016; McMahon et al., 2013; Voisin & Neilands, 2010).

Various factors contribute to the difference in crime rates across different countries. According to a report by the World Population Review (2022), high levels of unemployment and poverty are associated with increased crime rates. On the other hand, strict law enforcement and severe punishments are linked to lower crime rates. Age is also a significant factor, with individuals in their 20s and 30s committing most violent crimes. The United States has an overall crime rate of 47.70, and there has been a significant decrease in violent crime over the past 25 years. Certain states, such as Alaska, New Mexico, and Tennessee, have higher crime rates than others, like Maine, New Hampshire, and Vermont. Interestingly, countries like Switzerland, Denmark, Norway, Japan, and New Zealand have some of the lowest crime rates globally, which can be attributed to their effective law enforcement. According to the report, Denmark, Norway, and Japan have the most restrictive gun laws worldwide.

As cited in the article about violent crime by Rosenfeld (2017, violent crimes are violations of criminal law that involve the intentional use of violence by one person against another. However, social scientists disagree on a single or unified definition of violence. Criminologists favor narrow definitions of violence, focusing on physical harm or threats. Many, but not all, criminologists accept the definition provided by an influential National Research Council study, which defined violence as "behaviors by individuals that intentionally threaten, attempt, or inflict physical harm on others" (Reiss & Roth, 1993, p. 2; General Overviews). This concept encompasses a wide range of actions, such as murder, assault, robbery (theft committed with the use of force or threat of such), rape, torture, and boxing. However, it does not include many acts covered by other, equally logical definitions. How violence is defined affects what behaviors are considered violent, how much violence has been seen in various locations and times, what theories have been developed to explain violent conduct, and how society has reacted to violent behavior.

Apart from violent crimes that have the primary intention of committing violent acts, such as murder or rape, violent crime also encompasses those where violence is utilized as a means to an end, like theft or blackmail. In an article written by Matthews (2002), he stated that armed robbery is regarded as one of the most serious crimes, carries a lengthy prison sentence, and receives a lot of media coverage. Four categories emerged for the motivations for committing a crime in the study by Bersamina et al. (2021) that examined the experiences of people deprived of their liberty. Financial gain is one of these reasons. Motivation is sparked by the anticipation of money or monetary benefit from completing the act to meet their fundamental and financial necessities.

However, there is a dearth of academic study on robbery. Hence, future robbery rates are projected with far less attention. As a result, this study aims to examine the connections between robbery and the variables that affect robbery rates, such as the unemployment rate, average household size, and poverty index among nations. Therefore, it would be helpful for criminologists and criminal justice professionals who manage sizable crime databases and use crime data for analysis and research to understand the precise nature of the relationships between these variables and compare crimes across jurisdictions in a responsible manner.

The results of this study may also be used as the basis for advancing plausible recommendations by concerned agencies in possibly coming up with a general framework to address robbery cases. Mallubhotla (2013) stated that crime prediction is crucial for law enforcement and public policy since it can greatly impact making wise judgments. This can lower the cost of law enforcement while also improving the effectiveness of anti-crime initiatives. Communities in the twenty-first century need individuals with interdisciplinary training and experience to handle many difficult challenges, such as analyzing crime statistics, managing courts, and law enforcement, and maintaining public order (Pariñas & Bestre, 2015). Furthermore, the findings of this study could offer empirical support for the criminal opportunity impact idea and provide policymakers and the law enforcement community with new information.

Literature Review

According to the United Nations Office on Drugs and Crime's 2019 global study on homicide, 464,000 people died from violent crimes in 2017. According to the study, intentional homicide rates are greater in nations with higher gun ownership rates. Europe has some of the lowest rates of violent crime. Violent crime rates in many European nations are below one incidence per 100,000 people. In addition to having stronger gun prohibitions, these nations also have efficient law enforcement.

Numerous crime theories link unemployment to criminality. Becker (1968) develops a crime model in which an unemployed individual will be more likely to engage in crime than an employed individual. This is true since someone unemployed makes less money. This is supported by the study of Grönqvist (2011), which investigates the link between youth unemployment and crime in Sweden. His research revealed that the overrepresentation of young men in crime statistics is mostly due to unemployment. He also investigates whether there is any difference between crimes committed during weekdays and on weekends. He discovers evidence that demonstrates how having more free time increases the likelihood that someone will commit a crime.

On the contrary, Gao et al. (2017) examined how unemployment was related to crime rates in the State of Indiana. This study uses a fixed-effect model and employs balanced panel data of 23 counties in the State of Indiana from 2006 - 2013. After controlling for population size and demographic, socioeconomic, and county-specific characteristics, they found that unemployment has a contemporaneous negative effect on the violent crime rate and a null influence on the property crime rate.

As stated by the United Nations Department of Economic and Social Affairs, Population Division (2017), a household is a fundamental socioeconomic entity in human societies, comprising a collective of individuals who share provisions for food, shelter, and other essential requirements for daily living. Households are the centers of demographic, social, and economic processes. Decisions about childbearing, education, health care, consumption, labor force participation, migration, and savings occur primarily at the household level. In larger families, according to Wagner et al. (1985), child-rearing becomes more rule-ridden and less individualized, with corporal punishment and less investment of resources. Several conclusions can be made from the evidence presented in many related studies, as Orbeta (2005) mentioned. One, having more children generally has a negative influence on the welfare of the home. Two, perhaps more significantly, these negative effects are regressive, meaning they are more severe for poorer households. Three: Strong and long-lasting relationships exist between bigger family sizes, poverty incidence, and poverty vulnerability. These findings significantly impact efforts to reduce poverty, a major initiative of several Philippine administrations that hasn't had much luck. Many blame the slow and erratic growth rates for this failure. Large family sizes, he continued, are a clear but poorly understood cause of many negative features of household welfare, including low and inconsistent economic growth rates.

One of the forms of crime is robbery. According to the article published in FindLaw in November 2021, robbery is a theft accomplished by violence or the threat of violence. Unlike theft or burglary, robbery almost always requires the presence of a victim who is threatened with bodily harm. If a weapon is used or the victim suffers an injury, the robbery may be charged as "armed" or "aggravated" robbery. Based on the report of the United Nations Office on Drugs and Crime (2010), robbery is most common in Southern Africa and the Americas. East and Central & West Europe, North Africa, and Oceania are on the global average level.

Most research on understanding crime rates in the United States and elsewhere has been limited to identifying factors associated with past crime rates (Rosenfeld, 2011). It is uncertain if crime rates, particularly those for robberies, will keep decreasing, stabilizing, or rising.

In the study of Dikko and Osi (2014), discriminant analysis was employed to develop a rule that categorizes States as safe or unsafe They found that the classification results yielded 18 States as unsafe and 19 States as safe. They have demonstrated that a number of factors, including population, sex distribution, voter turnout, police presence, and unemployment rates, may be used to determine whether a State is safe and contribute to its improvement.

Moreover, several studies investigated crime phenomenon using techniques such as Data Mining Technique (Awal et al., 2017), Discriminant Analysis (Kaur et al., 2019), Principal Component Analysis (Usman et al., 2012) Log-Linear Analysis (Crowly & Lynne, 1992), and the more sophisticated Structural Equation Analysis (Liu & Kaplan, 1999). In each of these studies conducted, these techniques have become a vital part of crime detection and prevention in many countries.

Overall, the variety of robberies and the depths to which they can be understood leave a lot of room for scientific investigation into the distribution of robberies across locations, how people get involved in robberies, how robbers choose their targets, and how offenders and victims interact in particular encounters. These are only a few examples of problems that could arise when researching robbery, along with a selection of theoretical frameworks that can help address them.

Research Objectives

This study employed the multivariate statistical method of discriminant analysis to classify and predict the countries into two categories, low and high robbery rate groups, based on data recorded in 2018.

Specifically, the study sought answers to the following:

1. Analyze the robbery rates of countries with independent variables such as unemployment rate, average household size, and poverty index; and

2. Propose a model for predicting and classifying countries with low and high robbery rates.

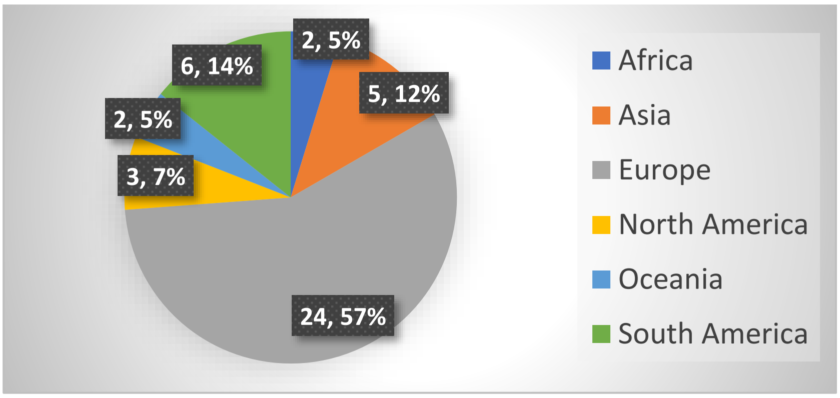
Research Methodology

Research Design. This study utilized exploratory data analysis, particularly the discriminant analysis technique, to classify and predict the countries in terms of their robbery rates category (low and high) as explained by the selected independent variables.

Sources of Data. The dataset on the robbery rates (from United Nations Office on Drugs and Crime) as the dependent variable was based on 2018 records. Meanwhile, the independent variables that were considered as causes of robbery included the unemployment rate (from The World Bank Group), average household size (from Database on Household Size and Composition), and poverty index (from World Population Review) of the different countries. These were based on theories and related literature as the focus of investigation involving studies on violent crimes.

Data mining was employed to obtain relevant data from these sources, leading to only 48 countries with recorded data in all the selected variables. These countries are classified into six regions based on Our World in Data. These are Africa, Asia, Europe, North America, Oceania, and South America. After correcting data when outliers were removed, these 48 countries were reduced to 42. Figure 1 shows the compositions of the 42 countries as the final data set.

Figure 1. Distribution of Countries Per Region as Sources of Data



Data Gathering Procedure. A data mining technique was employed to obtain relevant data from the sources. The data were encoded and analyzed using Microsoft Excel to extract the data gathered.

Ethical Considerations. Research ethics were properly observed in the study's conduct in compliance with the requirements of the Ethics Review Committee in the university. The data collected and analyzed in the study were for public information. Hence, there is no need to request permission to access these data. There were no risks in the study's social and psychological aspects since no specific individuals were involved. The study's limitations in applying data mining techniques were taken into consideration by the researchers.

Analysis of Data. The study primarily used Discriminant Analysis, a multivariate statistical technique to parse out variables that distinguish particular groups. It is a tool that identifies variables that discriminate between mutually exclusive, categorical groups. Assigning objects to previously established classes is possible using the resulting combination as a classifier. This study is similar to the study of Kaur, Ahuja, & Kumar (2019), which used multiple discriminant analysis techniques to classify and predict sexual offenders with two categories, i.e., minor and major. Pre-Testing was employed to check the assumptions for Discriminant Analysis. Microsoft Excel and IBM SPSS version 25 were used in analyzing the data.

Pre-Testing. The following assumptions were checked for the use of Discriminant Analysis:

a. The dependent variable is a nominal or categorical scale. Though the dependent variable in this study is robbery rates, it was converted into a categorical variable by classifying the data set into two groups. The 48 countries were categorized into two classes of groups based on their robbery rates. The average robbery rate of 89.404 was computed for all the countries in the data source. Countries with a robbery rate < 89.404 of all the countries in the data source are considered with low robbery rates (group 1). On the other hand, countries with a robbery rate > 89.404 are considered with a high robbery rate (group 2).

b. The independent variables are metric data. The independent variables (IVs) or explanatory variables are in metric data. The employment rates and poverty indices are in terms of percent, while the household sizes are the average number of usual residents (members of a household) per household. Hence, all the independent variables are continuous or metric data.

c. Testing of an outlier. The discriminant analysis can only be executed when all the values in the dataset are free from outliers. The boxplot method detected and corrected the outliers or extreme values in the original data set. As a result, the 48 observations were reduced to 42 after cleaning the outliers. The final data set consists of 32 countries in Group 1 (with low robbery rates) and 10 in Group 2 (with high robbery rates).

d. Treatment of missing value. The original data set did not have missing values.

e. No Multicollinearity between independent variables. It is evident in Table 1 that no multicollinearity exists because there is no significant relationship between the pairs of the independent variables. It further shows a very low correlation for each pair of independent variables.

Table 1. Correlation between the Independent Variables

Variables	Unemployment Rate	Average Household Size	Poverty Index
Unemployment Rate	1.000	-.129	-.134
Average Household Size	-.129	1.000	.013
Poverty Index	-.134	.013	1.000

f. Equality of covariance matrices. A statistical test using Box's M for equality of the covariance matrices of the independent variables across the dependent variable groups is presented in Table 2.

Table 2. Test of Equality of Covariance Matrices

Box's M		6.605
F	Approx.	.956
	df1	6
	df2	1658.032
	Sig.	.454

Based on the result of analysis using Box's M test, it obtained the approximate value of F (6, 1658.032) = 0.956, with a statistical significance that does not exceed the critical level (Sig. = 0.454). Hence, the equality of the covariance matrices is supported.

Results and Discussions

After checking and fulfilling all the assumptions, the following results are presented and discussed pertaining to the data analysis to classify and predict the robbery rates of the resulting 42 countries considered in the study.

1. Analysis of the robbery rates of countries with independent variables such as unemployment rate, average household size, and poverty index

a. Descriptive Statistics. The results of the descriptive analysis of the variables are presented in Table 3 below.

Table 3. Descriptive Analysis of the Variables

Group	Independent Variables	Mean	Std. Deviation	Valid N (listwise)	
				Unweighted	Weighted
Low Robbery Rate	Unemployment Rate	5.825	3.247	32	32
	Average Household Size	2.847	0.765	32	32
	Poverty Index	15.069	7.107	32	32

High Robbery Rate	Unemployment Rate	7.438	3.962	10	10
	Average Household Size	3.454	0.819	10	10
	Poverty Index	20.930	12.243	10	10
Total	Unemployment Rate	6.209	3.450	42	42
	Average Household Size	2.991	0.811	42	42
	Poverty Index	16.464	8.802	42	42

It can be gleaned from the table that there are 42 cases in which 32 countries have low robbery rates while 10 countries have high robbery rates. Comparing the two groups shows that based on mean values, the countries with high robbery rates have higher unemployment rates, average household size, and poverty index than the countries with low robbery rates.

b. Ranking of Variables. Table 4 shows the value of Wilks' Lambda and the significance level for each of the three independent variables. Each function in Wilks' Lambda's series of procedures divides cases into categories. It is the proportion of the overall variance within the discriminant scores that is not explained by differences in one of the groups. Wilks' smaller Lambda values suggest the function has a better discriminatory ability.

Table 4. Assigning Ranks to Variables

Variables	Wilks' Lambda	Sig.	Rank
Unemployment Rate	.959	.201	3
Average Household Size	.896	.037	1
Poverty Index	.918	.065	2

Among the three independent variables, only the average household size obtained a significant value of less than 0.05. Based on Wilk's Lambda values, the average household size also has the smallest value, equal to 0.896, which shows that it is the best predictor variable to predict or classify the robbery rates of the countries. The poverty index is the second highest predictor among the three variables, with its Wilk's Lambda value equal to 0.918. Moreover, the unemployment rate exhibits the least predictor variable through its Wilk's Lambda value equal to 0.959.

c. Eigenvalue with Canonical Correlation. Table 5 presents the canonical discriminant function analysis that provides the eigenvalue and canonical correlation. The eigenvalue is generated in this analysis, which explains or represents the amount of variance accounted for by the factors. Canonical correlation is the association output between discriminant scores and the groups.

Table 5. Eigenvalue with Canonical Correlation

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.290[a]	100.00	100.00	.474

The table provides the eigenvalue of 0.290 and a canonical score of 0.474. These values indicate not much high amount of variance in the model by the independent variables. However, the canonical correlation coefficient of 0.474 represents the moderate degree of prediction of the robbery rates of the countries based on their unemployment rate, average household size, and poverty index.

d. Overall Model's Significance Testing. Table 6 presents the overall evaluation of Wilk's Lambda based on the independent variables unemployment rate, average household size, and poverty index to describe how the prediction model fits.

Table 6. Overall Evaluation of the Model

Test of Function	Wilks' Lambda	Chi-square	df	Sig.
1	.775	9.796	3	.020

It was found in the preceding result of the individual testing of the independent variables based on their Wilks' Lambda values that only the average household size is significant. However, the table above displays that the prediction model is statistically significant, as supported by sig. Value less than 0.05, meaning that when all three independent variables are considered, they could classify the two groups of countries regarding robbery rates. This means that the overall model rejects the null hypothesis of no distinction between the two groups of countries, classified as low and high robbery groups. This is similar to the results of Kaur et al. (2019), which found that three independent variables, namely: age, weight, and height were significant predictors for classifying sexual offender categories.

In addition, Table 7 presents the standardized canonical discriminant function coefficients and the structure matrix resulting from the overall testing of the discriminant function model.

Table 7. Standardized Canonical Discriminant Function and Structure Matrix Coefficients

Independent Variables	Standardized Canonical Discriminant Function Coefficients	Structure Matrix Coefficients
Unemployment Rate	.555	.382
Average Household Size	.697	.633
Poverty Index	.622	.557

The table shows the importance of the three predictors or independent variables based on their coefficients. It reveals that it conforms with their assigned ranks, as presented in Table 4 earlier. The average household size is the best predictor, with a coefficient of 0.697, followed by the poverty index, with a coefficient of 0.622. and the unemployment rate as the least predictor with a coefficient of 0.555. Based on the structure matrix coefficients, the independent variables are consistent with their order of predicting powers. It can also be noted that no value of the structure matrix coefficients is less than 0.3.

2. Prediction and classification of countries with low and high robbery rates

e. Predictive Discriminant Regression Equation. The predictive discriminant regression equation of the model could be generated from Table 8 using the unstandardized beta values of the constant unemployment rate, average household size, and poverty index.

Table 8. Prediction Equation Coefficients

Independent Variables	Unstandardized coefficients
(Constant)	-4.890
Unemployment Rate	.162
Average Household Size	.897
Poverty Index	.073

The predictive discriminant regression equation of the model that calculates the discriminant scores is given by: Robbery Rate Category = – 4.890 + 0.162 * Unemployment Rate + 0.897 * Average Household Size + 0.073 * Poverty Index. This equation is used to predict the value of the target variable, i.e., the robbery rate category, by putting the values of the unemployment rate, average household size, and poverty index.

Table 9 below displays the group probabilities of the dependent variable, which is defined in the study with two groups, namely: low robbery rate and high robbery rate. The probability of countries with low robbery rates is 0. 762 or 76.2%, while the group with high robbery rates is 0. 238 or 23.8%. It also shows in the table that 32 cases are taken for the analysis of the low robbery rate group, and 10 cases are for the high robbery rate group.

Table 9. Group Probabilities

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Low robbery rate	.762	32	32
High robbery rate	.238	10	10
Total	1.000	42	42

f. Model accuracy and classification summary. Table 10 below presents the group centroids of the discriminant function evaluated at group means.

Table 10. Functions at Group Centroids

Group	Centroid
Low robbery rate	-.294
High robbery rate	.940

The prediction of countries' robbery rates is found through the discriminant function with a boundary value of -0.294 for the low robbery rate group and 0.940 for the high robbery rate group. This means countries with low robbery rates have a predictive value below -0.294. Meanwhile, the countries with a predictive value above 0.940 are categorized under the high robbery rate group.

The classification summary is generated and displayed in Table 11 based on the group centroids.

Table 11. Classification Results Summary

<table>
<tr><th colspan="3" rowspan="2">Group</th><th colspan="2">Predicted Group Membership</th><th rowspan="2">Total</th></tr>
<tr><th>Low robbery rate</th><th>High robbery rate</th></tr>
<tr><td rowspan="4">Original</td><td rowspan="2">Count</td><td>Low robbery rate</td><td>28</td><td>4</td><td>32</td></tr>
<tr><td>High robbery rate</td><td>5</td><td>5</td><td>10</td></tr>
<tr><td rowspan="2">%</td><td>Low robbery rate</td><td>87.5</td><td>12.5</td><td>100</td></tr>
<tr><td>High robbery rate</td><td>50.0</td><td>50.0</td><td>100</td></tr>
</table>

a. 78.6% of initially grouped cases were correctly classified.

The classification results by discriminant analysis algorithm for groups with low and high robbery rates show that the prediction has an overall accuracy rate of 78.6%. This implies that the proposed model is good at predicting 78.6% of the robbery rates of countries correctly based on the three characteristics, such as their unemployment rate, average household size, and poverty index.

The table also reflects the number and percentage of predicted and unpredicted cases about their original group membership. Of the 32 countries classified under the low robbery rate group, 28 countries, or 87.5%, are correctly classified, while 4 countries are misclassified. Looking into the data sets, the following countries are misclassified: Albania, Greece, Kenya, and Paraguay.

On the other hand, out of the 10 countries classified under the high robbery rate group, 5 countries, or 50.0%, are correctly classified. These include Bolivia, Brazil, Mexico, Morocco, and Spain. The other 5 or 50.0% of misclassified countries are Belgium, Chile, Dominican Republic, Ecuador, and Uruguay. These last five countries should have been classified under the low robbery rate group.

Conclusions and Recommendations

By employing the multivariate statistical discriminant analysis method, this study could classify and predict the countries into two categories: low and high robbery rate groups. Based on standardized beta, Wilk's Lambda, canonical correlation discriminant function coefficients, and structure matrix coefficients, the average household size was the best and significant predictor variable, followed by the poverty rate, and the unemployment rate was the least predictor variable. The overall model significantly predicts the classification of the countries into two groups. The countries with low robbery rates could be predicted when the discriminant score is below -0.294. In contrast, the countries with a discriminant score above 0.940 are categorized under the high robbery rate group. The classification results by discriminant analysis algorithm for groups with low and high robbery rates show that the prediction has an overall accuracy rate of 78.6% based on the differences based on the three characteristics, such as their unemployment rate, average household size, and poverty index. Of the 32 countries classified under the low robbery rate group, 28 countries, or 87.5%, are correctly classified, while out of the 10 countries classified under the high robbery rate group, 5 countries, or 50.0%, are correctly classified.

Safety enforcers and policy-makers in different countries can use the proposed model to implement programs that may reduce robbery cases. A similar study may be conducted to include a larger group of countries for prediction and classification using discriminant analysis.

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