**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).

It is our aim to continue in these efforts by 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. 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). While research is uncertain on if this is a causal relationship or due to some underlying trait or environmental correlation (Turanovic & Pratt, 2013), it is our hope that by reducing the number of victims that we will be able to break the cycle of victims becoming victimizers.

For the model to be successful, it must be able to provide actionable findings for law enforcement, community leaders, and hospital administrators.

2 Literature Review

**2.1 Violent Crime and Overdoses**

With the Department of Justice estimating that more than 50% of violent crimes go unreported (Kollar et al., 2018), the burden to capture or model the missing data falls on the field of crime science. Nationwide, the FBI crime report shows a flattening in total violent crimes in 2019 back to 2015 numbers (Violent Crime, 2019). While we can’t glean any metrics about current crime statistics, we can see that there were 366.7 per 100,000 people in 2019. When comparing this to our city of interest, Las Vegas, we see a 143% increase in violent crimes per 100,000 people. Additionally, the CDC estimates that more than 109,000 people died in 2022 due to drug overdose (Tanz et al., 2024). Nearly 70% of those deaths were associated with synthetic drugs like fentanyl.

The combined crime rate in Las Vegas and rising drug use is a recipe for disaster if we are to believe the findings of Turanovic and Pratt (2013). They showed that victims with low self-control are more likely to use drugs and alcohol post-victimization. Furthermore, victimis who use drugs and alcohol post-victimization are more likely to become perpetrators of violence. This phenomenon is seen across literature (Cite). While it is unclear if the overlap between victims and victimizers is causal in nature or correlated to some underlying trait like low self-control, it is clear that victims are more likely to victimize (Averdijk et al., 2016). Averdijk et al. (2016) 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.

One of the primary tools in the belt of law enforcement to combat crime is through hotspot policing (HSP). Generally speaking, 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.

**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 Statues 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, the 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.

**2.2 Spatial/Temporal Modeling**

Traditional methods to model crime use tools like ArcGIS to generate temporal and/or geographic hot spots (Dakalbab et al.,2022). Of the 128 analyzed research papers in Dekalbab et al. (2022), they found that crime density was the primary method for prediction. This method takes designated areas like neighborhoods or a map grid and calculates population and crime incidents. The subsequent density metric provides policy makers and police with areas to implement techniques like hotspot policing (HSP). The primary downfall to these density metrics is that they remove the element of time. They might provide different maps by day of the week, but they are unable to produce predictions based on the historical trends in the same way a time series model would. This was further corroborated by Prathap, (2023). They also showed that the addition of Kernel density estimation (KDE) for pattern analysis and hotspot identification allowed for maps that with a user tunable metric on the maps. For those who were found to implement machine learning (ML) algorithms in the Dekalbab et al. (2022) study, the majority used supervised techniques. In a day where public trust of law enforcement is in question, producing models with explainable components comes at a premium. They also found that the majority of research papers were utilizing multiple performance metrics to validate their data and advised against using any singular metric due to the opportunity for unintended skewness in the results.

When digging further into the methodology of crime science, we see most analysis being done at the week level (Curiel, 2021). In order to drive down to the daily or hourly level, researches must account for the higher prevalence of zero values. While crime is prevalent at the week and month scale, it is much rarer at 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.

In order 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 that the sum of its parts. It enabled them to model the underlying trends while still being able to include more current external events.

Include your hypothesis. This study aims to gives meaningful and actionable data to the key stakeholders of the City of Las Vegas.

1. Method
2. Data  
   Where are getting the data? Or where are you thinking you can find the da-ta?
   1. Our project advisor and sponsor is 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 data-base records.
3. 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 a 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

What do you hope to find in your research? Accept or reject the hypothesis

We hope to find that we are able to produce a highly accurate predictive time series model that can show the kind of violent crime, the time, and the place they are likely to occur.

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 the means by which 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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