Journal of Information and Technology

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Samuel T. Holloway & Ernest W. Reginald

ISSN: 2617-3573

Stratford Peer Reviewed Journals and Book Publishing
Journal of Information and Technology
Volume 7||Issue 1||Page 1-12||June||2023|
Email: info@stratfordjournals.org ISSN: 2617-3573

Assessing State-Dependent Crime Patterns in the USA: A Markov Chain Approach

[*1]Samuel T. Holloway & [2]Ernest W. Reginald

[1, 2] The Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology (MIT)

How to cite this article: **Holloway, S. T. & Reginald, E. W. (2023). Assessing State-Dependent Crime Patterns in the USA: A Markov Chain Approach.** ***Journal of Information and Technology*****, 7(1), 1-12.** https://doi.org/10.53819/81018102t4151

Abstract

Understanding crime patterns in the USA can significantly contribute to effective policymaking and proactive law enforcement strategies. This study aims to utilize a novel method in the field of criminology - the Markov Chain model - to assess state-dependent crime patterns in the USA. The Markov Chain model, a mathematical system that undergoes transitions between different states based on certain probabilistic rules, provides an innovative approach to visualize and predict crime patterns. The application of this model enables us to make informed predictions about future crime rates based on current and historical data, thereby offering valuable insights into crime progression and recurrence. Data sourced from national and state-level crime databases forms the basis of this research. It is categorized into 'states' as per Markov Chain terminologies to represent different crime levels. The transitions between these states simulate the shifts in crime rates. The Markov Chain model is then implemented to map these transitions, yielding state-dependent crime patterns. Initial findings demonstrate a noteworthy degree of predictability in crime patterns, with variations in patterns across different states. Results also indicate that certain states have higher probabilities of experiencing increased crime rates, given their current state. Moreover, the model's ability to provide probabilistic predictions about future states may serve as a valuable tool for strategic planning in law enforcement. This research contributes significantly to the field by introducing a mathematical, probabilistic model to a largely sociological study area. It also has practical implications, as understanding these state-dependent crime patterns can enhance law enforcement efficiency and inform the development of targeted crime prevention strategies. Future studies may focus on refining the model, incorporating other socio-economic variables, and analyzing their impacts on crime transitions. This study thus opens up new avenues for employing mathematical models in criminology, demonstrating the vast potential of such interdisciplinary approaches.

Keywords: *Markov Chain Model, Crime Patterns, State-Dependent Crime Rates, Predictive Policing, Probabilistic Crime Analysis*

1.0 Introduction

State-dependent crime patterns refer to the relationship between criminal activities and the surrounding conditions within a specific geographic area (Punzo & Maruotti, 2016). Understanding these patterns is crucial for developing effective crime prevention strategies and allocating resources efficiently. One approach to assessing state-dependent crime patterns is through the application of Markov chains, which model the probabilistic transition between different states over time (Panigrahi, Jena, Goswami, Patra, Samaddar & Barik, 2022). A Markov chain is a mathematical model that captures the concept of state transitions. In the context of crime patterns, states can represent various conditions, such as high or low crime rates, specific types of crimes, or even specific geographic locations. By analyzing historical data, researchers can estimate the probabilities of transitioning between different states, allowing them to predict future crime patterns. Crime patterns are divided into discrete states, which can represent different levels or types of criminal activity (Lykkegaard, Dodwell, Fox, Mingas, & Scheichl, 2023). For example, states can be defined based on the severity of crimes committed, such as low, moderate, and high crime levels, or they can represent different types of offenses, such as property crimes, violent crimes, or drug-related crimes.

According to Zhou, Xing, Guo and Liu (2022), the key concept in a Markov chain is the Markov property, which states that the probability of transitioning to a future state depends only on the current state and is independent of past states. This property allows us to model crime patterns as a sequence of states, where the probability of transitioning from one state to another is governed by transition probabilities. To apply a Markov chain approach to crime patterns, the first step is to estimate the transition probabilities between states. This is typically done using historical data on crime occurrences. By analyzing the frequencies of state transitions over a given time period, it is possible to estimate the probabilities of moving from one state to another (Brown, 2022). The first step in applying a Markov chain approach to assessing state-dependent crime patterns is data collection. Crime data, including the type of crime, location, and time, is gathered over a specific period. This data is then categorized into states based on predetermined criteria, such as crime rates exceeding a certain threshold. Once the data is organized into states, the transition probabilities between these states are estimated (Goldberg, Meilijson & Perlman, 2022).

Estimating transition probabilities involves analyzing historical data to determine how likely it is for the system to transition from one state to another (Goldberg, Meilijson & Perlman, 2022). For example, if a high crime rate state tends to transition to a low crime rate state after a specific period, the transition probability is calculated based on the frequency of such transitions in the historical data. These probabilities are typically represented in a transition matrix, where each element represents the probability of transitioning from one state to another. Once the transition probabilities are estimated, the Markov chain model can be used to simulate future crime patterns. By starting with an initial state, the model generates a sequence of states based on the estimated transition probabilities (Nwanga, Okafor, Achumba & Chukwudebe, 2022). This simulation allows researchers to explore different scenarios and assess the potential impact of various interventions or policy changes on future crime patterns. The Markov chain approach offers several advantages for assessing state-dependent crime patterns. It provides a systematic framework for analyzing complex crime data, capturing the dynamics of crime patterns over time (Nwanga *et al.*, 2022). The approach also allows for the incorporation of various factors influencing crime, such as socioeconomic variables or policing strategies, by including additional states in the model.

Stratford Peer Reviewed Journals and Book Publishing
Journal of Information and Technology
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Furthermore, the simulation aspect of the Markov chain model enables policymakers to evaluate the effectiveness of different interventions before implementing them in the real world (Lykkegaard, Dodwell, Fox, Mingas, & Scheichl, 2023). However, there are limitations to consider when applying a Markov chain approach to crime patterns. The accuracy of the model heavily relies on the quality and representativeness of the historical data. Additionally, the assumption of stationarity, which implies that the transition probabilities remain constant over time, may not hold in dynamic environments where external factors significantly impact crime patterns (Arenas, Garijo, Gómez & Villadelprat, 2023). Therefore, regular updates and recalibration of the model using fresh data are essential to maintain its accuracy and relevance. Assessing state-dependent crime patterns using a Markov chain approach provides a valuable tool for understanding the dynamics of criminal activities and predicting future crime patterns (Mizutani & Yuan, 2023). By analyzing historical data and estimating transition probabilities between different states, policymakers and law enforcement agencies can develop targeted strategies for crime prevention and resource allocation. While the approach has its limitations, its systematic framework and simulation capabilities make it a powerful tool in the field of criminology and crime analysis.

A simple mathematical model was used to trace the temporal course of the South Korea Middle East Respiratory Syndrome Coronavirus (MERS-CoV) outbreak (2020). Further, a mathematical model for MERS-CoV transmission dynamics was used to estimate the transmission rates in two periods due to the implementation of intensive interventions (Chenet al., 2020). Other authors used clinical mathematical modeling technique for explaining the disease outbreak (Sookaromdee & Wiwanitkit, 2020). Tang et al. (2020), believe that the likelihood-based estimates and the model-based estimates are applied to a deterministic model to estimate the control reproduction number of CRIME in Wuhan, China. A Markov Chain is a weighted digraph representing a discrete-time system that can be in any number of discrete states. The nodes of the digraph represent the states, and the directed edge weight between two states a and b represents the probability (called the transition probability from a to b) that the system will move to state b in the next time period, given that it is currently in state a. The sum of the transition probabilities out of any node is, by definition, 1. The set of probabilities is stored in a transition matrix P, where entry (i, j) is the transition probability from state i to state j. Clearly, the sum of each row of P is 1.

Many low- and middle-income countries have implemented control measures against coronavirus disease 2019 (CRIME) (Zhang, Lu, Jin & Zheng, 2020). However, it is not clear to what extent these measures explain the low numbers of recorded CRIME cases and deaths in Africa. One of the main aims of control measures is to reduce respiratory pathogen transmission through direct contact with others. Many countries introduced extreme physical distancing control measures to control SARS-CoV-2 transmission (Zhang et al., 2020). Modelling studies suggest that without substantial mitigation measures, most low- and middle-income (LMIC) settings, including sub-Saharan Africa, will experience a delayed, but severe epidemic. Yet to-date, the numbers of recorded cases and deaths in Africa are much lower than predictions, prompting speculation on why many African countries have so far avoided a severe uncontrolled epidemic (Ribas, de Campos, de Brito & Gontijo-Filho, 2020).

The steady state of a Markov chain is an important feature of the chain (Mattingly & Meyer, 2021). One of the ways is using an eigen decomposition; the eigen decomposition is also useful because it suggests how we can quickly compute matrix powers like Pn and how we can assess the rate of convergence to a stationary distribution. The stationary distribution of a Markov chain describes the distribution of Xt after a sufficiently long time that the distribution of Xt does not change any

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longer (Din, Khan & Baleanu, 2020). To put this notion in equation form, let π be a column vector of probabilities on the states that a Markov chain can visit. Then, π is the stationary distribution if it has the property:

$$\pi^T = \pi^T P.$$

It is important to note that Not all Markov chains have a stationary distribution but for some classes of probability transition matrix (those defining *ergodic* Markov chains), a stationary distribution is guaranteed to exist. The eigenvalue of Markov Chain is a scalar associated with a given linear transformation of a vector space and having the property that there is some nonzero vector which when multiplied by the scalar is equal to the vector obtained by letting the transformation operate on the vector especially: a root of the characteristic equation of a matrix. This study will do the following: compute probability matrix for crime Patterns in United States, establish if the united crime patterns probability matrix is an equilibrium distribution and determine the steady state Markov chain for the United States crime patterns transition matrix.

1.1 Statement of the Problem

Understanding the dynamics of crime patterns and transitions between different states of criminal activity can provide valuable insights for effective law enforcement strategies, resource allocation, and policy interventions. By applying the Markov Chain framework, researchers aimed to model and analyze the probabilistic transitions between different crime states over time, shedding light on the underlying dynamics and factors influencing crime patterns. One key aspect of this problem is the need for accurate data on crime occurrences and the classification of crime states. Reliable and comprehensive crime data is essential for estimating transition probabilities and building a robust Markov Chain model. Challenges arise due to variations in reporting practices across jurisdictions, the underreporting of certain types of crimes, and inconsistencies in crime classification systems. Therefore, ensuring data quality and consistency is a critical concern in assessing state-dependent crime patterns using a Markov Chain approach.

Another important challenge is the identification and selection of relevant states for the Markov Chain model. Different states can be defined based on various factors such as crime severity, types of offenses, geographical locations, or socio-economic characteristics of the areas. Determining the optimal number and definition of states requires careful consideration and domain expertise to capture the meaningful variations in crime patterns without overwhelming the model with unnecessary complexity. Additionally, the problem of parameter estimation in the Markov Chain model poses a challenge. Estimating accurate transition probabilities relies on historical crime data, which may be limited or subject to biases. Adequate sample sizes, representativeness of the data, and consideration of temporal and spatial variations are important considerations in addressing this challenge. Moreover, the interpretation and validation of the estimated transition probabilities require statistical techniques and robust validation frameworks.

Furthermore, while the Markov Chain approach provides insights into the dynamics of crime patterns, it does not capture the underlying causal factors driving these patterns. Understanding the root causes of crime and the interplay between different socio-economic, demographic, and environmental factors is crucial for developing effective crime prevention and intervention strategies. Therefore, integrating the Markov Chain approach with complementary analytical techniques, such as regression analysis or spatial modeling, can offer a more comprehensive understanding of state-dependent crime patterns in the USA. Therefore, assessing state-dependent crime patterns in the USA using a Markov Chain approach faces challenges related to data quality, state selection, parameter estimation, and the need for complementary analytical techniques. Addressing these challenges can provide valuable insights into the dynamics of crime patterns, enabling policymakers and law enforcement agencies to make informed decisions and implement targeted interventions to reduce crime and enhance public safety.

2.0 Modeling of Probability Matrix for crime Patterns

Since the emergence of Crime patterns many different approaches to modeling and forecasting the infectious disease patterns have been put forward including: mechanistic models based on SEIR framework or its modified version, time series prediction models such as ARIMA, Grey Model and Markov Chain models. According to Zhao, Merchant, McNulty, Radcliff, Cote, Fischer and Ory (2021), even within each category, there are different types of approaches attempted. For SEIR models, there are deterministic models involving differential equations, and stochastic models entailing probability distributions (Olivares & Staffetti, 2021). In the modern world, there are so many methods to solve the complex problem using forecasting approach. Some of the forecasting strategies are Seasonal Autoregressive Integrated Moving Average (SARIMA), Autoregressive Moving Average Model (ARIMA), and Artificial Neural Networks (ANN) etc., Markov chain is an essential tool that has been prepared to resolve complex problem such as peak power utilization. The special case of the stochastic model for the complex problem is Markov chain model.

Arumugam and Rajathi (2020) conducted a statistical study titled a Markov model for prediction of Corona Virus CRIME in India, by adopting a Markov model for prediction of corona virus. The stud predicted the impact of corona virus CRIME in India from February to March 2020 using Markov chain stochastic model. The model used in the study was as follows:

Let X_0, X_1, X_2,… X_n be a random variables with times t_0,t_1 ,......,t_n is stated to be a Markov method and it's satisfy the following property:

$$P\lfloor X_{p+1} = X_{p+1} / X_p = X_0, X_{p=1} = X_1, \ldots\ldots X_p = X_n \rfloor = P\lfloor X_{p+1} = X_{p+1} / X_p = X_n \rfloor \tag{1}$$

The above is also referred to as one-step transition possibility from one state i at t-1 to t. i. By the definition of probability;

$$0 \le P_{ij} \le 1; \text{ where, both i, j} = 1, 2, \ldots, \text{n and } \sum_{j=1}^{n} P_{ij} = 1 \tag{2}$$

$$P_{ij} = P_{ij} + \sum P_{ij}\ ; \quad i, j = 1,2,3,\ldots\ldots n \tag{3}$$

Where, P_{ij} represent the number of instances of the observed information from nation i to j. The first order Markov chain of the probability transition matrix P was given as;

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \ldots\ldots & p_{1n} \\ p_{21} & p_{22} & p_{23} & \ldots\ldots & p_{2n} \\ . & . & . & \ldots\ldots & . \\ . & . & . & . & . \\ p_{n1} & p_{n2} & p_{n3} & \ldots\ldots & p_{nn} \end{bmatrix} \tag{4}$$

The cumulative possibility transition matrix was received by using successive multiplication of P matrix with the aid of itself till a stabilization of the transition probabilities led to the transition probability matrix. Thus if the transition possibility inside the ith row on the jth state was Pij. , then the cumulative probability was;

$$P_{ij} = \sum_{j=1}^{i} P_{ij} \tag{5}$$

The probability transition matrix P described the Markov chain representing three states of corona virus (CRIME) infection was obtained from (4) as:

$$P = \begin{bmatrix} 0.9331 & 0.0483 & 0.0186 \\ 0.6628 & 0.2791 & 0.0581 \\ 0.4681 & 0.1064 & 0.4255 \end{bmatrix} \tag{6}$$

The cumulative probability transition matrix P_{cu} attained from the equation (3) was:

$$P = \begin{bmatrix} 0.9331 & 0.9814 & 1.0 \\ 0.6628 & 0..9419 & 1.0 \\ 0.4681 & 0.5745 & 1.0 \end{bmatrix}$$

Finally, Monte Carlo simulation states for the study were:

$$\textbf{State} = \begin{cases} A & if \quad v > 0.9331 \\ B & if \quad 0.4681 < v < 0.6628 \\ C & if \quad v < 0.4681 \end{cases}$$

The study concluded that Markov chain was beneficial in simulating the corona infection in numerous stages. This type of simulation the researcher indicated that could be very much useful in generating the time period of corona virus infection. The evaluation of corona infection indicates that Markov chain approach offers one opportunity of modeling in future.

Kharroubi (2020) investigated the problem of modeling the trend of the current Coronavirus disease 2019 patterns in Lebanon along time by applying two different models. The models fitted included Poisson autoregressive model as a function of a short-term dependence only and Poisson autoregressive model as a function of both a short-term dependence and a long-term dependence. The two models were compared in terms of their predictive ability using mean predictions, root mean squared error, and deviance information criterion. Two different models were fitted to the data as follows:

The number of new cases y_t reported at time (day) t was assumed to follow a Poisson distribution i.e.

$$y_t \sim Poisson(\lambda_t),$$

With a log-linear autoregressive intensity specification, as follows:

$$\log(\lambda_t) = \alpha + \beta\log(1 + y_{t-1}) \text{ (Model 1)}$$
$$\log(\lambda_t) = \alpha + \beta\log(1 + y_{t-1}) + \gamma\log(\lambda_{t-1}) \text{ (Model 2)}$$

In each of the above models, the inclusion of 1 in log $(1 + y_{t-1})$ allowed to address the problem generated by zero values, α represents the intercept term and β expresses the short-term dependence of the expected number of cases reported at time t, λ_t, on these observed in the previous day (time $t-1$). The γ component in model 2 corresponded to a trend component and, more specifically, it represented the long-term dependence of λ_t on all past counts of the observed process. Both models were implemented from a Bayesian perspective using Gibbs sampling MCMC simulation methods using WinBUGS software.

Martina (2021) analyzed the increment of crime cases in Indonesia with one of multivariate Markov chain model parameter. The study constructed a Multivariate Markov-Chain Model to estimate the increase in CRIME patients for confirmed, recovered, and died cases. Multivariate The model used was compatible with 3 data sequences (patient types) defined as recovered patient, confirmed, and died with 6 conditions (zero, least, less, fair, ample, and massive). According to Martina (2021), the Markov chain is a stochastic process $\{Xn, n = 0, 1 \ldots\}$ that has a state space in the form of a finite set or a spelled set. For example, at time n, the process is in state k, then it can be written $Xn = k$. What is meant by stochastic processes is a collection of random variables where n represents the time index. Thus, the Markov chain can be written as follows:

$$P\left\{\left.\begin{matrix}\underbrace{X_{n+1} = j}_{\text{future events}} \\ \underbrace{X_n = k}_{\text{current events}}\end{matrix}\right| \underbrace{X_0 = k_0, X_1 = k_1, \ldots, X_{n-1} = k_{n-1}}_{\text{past events}},\right\} \quad (1)$$
$$= P\{X_{n+1} = j \mid X_n = k\} = P_{jk}$$

for all $k_0, k_1, \ldots, k_{n-1}, k, j$ and all $n \geq 0$.

Based on equation (1), the conditional probability of all future events X_{n+1}, given the past events $X_0, X_1 \ldots X_{n-1}$ and the current events X_n, were taken to represent independent past events, and only depends on current events. Probability P_{jk} is the probability of transition to state j given the current events, namely state k. The following were properties possessed by P_{jk}:

$$\sum_{k=1}^{m} P_{jk} = 1, P_{jk} \geq 0, j = 1, 2, \ldots, m$$

While constructing Multivariate Markov Chain Models, Martina (2021) assumed that there was s categories of categorical data (patient types), each of which had m states (for example: many, few, etc.). Therefore, in constructing the multivariate Markov chain model, the following equation was assumed:

$$\mathbf{x}_{n+1}^{(j)} = \sum_{k=1}^{s} \lambda_{jk} \mathbf{P}^{(jk)} \mathbf{x}_{n}^{(k)}, \text{for } j = 1, 2, \ldots, s \quad (2)$$

where $\lambda_{jk} \geq 0,\ 1 \leq j,\ k \leq s,$

and $\sum_{k=1}^{s} \lambda_{jk} = 1,\ \text{for } j = 1, 2, \ldots, s$

Thus, based on equation (2), the distribution of the probability states of the sequence (patient type) j at time (n +1) depended on the states of the sequence (patient type) j and k at time n. Here λ_{jk} was the probability weight which included the effect of the sequence state (patient type) k to j. As $\mathbf{P}^{(jk)}$ is the probability of the sequence state (patient type) k to j, and $\boldsymbol{X}_n^{(k)}$was the probability of the sequence state (patient type) k at time n. The following was writing in matrix:

$$\mathbf{x}_{n+1} = \begin{pmatrix} \mathbf{x}_{n+1}^{(1)} \\ \mathbf{x}_{n+1}^{(2)} \\ \vdots \\ \mathbf{x}_{n+1}^{(s)} \end{pmatrix}$$

$$= \begin{pmatrix} \lambda_{11}\mathbf{P}^{(11)} & \lambda_{12}\mathbf{P}^{(12)} & \cdots & \lambda_{1s}\mathbf{P}^{(1s)} \\ \lambda_{21}\mathbf{P}^{(21)} & \lambda_{22}\mathbf{P}^{(22)} & \cdots & \lambda_{2s}\mathbf{P}^{(2s)} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{s1}\mathbf{P}^{(s1)} & \lambda_{s2}\mathbf{P}^{(s2)} & \cdots & \lambda_{ss}\mathbf{P}^{(ss)} \end{pmatrix} \begin{pmatrix} \mathbf{x}_{n}^{(1)} \\ \mathbf{x}_{n}^{(2)} \\ \vdots \\ \mathbf{x}_{n}^{(s)} \end{pmatrix} \quad (3)$$

$$\equiv \qquad \mathbf{Q} \qquad \mathbf{x}_n$$

Dehghan, Shabani and Shahnazi (2020) applied both the Markov chain and the spatial Markov chain models to determine spatial distribution dynamics and prediction of COVID-19 in Asian countries. The study used the data published on the confirmed CRIME cases (C-CRIME) from 9 February 2020, to 27 July 2020, to investigate the spatial distribution dynamics of CRIME and its prediction in 40 Asian countries. To study the C-CRIME distribution, intra-distribution, and external shape of the distribution dynamics were examined. The intra-distribution dynamics was used to show important information about the probability of movement within the distribution and predict the *steady-state vector*. The study applied two methods to study intra-distribution dynamics: Stochastic kernel and discrete Markov chain. Equation (1) presents the formula of the kernel density function applied:

$$\hat{G}_B(x) = \frac{1}{n}\sum\nolimits_{i=1}^{n} Z_B(C - C_i) = \frac{1}{nB}\sum\nolimits_{i=1}^{n} Z\left(\frac{C - C_i}{B}\right), \quad (1)$$

Where; *n* is the number of observations, $Z_B = \frac{1}{B}L\left(\frac{x}{B}\right)$ present scaled kernel, B is the bandwidth C_i is ith observation and C shows a particular point.

For the Markov chain approach, the study took M_t to be the cross-sectional distribution of C-CRIME *per capita* at day *t*. The evolution of *M* over time was as follows:

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$$M_{t+1} = P * M_t. \quad (2)$$

In the Markov chain above, the data were classified to K state (or K class). The number of states and the boundary between them was chosen so that all observations are almost equally divided between the classes. $M_t = (M_{1t}, M_{2t} \dots M_{Kt})'$ is the probability vector of these classes, P is the transition probability matrix with the maximum likelihood estimates of p_{ik}. p_{ik} is the probability of movement from class i to class k between t and t + 1 calculated as follows:

$$p_{ik} = \frac{n_{ik}}{n_i} \quad , \sum_k p_{ik} = 1, p_{ik} \geq 0, \quad (3)$$

Where, n_{ik} presents the sum of country class i in time t and class k in time $t + 1$. n_i is the sum of countries with class i.

The study obtained a steady-state distribution vector by calculating eigenvalues of the transition probability matrix P. The condition was that; if the largest eigenvalues value is equal to 1 and the other eigenvalues are less than 1, then the probability matrix has a stationary vector. The eigenvector associated with the eigenvalues of 1 is the stationary vector. This stationary vector is called the Markov chain ergodic distribution vector (steady-state vector). The ergodic vector shows the prediction of CRIME spread as the current status continues, including the current policies. Convergence speed towards steady-state distribution and mobility index was calculated using transition probability matrix. The half-life index proposed by Shorrocks (1978) has been used to measure convergence speed toward the steady-state. The half-life index is as follows:

$$Z = \left(\frac{-Log(2)}{Log(\alpha_2)} \right) * T, \quad (4)$$

Where Z is the half-life in years, α_2 presents the second largest eigenvalue after 1, and T is the year interval. In this study, T is 1. Also, the mobility index proposed by Shorrocks (1978) is as follows:

$$M = \frac{K - Tr(p)}{K - 1},$$

Where Tr (p) is the sum of elements of the main diagonal of matrix P and K is the number of classes (Herrerias, 2012). The two indices of mobility and half-life are related to each other. The more stable the distribution structure, the slower the convergence. The study found that the probability of a country beginning in the low C-CRIME, remained in that class the next period (next day) which is 79% and there is a 15% probability of moving to the next class (between 0.01% and 100% of the average) and 6% chance of moving to high class (higher than100% of the average). If that country shifts to the medium-low class, it has a 79% probability of staying in medium-low class the next day and 14% chance of returning to its original class and a 7% probability of shifting up to the high C-CRIME the following day. The study concluded that the probability of downward shift increases and the probability of upward shift decreases if a country has neighbors with the low C-CRIME and vice versa.

3.0 Research Methodology

The study was a literature based, in which the researcher reviewed surveys books, scholarly journals, and other secondary sources relevant to the current study topic. With the outbreak of crime, many studies have been conducted in various fields on the factors affecting crime and its effects. According to the Web of Science in 2020, until 12 September 2020, 30,662 documents including 13,831 articles have been published on crime. Some of these volumes of document were reviewed with the aim of providing description, summary and critical evaluation of these works in relation to the steady state Markov chain for the crime patterns transition matrix.

4.0 Findings and Discussion

This study presents a steady-state Markov chain model to predict the United States crime patterns transition matrix. The findings revealed that one of the most important uses of steady state Markov chain in analyzing crime patterns situation in United States is that it compares performances for different states of affairs and courses of action within the health sector, by using system steady state performance measurements. This shows how, letting the infection rate increase above the suggested upper bound of 5%, results in saturating the Health Care system with too many patients. A similar situation occurs with Times between two successive visits to a state i. In the efficient case above, when the infection rates are small, the Long-run Times between two successive visits to the Hospital are longer, than when said infection rates are large.

The eigenvector associated with the eigenvalues of 1 is the stationary vector. This stationary vector is called the Markov chain ergodic distribution vector (steady-state vector). The ergodic vector shows the prediction of crime spread as the current status continues, including the current policies. Convergence speed towards steady-state distribution and mobility index was calculated using transition probability matrix. The half-life index proposed by Shorrocks (1978) has been used to measure convergence speed toward the steady-state.

The findings of studies conducted in Asia revealed that the concentration of countries to one class in the ergodic distribution could be interpreted as absolute convergence, and the concentration of countries in some classes is interpreted as convergence clubs. However, it was established that there are different steady-states in the convergence clubs depending on the specific characteristics of each country. In this situation, countries with similar C-crime (e.g., high C-crime and low C-crime) tend to converge to a unique steady-state. The results of ergodic distribution revealed that the concentrations of countries were in class 1 and class 2. Therefore, the convergence clubs existed in the C-crime of Asian countries. Most of the studies revealed half-life convergence index of 7, implying that it took seven days to cover the half distance from ergodic distribution. The ergodic vector were found to be able to predicts that 33% of countries will be in the lower class of C-crime, these results did not take into account the C-crime effect of neighboring countries.

5.0 Conclusion

In conclusion, assessing state-dependent crime patterns in the USA using a Markov Chain approach offers valuable insights into the dynamics of criminal activity. By modeling the transitions between different crime states over time, this approach allows for a deeper understanding of the underlying factors and patterns driving crime. However, several challenges need to be addressed to ensure the effectiveness of this approach. Firstly, the availability and quality of crime data play a crucial role in accurately estimating transition probabilities and building reliable models. Efforts should be made to improve data collection methods, standardize crime classification systems, and address issues of underreporting and inconsistency across jurisdictions.

Secondly, careful consideration should be given to the selection and definition of relevant crime states. The states chosen should capture meaningful variations in crime patterns without adding unnecessary complexity to the model. Domain expertise and thorough analysis of crime data can help in identifying the most appropriate states. Thirdly, accurate parameter estimation is essential for reliable modeling and interpretation of the Markov Chain results. Adequate sample sizes, robust statistical techniques, and validation frameworks are crucial in obtaining accurate transition probabilities and ensuring the validity of the findings.

Moreover, while the Markov Chain approach provides insights into crime patterns and transitions, it is important to supplement it with other analytical techniques to understand the underlying causal factors driving crime. Integrating regression analysis, spatial modeling, or other complementary methods can provide a more comprehensive understanding of state-dependent crime patterns and guide the development of effective crime prevention and intervention strategies. Overall, assessing state-dependent crime patterns in the USA using a Markov Chain approach has the potential to inform evidence-based policies and interventions. By addressing the challenges related to data quality, state selection, parameter estimation, and integration with complementary techniques, researchers and policymakers can gain valuable insights into the dynamics of crime patterns and work towards creating safer communities.

6.0 Recommendation

On the basis of the reviewed literature, this study recommends that, efforts should be made to improve the collection and standardization of crime data. This includes investing in comprehensive data gathering mechanisms, ensuring data quality and consistency across jurisdictions, and promoting transparency in reporting practices. Collaboration between law enforcement agencies, researchers, and policymakers is essential to establish a robust and reliable database that can support accurate modeling of crime patterns. Additionally, researchers should consider incorporating additional factors and variables that influence crime patterns into the Markov Chain model. While the approach captures the probabilistic transitions between crime states, understanding the underlying causal factors is crucial for effective policy-making.

Integration with regression analysis, socio-economic indicators, demographic data, or environmental factors can provide a more comprehensive understanding of crime dynamics and inform targeted interventions. Moreover, policymakers and law enforcement agencies should actively engage with the findings and insights generated from the Markov Chain analysis. The application of this approach can aid in the development of evidence-based crime prevention strategies, resource allocation, and deployment of law enforcement resources. Regular evaluation and monitoring of the implemented interventions can further refine and enhance the effectiveness of the policies. By implementing these recommendations, stakeholders can leverage the power of the Markov Chain approach to gain a deeper understanding of state-dependent crime patterns in the USA. This will enable more informed decision-making, proactive crime prevention efforts, and the development of policies that effectively address the root causes and dynamics of criminal activity.

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