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Integrated Science 3

**Background Research on Machine Learning and the Relationship Between Gun Laws and Gun Violence**

Guns have been a constant throughout American history and had become an integral part of American culture. Guns were so important that the right to bear arms was the second amendment to the Constitution. Ever since, the number of guns per population has generally increased over the years, while gun violence rates have varied. Gun violence rates spiked in the early-1980’s and 1990’s during crime surges, then receded until the late 2000s, when gun violence rates began to increase again and are still increasing (Cohn et al., 2013). Though gun ownership per household has decreased over the last 20 years from 51% in 1994 to 36% in 2017, number of guns per population has increased from 90 guns per 100 people in 1996 to 113 guns per 100 people in 2013. The number of guns in America surpassed the number of people in 2009, when the population was 310 million (Ingraham, 2015; Ingraham, 2016). In essence, the trends are show that less people own guns, but those people own more guns and there are more incidents of gun violence.

These trends are only seen in few other countries outside of the U.S.; as of 2007, Americans owned half of the civilian owned guns in the world, over 6 times that of any other country in the world. As a result, Americans own the most guns per population, nearly double that of any other country in the world. America also has the greatest gun violence rates of all High-Income nations, with American homicide rates nearly 25.2 times the average of High-Income nations. Because of all of the gun violence, the gun debate has drastically increased over the last few years. Horrid mass shootings over the recent years, such as that of Sandy Hook Elementary School in 2012 that claimed 26 lives, many of which were children, have received increased levels of media coverage and have fueled further debates and policy changes. (Fox, 2018). Though no major policy changes have occurred on the federal level in recent years, many states and municipalities have made policy changes regarding various gun laws.

In 2015, gun violence claimed 36,252 lives, at a death rate of 11.3 gun violence deaths per a population of 100,000; this number increased to 11.8 in 2016. This number varies greatly from state to state, with gun violence rates in Massachusetts at 3.4 and Alaska at 23.3 in 2016 (CDC, 2017; CDC, 2018). In addition to that, gun ownership and gun violence tend to corelate, as states with higher rates of gun violence tend to have higher gun ownership rates (Siegel, Ross, and King, 2013). These trends clearly show room for improvement and show that now is the time for American lawmakers to become informed on which gun laws reduce gun violence the most, so lawmakers can stem the gun violence epidemic and make America safer.

There are various major gun laws that can affect gun violence which are in place in certain states and municipalities. Some of these gun laws include right to carry laws, assault rifle and machine gun bans, mandatory background checks, gun permit requirements, and violence criminal gun bans. Each of these gun laws has been shown to affect gun violence.

Machine learning is a frontier math modeling system in which code systems can be taught, or even teach itself, how to analyze data to the data scientist’s preference. These “machines” can even learn how to make decisions as well as analyze and process data on a scale and proficiency that no other code system can. Tensorflow is an open source code framework that works using a deep learning algorithm. Essentially, Tensorflow brings data through multiple layers, each one with inputs and outputs. Each layer has several “neurons”, which represent computations, and certain inputs activate certain neurons, which provide outputs that move to serve as the inputs for the next layer. Tensorflow is used for a variety of purposes, from diagnosing Alzheimer’s using medical imaging to sorting photographs using digitized files. Many major companies that use data science, primarily Google, have applied Tensorflow to their work (Rampasek and Goldenberg, 2016).

There are two major types of machine learning: supervised and unsupervised learning. The main difference is whether the machine is taught externally or internally; supervised learning systems are trained externally by a data scientist with expected outputs, while unsupervised learning systems are trained internally by the machine itself. Supervised systems are relatively simpler and more accurate, while unsupervised systems are very complicated and inaccurate. Unsupervised systems are considered to be closer to artificial intelligence and are more frontier because the machine can train itself without external interference (Schmidhuber, 2015; Castle, 2017).

Research regarding machine learning, gun violence, and social sciences over the last 5 years has gone in various different directions. One example of a gun violence study is the 2013 paper “The Relationship Between Gun Ownership and Firearm Homicide Rates in the United States, 1981–2010.” In the study, the researchers collected data from state to state, as well as a number of other geographic, demographic, and economic factors present in each state. These factors were used to adjust the data. They then used a generalized estimating equation (GEE) approach, which created a negative binomial expression for the model of the data. They had discovered that states with significantly greater gun ownership rates also had higher rates of gun violence. In addition to that, they found various factors, such as crime and incarceration rates, that had the greatest effect on gun violence (Siegel et al., 2013).

An example of a gun violence study that showed the relationship between gun laws in one area and gun violence in the other is “Cross-Border Spillover: U.S. Gun Laws and Violence in Mexico.” This study focused in on the 2004 expiration of the U.S. Federal Assault Weapons Ban and how it increased gun violence in certain Mexican communities near the U.S.-Mexico Border. According to the study, gun violence rates increased drastically in Mexican communities near the Texas, New Mexico, and Arizona border ports as a result of the 2004 expiration. Unlike the other border states, California had restrictions in place regarding assault weapons. This caused gun violence rates to increase60% more in Mexican communities within 100 miles of non-Californian border ports verses within 100 miles of Californian border ports. This study was an example of how gun laws from one location can directly affect gun violence in another location (Dube, Dube, and Garcia-Ponce, 2013).

An example of deep learning being applied to behavioral trends is “Estimating Treatment Effect Heterogeneity in Randomized Program Evaluation.” The study focusses on the effect that different social programs and medical treatments have on social behavior. The study used various estimation algorithms to determine how much a given social program or medical program had on a given population. For example, various positive and negative treatment effects of a job training program show how much that social program helped or hurt a given demographic of people. This concept can be applied to determining the positive or negative effects of certain gun laws on different types of gun violence (Imai and Ratkovic, 2013).

There are various problems facing research regarding gun violence, social sciences, and machine learning. As for gun violence, the CDC was banned from researching causes and solutions with gun violence in 1996. This has multiple implications, including the fact that only private institutions can do gun violence research, which reduces the accuracy of available gun violence studies. In addition to this, controversies surrounding gun violence research can make it hard to receive funding and convince others of the legitimacy of the findings. These controversies also lead to increased bias in the research. As for research regarding social sciences, social sciences are hard to model and are highly unpredictable, meaning that even the best of models are only guesses. This unpredictability makes it hard to have expected outputs to train the machine with. As for machine learning, machine learning systems are complicated and unsupervised systems require enormous amounts of data. Unsupervised systems are also highly inaccurate. Overall, there are multiple errors in these fields of research.

Our research differs from past studies for a number of reasons. Firstly, it is focused on the correlation between multiple different gun laws and types of gun violence rates within a municipality. Most past research focusses in on a variety of factors that can affect gun violence, while our research focusses only on the factors that lawmakers can change. In addition to this, most gun violence research is done on the state and national level, while this is on the local level, so there will be less potential errors and biases on a smaller scale. Next, our research is controlled only by economic factors and external gun law factors, whereas most other research has other factors, such as race, that they are controlling their data by. This difference is significant because a decent number of relevant factors will be taken in, but not too many that there is data bias. Along with that, there are few applications of machine learning to gun violence. This is important because this study could provide a more complete picture of the relation between gun violence and gun laws. Finally, the expected outputs to train a supervised system will be provided by using statistical tests. This is important because many studies in the social science categories have to manipulate certain data to get expected outputs or have to use unsupervised systems, so this project will be unique in how it gets its expected outputs.

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