**Spatial and Temporal Analysis of**  
**Violent Crimes in Las Vegas and Its Applicability**  
**to Crime Reduction Through the Cardiff Model**

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**Abstract.** According to the Department of Justice, more than half of violent crimes go unreported to law enforcement in the United States (Kollar et al., 2018). This leaves a significant gap in community understanding of where violent crimes are most prevalent. Inherently, this reduces the opportunity to implement proven solutions in the areas with the greatest need. In 1966, Dr. Shepherd developed the Cardiff Model. It’s aim was to bring together hospitals, law enforcement, and community leaders by sharing data and building action plans from this unified picture of violence. We have partnered with ongoing efforts to implement the Cardiff Model in Las Vegas, Nevada. Our goal was to provide a predictive time series model based on the Las Vegas Metropolitan Police Department's (LVMPD) violent crime database. We used an ensemble composed of an autoregressive time series (ARIMA) and recurrent neural network (RNN) models to achieve this. By adding to the existing drug overdose heat maps built by Grard et al. (2023), we hope to provide local leadership with the necessary tools to achieve similar reductions in violent crimes seen in Cardiff Projects across the globe.

1 Introduction

According to the Department of Justice, more than half of violent crimes go unreported to law enforcement in the United States (Kollar et al., 2018). This, inherently, leaves a significant gap in our understanding of where and the volume to which crimes are occurring. In the 2019 FBI Crime Report, it's estimated that nationwide violent crimes reached 1.2 million (Violent Crime, 2019). This translates to a 366.7 per 100,000 people occurrence rate. Given the Department of Justice's estimated reporting rate, those numbers could be severely underestimated. It should be noted that those metrics do not count overdoses as violent crimes. For the purposes of our research and the problem at hand, we will be including overdoses due to their community importance.

In 1996, Dr. Shepherd developed and implemented a model for pooling the data resources to provide a better picture of violent crimes in Cardiff, Wales. A core tenant of the, now named, Cardiff Model is the ability to create violence maps with the combined data of law enforcement and hospitals. These maps provide not only the police, but community leaders with a better and more informed picture of violence in their neighborhoods. In the time since its creation, the Cardiff Model has been implemented in cities around the world. In the CDC's study of 14 similar cities to Cardiff, Wales, they found a "32% reduction in police recorded injuries" and a "42% reduction in hospital admissions for violence-related injuries" (Kollar et al. 2018).

To date, sixteen different cities across the United States have Cardiff Model projects underway (Sixteen US Cities in National Cardiff Violence Prevention Network, 2023). The model was officially adopted into US policy in 2018. Looking at the same 2019 FBI crime reports for Las Vegas, we see a violent crime rate of 525.7 per 100,000 people (Violent Crime, 2019). This is 1.43 times the national average. It's for this reason that Chris Papesh of the University of Nevada, Las Vegas (UNLV), started the process of bringing the Cardiff Project to Las Vegas. Over the last several years, they have begun the hard work of forging connections with critical stakeholders at the Las Vegas Metropolitan Police Department (LVMPD), Las Vegas hospital systems, and community leaders. One of the fruits of those efforts has come in the creation of an overdose heat map tool generated from hospital data (Girard et al., 2023).

Las Vegas offers a unique cocktail of social and political circumstances that appear to reinforce cycles of violence and crime. Long known as “Sin City”, the Las Vegas Convention and Visitors Authority has advertised the well-known slogan, “what happens here stays here”. Its tolerance towards high-risk activities has made Las Vegas a destination for many who seek to let loose. While Las Vegas offers significant low-risk activities like restaurants and shows, the primary attraction is gambling. Nevada gambling goes back nearly to its statehood. Only five years in, Nevada officially legalized gambling in 1869 (Task Force & Gemignani, n.d.). By the late 1940s, Nevada began to see increased growth due to California beginning to shut down illegal casino operations (Task Force & Gemignani, n.d.). According to the UNLV Center for Gaming Research, between 1984 and 2023, Las Vegas strip casino revenue went from $2.16 billion to $23.75 billion (University Libraries, University of Nevada, Las Vegas, n.d.). The US Bureau of Labor Statistics estimates the 1984 dollar to be worth $0.34 compared to 2023 (CPI Inflation Calculator, n.d.). Adjusting for inflation, this brings the revenue growth to 270% over the 19-year period of the study. Next on the list of high-risk activities are sex, drugs, and alcohol. Nevada is the only state with legalized prostitution. While it is no longer legal within Las Vegas, legal prostitution is available only 60 miles west of Las Vegas in Nye County. For anyone who has spent time in Las Vegas casinos, it is well known that alcohol is complementary when playing. In 2012 the Las Vegas-Paradise MSA showed statistically significant high rates of binge alcohol use (25.6%) in persons over the age of 12 (SAMHSA, 2012). This was compared to a national average of 23.2%. Furthermore, according to CDC data, over 109,000 nationwide fatalities in 2022 were due to drug overdoses, with synthetic opioids like fentanyl contributing to nearly 70% of these deaths (Tanz et al., 2024b). According to the latest 2021 CDC death rates, Nevada’s drug overdose death rate per 100,000 is 29.2 (Drug Overdose Mortality by State, n.d.). This compares to the national average of 20.1 per 100,000. Legalized gambling, legalized sex, higher than average alcohol and drug use gives Nevada a particularly unique cross section of overlapping high risk activities. We explore their connection to cycles of crime in the upcoming literature review section.

The FBI's national crime report indicates that the overall number of violent crimes in 2019 has leveled off, reaching the same levels as in 2015 (Crime in the United States, 2019). Although we don’t have current crime rates, it was recorded that there were 366.7 incidents per 100,000 individuals in 2019. In comparison, Las Vegas saw a dramatic 43% more violent crimes per 100,000 inhabitants. Now, more than ever, a strong and capable Cardiff Model implementation is needed in the city of Las Vegas. It is our aim to continue the work of SMU data scientists before us and increase the tools available to community leaders through predictive modeling. We will be using available data sets to provide a better understanding of violent crimes in Las Vegas communities. We will be utilizing data from the LVMPD violent crime database to build predictive models using autoregressive time series (ARIMA) and recurrent neural network (RNN) models. Additionally, we will evaluate how external features like temperature and large events impact crime rates at each classification level. ARIMA models allow us to account for any seasonality in the data and any changes in the mean crime levels over time. Given the correlation between crime levels and events like holidays and festivals established by Towers et al. (2018), it's necessary for us to incorporate a seasonal component in our model. Additionally, Towers et al. (2018) identified that the inclusion of temperature forecasts can increase the short-term prediction performance of violent crime models. Recurrent neural networks allow the inclusion of outside features beyond just the total or mean violent crime values that ARIMA models utilize. The combination of these two models will allow us to build out an ensemble model that can incorporate seasonal time series components with moving averages and external factors like the presence of festivals or other major events. Since Las Vegas is primarily a tourist city, the various events it hosts are likely to provide relevant data for our prediction model. Furthermore, the Recurrent Neural Network portion of our model will allow for the expansion of other relevant external factors. As it becomes available, we will be able to incorporate hospital data as either an expansion of the recurrent neural network or an additional model that suits the structure of the provided data.

Through the creation of these tools, we aim to accomplish three things. First, we want to provide more tools for the established hotspot policing (HSP) strategy meetings outlined in Corsaro et al. (2023). Second, we hope to show the capability and benefits available to any parties hesitant to get involved. Most importantly, we hope to reduce the number of violent crimes and overdoses in Las Vegas, Nevada. Previous studies have established an overlap between victims and victimizers (victim-offender overlap) (Averdijk et al., 2016). Research is uncertain on if this is a causal relationship or due to some underlying trait or environmental correlation (Turanovic & Pratt, 2013). None the less, it is our hope that by reducing the number of victims that we will be able to break the cycle of victims becoming victimizers.

2 Literature Review

**2.1 Violent Crime and Overdoses**

In our introduction, we outlined how Las Vegas’s unique offering of readily available high-risk activities like gambling, sex, alcohol, and drugs. When combining these with violent crime rates 43% higher than the national average, it creates an environment susceptible to self-reinforcing tendencies. At the forefront of this discussion is the overlap of these high-risk activities and the underlying trait of self-control. Self-control is the ability for an individual to change their response to align to some outside standard or goal (Findley et. al., 2018). In this same study, Findley et. al. (2018) ranks each state by the two underlying factors initiation self-control and inhibition self-control. They showed Nevada to rank last in both. On this standardized score, Nevada had a (-2.82) initiation and (-2.77) for inhibition. For comparison, the closest states on initiation self-control were West Virginia with (-2.24) and on inhibition self-control was Delaware with (-2.13). Rhode Island ranked number one with 1.66 for initiation self-control and Texas with 1.72 for inhibition self-control. This makes Las Vegas have both one of the highest cross sections of readily available high-risk activities, 43% higher than national average violent crime rates, and last in trait self-control.

Turanovic and Pratt (2013) outline the overlap between victims and offenders. Their findings show that victims with low self-control showed an increased likelihood to use drugs and alcohol as a form of self-medication. This is significant because the study showed that this increase was significant even when accounting for the train of low self-control. They go on to outline that low self-control, victimization, and drug use independently increase the likelihood of future violent offenses. Furthermore, victims who use drugs and alcohol post-victimization, are shown to engage in violent activities at a much higher rate (Turanovic & Pratt, 2013). Alternatively, those who exhibit higher trait self-control are more likely to see help in places that take longer to see a return and less destructive. An example of this would be seeking therapy or attending group sessions with those who have experienced similar trauma. This is reinforced by Gottfredson and Hirschi (1990) who argue that those with low self-control engage in activities that provide immediate gratification rather than long term gains. Sex, drugs, and alcohol are primary outlets for immediate and short-term relief. While much blame can be pointed at a lack of self-control, Averdijk et al. (2016) showed that even when accounting for external factors like self-control, anxiety, depression and many other pre-existing conditions, victims still have a statistically higher probability to become victimizers. They posit that victims undergo a shift in their cost benefit analysis that skews their perception to the benefits of performing violent crime and away from the costs. The perceived benefits of engaging in violence begin to outweigh the perceived costs. This shift in perception may arise from feelings of injustice, the need for retribution, or a desire to reassert control over one’s life. In this altered state of judgement, violent acts may be viewed as a necessary, even rational, response to one’s circumstances. This transformation from victim to perpetrator, although not necessarily casual and possibly linked to an underlying disposition such as low self-control, has been supported by various research, highlighting a concerning trend that victims are at higher propensity to victimize others (Averdijk et al., (2016).

Within the normal victim offender overlap, we see some that are injected into the cycle due to drug use. It’s estimated that between 3% and 19% of all people who take prescription pain medication will develop a subsequent addiction (Opioid Use Disorder, n.d.). Pierce et. al. (2017) outlines the relationship between heroin and opiate addicts to crime. They showed that those who are dependent on heroin or opiates have an increased relationship to criminal activity than those who are not dependent. These activities are typically related to gaining additional finances to obtain more drugs. The inverse was also seen. Those who are involved in criminal activities were more likely to use drugs. While states such as West Virginia, Lousisana, Kentucky, and Tennessee have some of the highest death rates per 100,000 people in the country, Nevada still finds itself above the national average. At nearly 43% higher overdoses per 100,000 than the national average, Nevada is faced with an uphill battle. This increased proximity to drug use and the violence that comes with it further complicates the challenges facing community leaders. Adding to the complexity, the cycle of violence theory suggests that witnessing or experiencing violence can set off a chain of violent acts. Such behavior is not solely the result of personal vulnerabilities but is also shaped by environment and social context. High-crime areas with limited access to mental health care, substance abuse treatment, and support networks fail to provide the necessary tools for individuals to cope with and recover from trauma, possibly leading to an increased risk of substance abuse and violent behaviors. This situation is exacerbated in socially disorganized neighborhoods where systemic inadequacies fail to arrest the cycle of violence, allowing it to persist and even escalate.

In a study assessing the relationship between alcohol consumption and violence in Norway from 1880 to 2003, while accounting for variables such as unemployment and divorce, Elin K. Bye finds a clear correlation (Bye, 2007). Bye, employing ARIMA models on time-series data demonstrates that a one-liter increase in alcohol consumption per person per year is linked to an 8% increase in violence rates. This association persists even when controlling for potential confounders. Only divorce showed a significant association with violence rates among the seven considered confounders. The findings suggest a potentially causal relationship between alcohol consumption and violence and highlight the role of alcohol as a critical factor in explaining variations in violence over time. This is further supported by Norström et. al. (2010) who demonstrate that increased heavy episodic drinking is significantly associated with heightened violent behavior, especially among individuals prone to suppressing their anger.

Policies aimed at breaking this cycle must address both the individual and environmental factors at play. They should not only focus on providing comprehensive support services but also on improving community resources and social infrastructure. Such holistic approaches may offer the dual benefit of aiding individual recovery while fostering community resilience against the perpetuation of violence.

Considering these insights, there is a pressing need for a concerted effort that spans across multiple sectors- healthcare, law enforcement, social services, and community organizations- to develop interventions that are sensitive to the nuanced relationship between victimization and subsequent violence. Strategies that emphasize rehabilitation over punishment, and that recognize the social determinants contributing to the cycle of violence, will be pivotal in transforming the narrative for victims and preventing the transition to victimizer.

**2.2 Policy and Policing**

Bohnert et al. (2021) explores the relationship between policing practices and overdose mortality in urban neighborhoods. Data from New York City’s police precincts from 1990 to 1999 were analyzed to determine if there was a correlation between misdemeanor arrest rates-a measure of police activity- and drug overdose deaths. The study found that higher levels of police activity were associated with increased overdose mortality. This suggests that intense policing, possibly creating a fear of arrest among drug users, could deter people from seeking medical help for overdoses. The implication of these findings is significant for public health and law enforcement policies, particularly in urban areas where drug is prevalent. The researchers suggest that while aggressive policing can lower crime rates, it might simultaneously increase the risk of drug overdose fatalities, indicating a complex balance between law enforcement and community health outcomes. These findings are consistent with the Cardiff Model which seeks to work with community leaders to drive change. Increased policing at the cost of increased overdoses is still a net loss for the community of Las Vegas. As discussed previously, drug use is another vector into the cycle of crime. Effective policy and process must simultaneously reduce crime and treat the causes to have a lasting effect.

One of the primary tools in the belt of law enforcement to combat crime is through hotspot policing (HSP). Braga and Wisburd (2022) showed a statistically significant reduction in crime in areas that received HSP. Additionally, they showed that the adjacent areas did not show a statistically significant increase in crime. It is reasonable to assume an overall reduction in crime rather than a shift in its spatial attribute. More specifically to Las Vegas, Corsaro et al. (2023) showed statistically significant reductions in calls for service of violent incidents and overall calls for service in areas that received HSP. Particularly important to the findings was that even areas with higher-than-normal policing also saw statistically significant decreases. This indicates no evidence of an observed cap to the effectiveness of HSP. The paper by Joseph G. Bock, titled "The efficacy of violence mitigation: A second look using time-series analysis," published in Political Geography, reassesses previous findings on violence mitigation efforts in the Horn of Africa. While earlier research by Meier, Bond, and Bond (2007) found a positive correlation between violence mitigation and organized raids, suggesting that mitigation efforts might inadvertently contribute to violence, Bock's analysis introduces a different statistical approach. By employing a "de-trending" method commonly used in economics and finance, Bock's study finds an opposite and statistically significant result: violence associated with organized raids is negatively correlated with mitigation efforts when data are de-trended for time and seasonality. This implies that, contrary to previous findings, mitigation efforts are negatively associated with violence, challenging the notion that such efforts do more harm than good. Bock's analysis underscores the importance of considering temporal dynamics in peace research and suggests that the timing and nature of mitigation efforts are crucial for their success in preventing violence.

**2.3 Cardiff Model**

To combat the rising crime rate in his community, Dr. Shepherd of Cardiff University in Wales developed a system that brought together data sources from hospitals and law enforcement to build more complete crime maps (Kollar et al., 2018). A core tenant of this model was the idea of data sharing. By bringing together the desperate data sources, all invested parties would gain a better understanding of where crime was occurring in their community. This information could then be used by law enforcement and community leaders to seek answers as to the why of hotspots and treat them accordingly. This method proved to be so successful that it has gone on to be implemented from the “Netherlands to Australia and South Africa” (Sixteen US Cities in National Cardiff Violence Prevention Network, 2023). It is also noted that the United States adopted the Cardiff Model as official policy in 2018. This resulted in the CDC creation of the toolkit referenced elsewhere in this study. To date, sixteen US cities have ongoing Cardiff Projects. In the UK, the recent 2022 study showed that across 14 similar cities to Cardiff, Wales, information sharing also lead to cost savings in addition to the reductions in crime (The Cardiff Model for Violence Prevention - Cardiff University, 2022). In an older but independent study, Boyle et al. (2013) were able to find a reduction in crime in a similar city to Cardiff. However, they were not able to attribute causal effects to the implementation.

Previous works done by Grard et al. (2023) have aimed to curb the drug overdose metrics outlined above through the creation of drug overdose heat maps in Las Vegas. Grard et al. (2023) utilized the chief complaint field of medical records to create heat maps but due to the inconsistent nature of the records, they were unable to build more predictive models from the source material. One avenue to improve the data quality coming from hospitals was assessed by Nguyen et al. (2022). They showed that by creating a short screening for nurses to fill out, they were able to gather data beneficial for implementing the Cardiff Model. Beyond that, they found that nursing staff found the additional screening to be in alignment with their overall mission and didn’t interfere with their workflow. These findings are important because the primary gap in implementing the Cardiff Model is effectively utilizing the hospital data. Nguyen et al. (2022) reaffirmed the sentiment shared by Grard et al. (2023) that hospital records were inconsistent and difficult to generate predictive analytics from.

**2.4 Spatial/Temporal Modeling**

Traditional crime modeling techniques, as detailed by Dakalbab et al. (2022) in their analysis of 128 studies, predominantly rely on tools like ArcGIS to identify temporal and geographic crime hotspots. This approach, known as crime density prediction, involves calculating the number of crime incidents within specific areas, such as neighborhoods or sections of a map, relative to the population. While this method helps in pinpointing regions for targeted policing strategies like hotspot policing, its major limitation is the lack of temporal analysis. It can differentiate crime rates by days of the week but fails to forecast future trends based on historical data. Prathap (2023) supported these findings and highlighted the integration of Kernel density estimation (KDE) to enhance pattern recognition and hotspot detection, allowing for adjustable metrics in the analysis. The study by Dakalbab et al. (2022) also noted a preference for supervised machine learning (ML) algorithms among researchers, emphasizing the importance of creating interpretable models, especially at a time when law enforcement's public credibility is under scrutiny. Furthermore, it was observed that relying on a single metric for validation could lead to biased outcomes, advocating for the use of multiple performance indicators to ensure the accuracy and reliability of predictive models.

When digging further into the methodology of crime science, we see most analysis being done at the week level (Curiel, 2021). To drive down to the daily or hourly level, research must account for the higher prevalence of zero values. While crime is prevalent on the week and month scale, it is much rarer in these smaller windows of time. Curiel (2021) outlines the trade-off between these windows of time by noting that the meaningfulness might be lost as the window is expanded to increase the number of occurrences. For example, is it relevant to know how many crimes happen between 12:00 AM and 10:00 AM? Does this allow authorities to create reactive action items? These questions must be considered when setting the window size. One method for handling this zero-occurrence phenomenon is to map the zero values as negative values (Liang et al., 2022). This maintains the relative importance of each measure while not causing as many issues with ML models. This technic is referred to as the Priori Knowledge-based Data Enhancement (PKDE) strategy. Liang et al. (2022) also used a Neural Attentive framework to generate their hourly crime predictions.

Towers et al. (2018) showed that the inclusion of events like holidays and festivals into the model can improve the predictive accuracy and precision of time-based crime models. Moreover, the addition of temperature forecasts can increase the short-term performance of violent crime predictions. They also showed that precipitation forecasts may provide additional short term prediction benefits for assault and batteries.

To incorporate the event, temperature, police, and hospital data, we believe the best option is to use an ensemble of ARIMA and RNN models. In a recent study done by Jagait et al. (2021) on load forecasting for the electric grid, they found that by using an ARIMA and RNN ensemble, they were able to produce a model more accurate than the sum of its parts. It enabled them to model the underlying trends while still being able to include more current external events. The study by Hu et al. (2022) investigates spatial-temporal patterns of fatal drug overdose risk in British Columbia from 2015 to 2018. Key findings indicate that rural areas face a higher risk of fatal overdoses compared to urban centers, possibly due to less access to harm reduction services. The research utilized logistic regression and Generalized Additive Models (GAM) to analyze the data, with results presented as heatmaps to identify high-risk regions. The presence of harm reduction sites correlated with lower overdose risks. The study emphasizes the need for targeted harm reduction services in rural areas to mitigate the increasing trend of fatal overdoses province wide.

This study aims to give meaningful and actionable data to the key stakeholders of the City of Las Vegas. By providing a spatial and temporal predictive model by crime classification, we hope to enable the LVMPD to more efficiently allocate their limited resources. Additionally, we hope to provide insights into spatial relationships that can assist community leaders in coming up with practical solutions to meet the needs of their community and curb violent crime rates.

1. Method

We are working with a dataset coming from the Las Vegas Metropolitan Police Department. In our initial analysis we have aggregated the crimes by date and added average daily temperatures from <www.visualcrossing.com>. In the coming weeks we will be adding event information to our dataset that includes historical conferences and festivals that drive higher than normal traffic through Las Vegas. Before aggregation, the raw dataset includes 1,345,306 crime observations. This composes 38 difference crime classifications. Of those 38, 10 would be considered violent in nature. Once filtered to only violent crimes, the dataset was trimmed down to 655,065 observations between 1/1/2019 and 2/29/2024. This represents 1886 days of historical crime observations.

We intend to apply a mix of ARIMA and Signal Plus Noise models to forecast the overall crime trend. Next, we will break down the Las Vegas map into a meaningful grid. Once the data has been assigned to a region, we will do further predictions using both ARIMA and RNN models to incorporate the categorical event features and temperature data.

1. Data  
   Where are getting the data? Or where do you think you can find the data?
   1. Our project advisor and sponsor are working on getting access to Las Vegas hospital violent Crime Records.
   2. If we are unable to get the required data in time for our project, we will utilize a combination of Nevada Police reports and CDC database records.
2. Methods plan to use
   1. We intend to create a predictive time series model using regional subsets that will be defined by the detail available in the dataset.
   2. We plan to combine our time series ARIMA model and RNN models into an ensemble to produce a model capable of incorporating information from other data sources.
   3. We also intend to create a classification model for the kind of violence by region.

4 Results

Our initial findings have shown seasonal components of at 7- and 91-day intervals. By applying an ARIMA and Signal Plus Noise model, we were able to achieve 14 day and 60-day prediction windows that modeled the shape and trend of the test data.

5 Discussion

* Interpretations: What do the results mean?
  + Implications: Why do the results matter? How should the reader apply these findings?
* What stood out as interesting/unique/unexpected?
* Limitations
  + What challenges occurred during analysis?
* Ethics
  + Future Research
* Are there areas of research where others can pick up and go deeper?
* Can the crimes be broken into types (e.g. drug OD, domestic abuse, assault).?
* Defining how to measure the success of the model and updating it moving forward.
* Can we provide suggested solutions to the findings?
* Does the crime seem to be related to specific establishments, days of the week, or events?

6 Conclusion

2 paragraphs max on the overall findings and summary of the research.

**Acknowledgments.** The heading should be treated as a 3rd level heading and should not be assigned a number.

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