Analysis of Washington State Traffic Stop Data

Brian Mackessy
Department of Computer Science
Gonzaga University
Spokane, WA
bmackessy@zagmail.gonzaga.edu

Elijah Michaelson
Department of Computer Science
Gonzaga University
Spokane, WA
emichaelson@zagmail.gonzaga.edu

Abstract

Due to increased concerns about bias in policing against certain demographics, we analyzed policing data in Washington State for correlations between a person's demographic and their likelihood of being cited or arrested during a traffic stop. To do this, we passed thousands of traffic stop records to a Self Organizing Map to visualize and categorize the data. We then discuss the problems brought to light by the data.

1 Introduction

In recent years, there has been an increased awareness of discrimination in policing. Policing agencies have been required to become more transparent about the specific details of police stops. The police all over the US now release records documenting traffic stops and their outcomes. This wealth of data offers a chance to analyze millions of traffic stops to see what factors contribute to traffic stops and arrests. The dataset we are using, produced by Pierson, et al. (2017) as part of the Stanford Open Policing Project, contains records for 9 million traffic stops in the state of Washington between 2009 and 2016. Each instance contains demographic information for the person stopped and whether or not they were ultimately cited or arrested. This dataset can be found at **https://openpolicing.stanford.edu/.**

Our goal is to analyze how a person's demographic effects whether or not they will be cited or arrested in a traffic stop. In particular, we want to see how age, race, and gender can influence police decisions. The strategy to identify this potential bias is to use unsupervised and supervised learning to visualize and predict police behavior. Visualization will allow us to see the natural groupings of traffic stops, and whether these groupings were more or less likely to be cited or arrested. To perform the visualizations, we have chosen to use an unsupervised neural network called a Self Organizing Maps, which performs clustering on the dataset. We have also incorporated a prediction component to our analysis. We believe that if we can use demographic data to create an accurate model of whether a traffic stop will result in citation or arrest, then we can infer that demographic data is playing a large factor. This has the potential to indicate if there are biases in policing that the predictive model is learning. To perform the prediction, we exploit the structure of the Self Organizing Map to find the most likely outcome of a data point that the model has (possibly) never seen before.

1.1 Literature review

In order to help give meaning to our statistical analysis, we have sought the help of other research into police bias. We were unable to find any published work on the use of neural networks for analysis of police bias, so we have mostly relied on sociological investigation of police bias. Although other research groups have used simpler models to analyze this same dataset. A paper called "By the Numbers: A Guide for Analyzing Race Data From Vehicle Stops" by Fridell (2004) provides a methodology to investing police stop data. She uses other statistical analysis of police stops to

31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

determine how racial bias can affect whether or not someone will be arrested. This data allows her to investigate how bias varies amongst police departments. Fridell's work allows us to follow her strategy for identifying in race from a statistical analysis of police data.

2 Modelling and analysis

For our analysis we ran unsupervised learning algorithms over our data to get visual representations of the structure of the data. In particular, we utilized a Self Organizing Map as part of this analysis. A Self Organizing Map is a neural network which uses competitive learning to model the underlying structure of the input space. We used a 2-dimensional map, which means that the data can be visualized as a rectangular grid of neurons. Each node in the grid represents a possible point in the input-space, where nodes with similar values are grouped spatially closer to one another as a result of the competitive learning process.

2.1 Unsupervised experiments and analysis

For our unsupervised experiments, we trained a 40 neuron by 60 neuron Self Organizing Map on 900 data points, which each training step utilizing 300 iterations. To visualize the patterns in the dataset, we then colored each neuron according to the value for a specific attribute that the neuron had learned to represent. We repeated this process for each attribute in the dataset, yielding Figures 1-6 below.

Note that the Age and Gender figures show a horizontal trend over the learned map, with the boundary between the red and blue coloring being largely in a vertical direction. Conversely, the Race and Outcome figures show a vertical trend over the learned map, with the boundary between the red and blue coloring being largely in a horizontal direction. This shows a possible independence of the Age and Gender attributes from the Race and Outcome attributes. Additionally, these trends indicate a possible correlation between an individuals race and the outcome of the stop.

Finally, it is of interest to compare the Searched and Contraband Found figures, where a shared pattern in the nodes weighting are apparent. In particular, there is a strong correlation between the event of a search with the event of contraband being found. This validates our model for two reasons: first, it is only possible for contraband to be found if there is a search conducted, and second, it is likely that a search would only be initiated if there was justification provided by the police officer. The first point means that the Found value of the Contraband attribute is a subset of the Searched value of the Searched Attribute.

As can be observed from the figures below, the Self Organizing Map preserves topological similarities in the data by grouping similar-valued neurons closer together. This allows the data to be visualized using the technique that we applied to Figures 1-6, resulting in an intuitive and simplified overview of associations that exist within the dataset. Additionally, this property of Self Organizing Maps facilitates predictions on unseen data points.

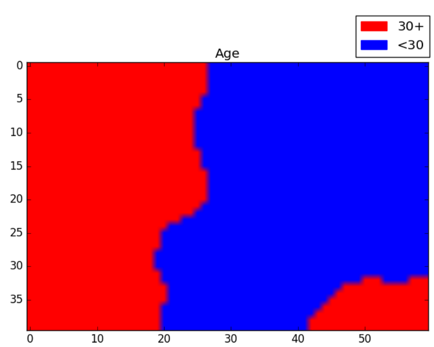

Figure 1: Age

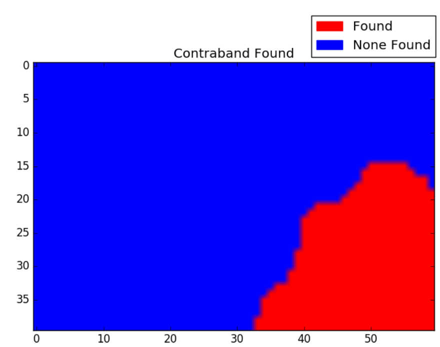

Figure 2: Contraband Found

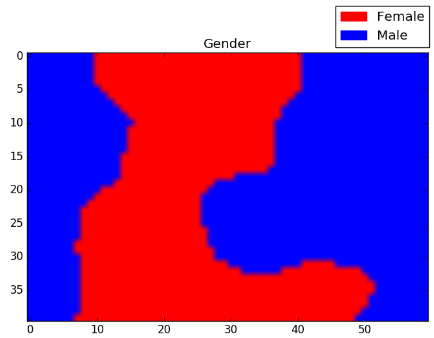

Figure 3: Gender

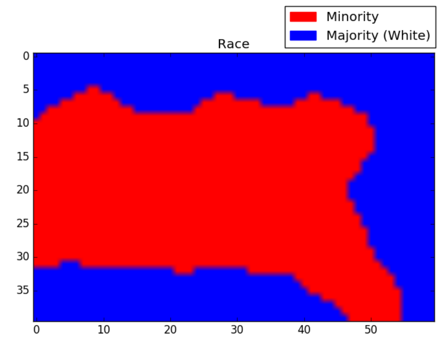

Figure 4: Race

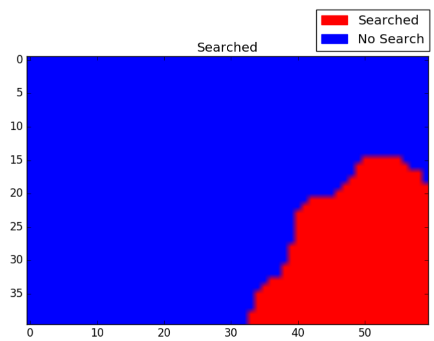

Figure 5: Searched

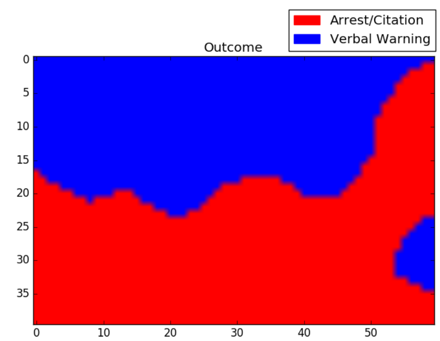

Figure 6: Outcome

2.2 Supervised experiments and analysis

Once trained, the map can classify unseen instances by finding the node in the grid that is closest to the input data. This is important for our analysis as we can give it crafted data and see how the model responds. Translating this back to its real-world implications, it means that we can run experiments on the model to elucidate biases hidden in the training data. Since the end result of the stop was of most interest to us, we used the following coloring scheme: red grid-points corresponded to "Arrest/Citation", while blue grid-points corresponded to "Verbal Warning". This was consistent across the following experiments. The supervised and unsupervised portions of our analysis followed very similar processes. The supervised and unsupervised models were trained using the same data and same training algorithm. Both models also used testing data, which was then correlated each instance to the nearest neuron using euclidean distance. The difference between the two was the data used for testing. The unsupervised labeling required all of the attributes: gender, age, race, contraband found, searched, and cited/arrested. Whereas the supervised portion only relied on the demographic data: age, race, and gender. The reason for only using demographic data, is to find potential associations between demographic data and whether or not a traffic stop would result in a citation or an arrest. Not only does this analysis tell us whether or not demographic data has any association with being cited or arrested, but it also tells us how much it associated with being cited or arrested.

The data points used for classification were as follows:

- Minority, Male, Over 30
- Minority, Male ,Under 30
- Minority, Female, Over 30
- Minority, Female, Under 30
- White, Male, Over 30

- White, Male, Under 30
- White, Female, Under 30
- White, Female, Over 30.

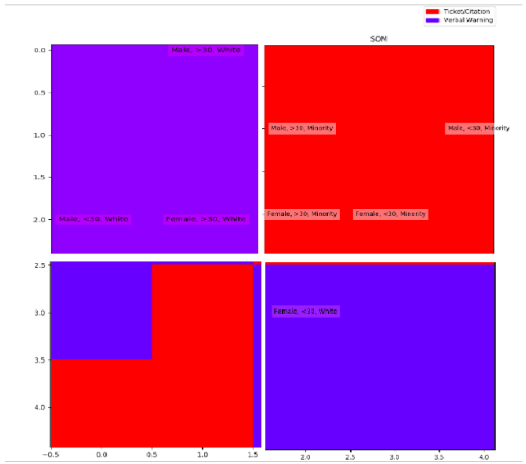

Figure 7: Supervised experiment SOM

Minority, Male, Over 30	Cited or Arrest
Minority, Male ,Under 30	Cited or Arrest
Minority, Female, Over 30	Cited or Arrest
Minority, Female, Under 30	Cited or Arrest
White, Male, Over 30	Just a Warning
White, Male, Under 30	Just a Warning
White, Female, Under 30	Just a Warning
White, Female, Over 30.	Just a Warning

Figure 8: Supervised experiment results

As Figures 7 and 8 show, passing demographic data alone to Self Organizing Map shows a serious skew in the data. The factor that most obviously determines whether or not someone is likely to be cited or arrested is race. This is troubling correlation to find in the data, but it must also be taken with a grain of salt. Another explanation for these results is that race does not truly predict whether someone will be arrested or cited, but only has a stronger correlation than age or gender.

2.3 Final remarks

Both the unsupervised and supervised portions of this project indicated a correlation between race and being arrested or cited during a traffic stop. Of course, both types of analysis rely on the same model, so it is natural that they both indicate the same correlation. It is also important to note that the data is not fully representative of the realities of a traffic stop. This data only provides a simplified snapshot of traffic stops.

Although we must be careful not to jump to any conclusions due to the result of our analysis, the correlation between race and disciplinary action by police is alarming and cannot be ignored. The results of the this study matches the common thinking on implicit bias in policing against minorities, which has been explored by other analysis of traffic stops (Fridell, 2004).

Acknowledgments

We would like to thank Nadra Guizani for her guidance on this project.

References

[1] E. Pierson, C. Simoiu, J. Overgoor, S. Corbett-Davies, V. Ramachandran, C. Phillips & S. Goel. (2017) A large-scale analysis of racial disparities in police stops across the United States.

[2] Fridell, Lorie. (2004) *By the Numbers.* Washington, D.C: Police Executive Research Forum.