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Racial Bias in Risk Assessment Algorithms

Nol Zulfiu

1443992

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Bachelor of Science

Brunel University

Department of Computer Science

Uxbridge

Middlesex

UB8 3PH

United Kingdom

T: +44 1895 203397

F: +44 (0) 1895 251686

Abstract

Risk assessment algorithms are being used in the US criminal justice system to score the likelihood (risk level) of the defendant reoffending. The scores are used throughout the sentencing process, from setting bail to deciding whether the defendant should be convicted or not. Since these algorithms carry such influence on the lives of the defendants they need to be tested and studied thoroughly.

An in-depth analysis of the COMPAS scores will be conducted. A neural network algorithm will be implemented which will attempt to outscore the COMPAS algorithm in terms of accuracy rates and eliminate racial bias.

Many studies have shown that COMPAS (one of the most widely used algorithms in the US) contains a racial bias. This is what this project will set out to determine. Potential social outcomes of these algorithms will also be looked at in this project, and the racial bias that exists in the US criminal justice system will be explained.

The analysis is on racial bias, a comparison of the COMPAS and neural network scores, and other factors that lead to recidivism. The analysis showed a clear racial bias in the COMPAS scores. It also showed why some studies could have missed it. The neural network algorithm on the other hand outscored COMPAS, and showed no clear signs of a racial bias.

Other factors that lead to recidivism (marital status, age, prior convictions, etc) mostly showed the same results as those by other studies and were in accordance with proven statistics.

Acknowledgements

I would like to thank my family and friends for supporting me during this time. I would also like to thank my supervisor who helped me through every problem and gave me the guidance I needed to finish this project.

I certify that the work presented in the dissertation is my own unless referenced.

Signature: Nol Zulfiu______________________________

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1. Introduction

As the age of AI ushers us into a new era we must remember the shortcomings of algorithms to stop us from relying too heavily on them. Most western countries are faced with similar problems, prison overcrowding and a faulty justice system (more on this later). One solution to this is implementing risk assessment algorithms to help judges/juries to determine the likelihood of the defendant reoffending, setting bail, etc.

This project will focus on the US' judicial system, as they have the highest imprisonment rate (737 for each 100,000 residents (Walmsley, 2013)) and the highest use of algorithms in the judicial system. The use of these algorithms has been highly controversial and has been met with criticism from both the media and the defendants. The main issues surrounding the use of algorithms in the judicial system are racial bias, lack of controls in place, no individualised sentencing and the lack of transparency of the algorithm.

The main aim of the project will be to determine whether there is a racial bias in one of the most widely used risk assessment algorithms in the US justice system (COMPAS). The COMPAS scores will be analysed not only to determine racial bias, but to also to compare the scores to the scores of a neural network risk assessment algorithm which will be developed for this project.

The result will be analysed and compared in the evaluation chapter. Other than the results, this project will also look at the effect other factors have on recidivism. The other factors that will be analysed are marital status, difference between the sexes in terms of conviction rates, difference in reoffending between different age groups, the link between juvenile convictions and recidivism, and finally the connection between prior jail/prison time and reoffending.

A step by step explanation will be provided to show how the data was pre-processed for the algorithm, and how the neural network was implemented for this project. There will also be an explanation as to how the questionnaire was constructed and why a neural network was chosen as the type of algorithm for this project.

Since this project is on racial bias in risk assessment algorithms, two widely used algorithms will be talked about in the background and potential social outcomes chapter. The project will focus on COMPAS since there are more studies conducted on it, and since it is one of the most widely used algorithms of its kind. Chapter 2.1 will show the racial bias that is already present in the US justice system. It will also go into factors that could lead to racial bias in risk assessment algorithms, providing references to validate what is written.

One of the first cases of its kind (*State V. Loomis*) questioning the use of risk assessment algorithms in the justice system will be talked about. Chapter 2.2 will look into the issues raised in the case (Due Diligence, Automation Bias, and Individualized Sentencing). This case could set a precedent for future cases regarding the use of these algorithms, and as such could have a huge influence on the future of algorithms in the courtroom.

Risk assessment algorithms have the power to improve the justice system and provide a platform free of biases. Implemented incorrectly however, they also have the power to continue and amplify racial bias, and ultimately could ruin lives with wrong scores.

1.1 Aims and Objectives

The aim of this project is to determine whether there is a racial bias within one of the most widely used risk assessment algorithms. If a racial bias is found then this project will also explore the reason the bias exists and whether it lies in the algorithm, dataset, or both.

The objectives of the project are:

1. Analyse results of COMPAS Scores to determine racial bias and see which ethnic groups are affected most
2. Implement a neural network algorithm which achieves a higher accuracy rate and lower racial bias
3. Find relevant studies in this area to build upon and to identify current issues within risk assessment algorithms
4. Analyse the impact of different factors which lead to recidivism, such as: age, marital status, etc.

1.2 Project Approach

The approach of the project will be firstly to gather the data needed for the algorithm to be trained on. The data that is required for this project is publicly available through public records requests. As this project is being written in the UK it was considerably harder to get a response from counties through these requests. Due to those circumstances this project will be using data gathered from ProPublica's article, as the data in question was retrieved through public record requests.

Once the dataset is ready it will be pre-processed, partially in SQL and partially in VBA. This is to make it easier and faster as the data comes from different tables, has different types of columns, formatting etc. The data will be processed to fit the questionnaire that was built for this project, and then will be ready to be used for the algorithm.

A neural network will be developed in R with the purpose of serving as a risk assessment algorithm. This algorithm will attempt to reduce the misclassification rates from the COMPAS scores and the racial bias, if one is found. There will be tests on different numbers of hidden layers, with all the accuracy rates for each put up against each other to determine the most efficient way to implement the algorithm.

After the algorithm is run and tested, the scores of one of the most widely used risk assessment algorithms in the US (COMPAS) will be analysed, which will determine if a racial bias exists. The COMPAS scores will also be analysed to see which ethnic groups are affected the most from risk assessment algorithms. There will then be a comparison between the COMPAS scores and the scores from algorithm created for this project, comparing accuracy rates and level of racial bias. This project will also analyse which other factors (age, sex, marital status etc) affect recidivism rates and which ones have the highest impact.

The project will also study the potential social impacts of risk assessment algorithms and possible solutions to some of the major problems surrounding them. This project will look at how the precedent set by the **State v. Loomis case** (explained in chapter 2) will have an impact on judges blindly following risk assessment score, especially when the defendants do not receive an explanation of how their score was calculated.

1.3 Dissertation Outline

Chapter 2: Background & Potential Social Outcomes

Chapter 2 will be focused on the background research conducted for this project and the possible social outcomes of using risk assessment algorithms in the judicial system. It will contain three sections, the first being including public criticisms of the use of these algorithms and a general description of COMPAS, one of the most widely used risk assessment algorithms in the US. The second section will be dedicated to racial bias in these algorithms, reports written about the matter and the different factors that could lead to this happening.

The third section will focus solely on the State VS Loomis case and all the issues that the case brought up. This was the first case of its kind to oppose the use of risk assessment algorithms during sentencing.

Chapter 3: Methodology

Chapter 3 will be an in-depth view of the methodology chosen for this project. It will show how the questionnaire (used as input for the Neural Network) was constructed and why the questions were chosen. It will explain the approach taken for data pre-processing and why this project will also be looking at the other factors that contribute to recidivism.

Lastly this chapter will go into why a neural network was chosen over other types of algorithms and why R was used.

Chapter 4: Implementation

This chapter will have a guide to the whole implementation process, from data pre-processing to the neural network. It will start off with how the data was extracted from the database into a csv file. Then it will show how the data was sorted in Excel to suit the needs of this project and to fit the questionnaire.

After the data pre-processing this chapter will provide a step by step explanation of how the neural network was implemented. It will go into which methods were used, why the data was normalized, and which validation methods were used.

Finally, it will go through the way the analysis was conducted.

Chapter 5: Evaluation

The results of the analysis will be revealed and explained. This chapter will evaluate the whole project, if it succeeded or failed its aim, what could have been done better, etc.

Appendix A: Personal Reflection

This part will contain a personal reflection on the project. It will go into how the project could have been conducted differently and how some of the problems could have been avoided in hindsight.

2. Background & Potential Social Outcomes

There has been much public criticism of risk assessment algorithms, but perhaps the most important came from Eric Holders' (Attorney General at the time) speech at the Criminal Justice Network Conference.

"Although these measures were crafted with the best of intentions, I am concerned that they may inadvertently undermine our efforts to ensure individualized and equal justice. By basing sentencing decisions on static factors and immutable characteristics – like the defendant's education level, socioeconomic background, or neighbourhood – they may exacerbate unwarranted and unjust disparities that are already far too common in our criminal justice system and in our society." (Holder, 2015)

Correctional Offender Management Profiling for Alternative Sanctions (COMPAS)

COMPAS is one of the most widely used algorithms in the US judicial system. It is owned by Northpointe (Now Equivant as Northpointe and two other companies have merged), a for-profit company, which has been around since at least 1989.

The arresting officer or the defendant is required to fill out a questionnaire which ranges from previous convictions to social integration (Northpointe, 2011). The algorithm analyses all the answers from the questionnaire and feeds them into the decision tree algorithm, which then provides the scores.

The defendants are scored on three different sections: recidivism, violence, and failure to appear.

Recidivism

This score shows how likely the defendant is to reoffend. This is the score which carries the most importance as it is usually used during sentencing, which means that the defendant can get a harsher or more lenient sentence because of the score.

Violence

The defendant is scored on how likely they are to be violent. This can range from assault to much more serious crimes.

Failure to Appear

This score helps the judge to determine bail, how high it should be or whether or not bail should be set at all. This score will have an impact on the amount of people sent to jail while they await trial. It shows how likely the defendant will not show up for their court hearing, or flee custody.

Northpointe does not disclose the source code of COMPAS as it is of a proprietary nature to the company. This means that defendants cannot see how the algorithm works, if it is calibrated correctly, or even try to make the score inadmissible as they only receive minimal information.

Level of Service Inventory - Revised (LSI-R)

The LSI-R is another risk assessment algorithm used in the US. It seeks to classify not only an offender's risk of reoffending as well as to identify their particular criminogenic needs (Watkins, 2001). LSI-R is also used in Australia, and has been tested and studied multiple times.

It provides scores for an individual defendant and it can also show the progress over time, comparing up to four assessments for the same offender (D.A. Andrews, n.d.). The company that owns LSI-R claims that it is the most widely used and widely researched risk/need assessment in the world, however since it is not the most widely used in the US and since it has been studied thoroughly this project will focus on the COMPAS risk assessment algorithm.

Studies Conducted on COMPAS

A study (Thomas Blomberg, 2010) on the validity of **COMPAS** conducted by members of the College of Criminology and Criminal Justice in the Florida State University produced some worrying results at the time. There were no real differences in the scores for white and black defendants, with the scores being within a reasonable range from each other. The worrisome results were the overall score accuracies, in particular the recidivism scores compared to who actually reoffended within a year of their initial arrest.

Over a 12-month observation period 61% of the high risk scored defendants reoffended. This means that 39% of the high risk scored defendants were misclassified as they did not reoffend. This could have massive consequences for the defendants, as they could receive harsher sentences, no bail, etc. just because an algorithm, with an accuracy rating just about better than a coin toss, decided to put them into a group they did not belong to. This in turn causes the very same problems that these algorithms are supposed to solve. It means that there are people staying in jail/prison for longer than they need to, which only further stains an already overcrowded prison system.

ProPublica analysed over 10,000 defendants and found that at first look there was not an obvious disparity between white Americans and African-Americans. This was the case for many other studies, however ProPublica decided to dive deeper and analyse misclassification rates.

They found that black defendants were misclassifies as high risk 45% of the time, compared to only 23% for white defendants. They also found that white defendants were almost twice as likely to be misclassified as low risk (48% vs 28%). The most worrying statistic was that black defendants, even after controlling for prior crimes, age, gender etc, were 77% more likely to be assigned a high-risk score than white defendants. (Jeff Larson, 2016)

2.1 Racial Bias

At their best, AI and algorithmic decision-support systems can be used to augment human judgement and reduce both conscious and unconscious biases. However, training data, algorithms, and other design choices that shape AI systems may reflect and amplify existing cultural prejudices and inequalities. (AI Now Institute, n.d.)

Racial bias can seep from many places, a faulty justice system, the data used to train the algorithm, the programmers subconscious bias, etc. There are many statistics that could be used in this section to show the disparity between white Americans and minorities, the two shown below are just to give an idea of the daily discrimination they are faced with.

African-American males are **six times** more likely to be incarcerated than white males and **2.5 times** more likely than Hispanic males (U.S. Bureau of Justice Statistics, 2012).

Police require less suspicion to search black and Hispanic drivers than whites (Stanford Open Policing Project, n.d.)

These statistics show that minorities do not face the same treatment as their counterparties. As they are incriminated far more times than whites, they are more likely to reoffend (nearly half of offenders who served time in federal prisons reoffended within 8 years of their release (Kim Steven Hunt, 2016)). Minorities are more likely to be searched, which leads to higher incarceration rates for them, which in turn leads to a justice system setting them up to fail.

With no research being conducted on how to stop the bias, and with risk assessment algorithms being trained on the data available, we are slowly getting to the point of no return. If these algorithms are used unchecked for long enough, minorities will continue to face discrimination for the foreseeable future.

Bias against defendants is what the U.S. legal system is designed to prevent. “The whole point of due process is accuracy, to prevent people from being falsely accused,” says Danielle Citron, law professor at the University of Maryland. “The idea that we are going to live with a 40% inaccurate result, that is skewed against a subordinated group, to me is a mind-boggling way to think about accuracy.” (Julia Angwin, 2016) Many studies have shown that the accuracy of these risk assessment algorithms is only slightly better than a coin toss, which makes it hard to understand why they are allowed to be used, when these scores carry such a big influence.

No risk assessment questionnaire has a section for race, as it would provide clear grounds for appeals and could make the scores inadmissible to court. Even though race is not specified, the algorithm can still show a bias towards it, by inferring that data point from the other available data.

Excluding race itself does not necessary mean that factors that correlate heavily to an individual’s race—serving essentially as proxies for race—are excluded from these algorithms (Michal Kosinski, 2013)

In 2014, then-U.S. Attorney General Eric Holder called for the U.S. Sentencing Commission to study the use of algorithms in courts, concerned that the scores may be a source of bias. At the same time, the Justice Department expressed concern about the use of factors such as education levels, employment history, family circumstances, and demographic information. (Anon., 2018)

These are the different types of questions that would help the algorithm infer the race of the defendant (education levels, employment history, family circumstances, and demographic information).

For example, if the defendants are asked how many times they are stopped by the police, the question does not immediately raise alarms for potentially being racially biased. However, if you keep in mind the statistic from earlier (African-American males are **six times** more likely to be incarcerated than white males (U.S. Bureau of Justice Statistics, 2012)) you can see that African-Americans would score far worse than white Americans. This question, together with others would help the algorithm infer the race, which then in turn could discriminate defendants.

Questions such as prior jail or prison history can also be heavily correlated with race. Figure 1 shows that a much higher rate of minorities face jail/prison time compared to white Americans. That kind of question, together with questions about the neighbourhood that the defendant lives in (Affluent blacks and Hispanics live in poorer neighbourhoods than where the average low-income white person lives (Izadi, 2011)) alone could help the algorithm predict the race of the defendant.

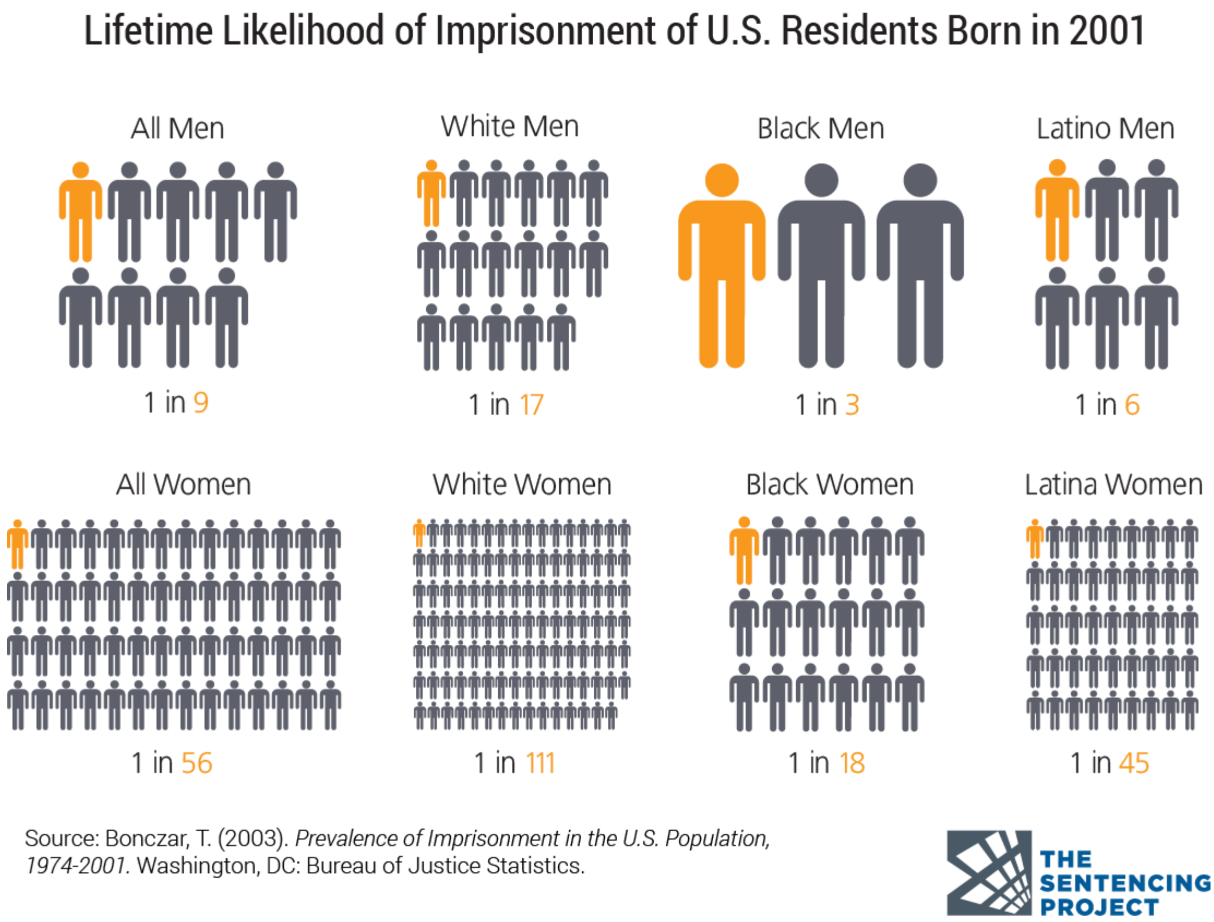

Figure 1: Lifetime Likelihood of Imprisonment of US Residents (The Sentencing Project, 2003)

2.2 State V. Loomis

The State V. Loomis case all started with Eric Loomis first being sentenced to prison. During the trial, the COMPAS risk assessment algorithm was used to give a core for Loomis. The judge told Loomis that the compass score had classified him as a '"high risk" to the community and handed down a six-year prison term' (Smith, 2016). Loomis appealed his case to the Supreme Court of Wisconsin on the grounds of due diligence and individualised sentencing rights being disregarded, and because of the proprietary nature of the algorithm.

Thus, started one of the most significant cases concerning the use of risk assessment algorithms in the judicial system.

Due Diligence

Loomis argued that it violates a defendant's right to be sentenced based upon accurate information, in part because the proprietary nature of COMPAS prevents him from assessing its accuracy; it violates a defendant's right to an individualized sentence; and it improperly uses gendered assessments in sentencing (State V. Loomis, 2016). The court rejected his appeal, instead opting for warning labels when the judges receive the scores.

"Risk assessments should be impermissible unless both parties get to see all the data that go into them," said Christopher Slobogin, director of the criminal justice program at Vanderbilt Law School. "It should be an open, full-court adversarial proceeding." (Anon., n.d.) The problem is not just that the defendant is not able to see the data that goes into the algorithm, but also that they do not have access to the source code. This makes it impossible, even if the defendant knows the data, to determine if there is a bias, or simply an issue with the algorithm which could skew it from a true result.

Automation Bias

An analysis conducted by ProPublica into COMPAS scores in Broward County, Florida found that "the algorithm was somewhat more accurate than a coin flip" (Angwin, et al., 2016). When you pair that with a study that found that people have an "automation bias" (the use of automation as a heuristic replacement for vigilant information seeking and processing), (Skitka, et al., 2000) it creates a worrying problem that judges may rely too heavily on the algorithm scores, rather than use the score as simply one possible metric which factors into their decision. The problem with having automation bias is that the judges most likely won’t realise the importance they place on the algorithm score, and as such it will hinder attempts to stop them from relying too heavily on the scores.

As also seen in Holders’ speech above, this case could set a very dangerous precedent, introducing a new standard for the judicial system, one which disregards a defendant’s due process rights, creates a norm for racial bias, and completely eliminates the right to an individualised sentencing.

The criminal justice system entrusts judges with making incredibly important decisions about technology and science within the courtroom, and for judges to make such decisions without any actual understanding of the technology they are ruling on can lead to damaging mistakes in judgment. (Freeman, 2016)

Individualised Sentencing

Individualised sentencing is where the punishment is made to fit the offender and not the crime (Sixth Form Law, n.d.). This means that the judge does not only base his sentencing on the evidence, but also looks at the defendants’ personal life, the reason behind the crime, etc.

Example: There are two defendants who have robbed small stores. The first defendant was recently fired from his job and robbed the store so he could provide food for his family. The second defendant robbed the store as part of a gang initiation. Even though the crime remains the same, because of the circumstances the judge gives the first defendant only a warning, and the second defendant 6 months in jail.

A COMPAS score is generated by scoring the defendant against a norm group. The way the norm groups are generated is described below:

COMPAS offers several norm group options at system configuration including community corrections, jail populations, prison inmates, and a composite norming group representing all of the above. The Northpointe R&D team can work with the site to design samples that will generate locally relevant norms. (Northpointe, 2012)

Individualized sentencing is effectively disregarded in the case of the score. Since it is scored against a norm group it does not make an individualized score, but instead scores against a predefined standard.

3. Methodology

3.1 Questionnaire

The questionnaire (Appendix B) was constructed using a number of different sources, such as current risk assessment questionnaires, studies showing certain factors that lead to a higher recidivism rate, etc. The questionnaire had to be constructed as such based on the data available, as data about the defendant's personal and family life is not publicly available. Questions relating to gang membership, family life, residential stability (Northpointe, 2011), which are present in the COMPAS questionnaire, are not included as part of this project.

The first six questions of the questionnaire (Age at Current Arrest, Current Violent Offense, Current violent offense & under 20 years old, Prior misdemeanour conviction, Prior felony conviction, Prior violent conviction) were taken from the PSA (Public Safety Assessment) risk assessment questionnaire (Laura and John Arnold Foundation, n.d.). The COMPAS questionnaire (Northpointe, 2011) also has very similar questions as to the first six in the questionnaire, as they are fairly standard questions.

The next two questions are about prior jail and prison time. Based on a report from the United States Sentencing Commission (USSC) nearly half of offenders who served time in federal prisons reoffended within 8 years of their release (Kim Steven Hunt, 2016). This shows a high inclination towards recidivism. This contributes a significant risk to society and considering that PSA and COMPAS both had similar questions in their questionnaires too, it should be accounted for in the algorithm.

The following couple of questions look at the defendants in their juvenile years. The questions check whether or not the defendant has been convicted for a felony or misdemeanour while they were a juvenile. According to a study conducted by the Illinois Criminal Justice Information Authority, they found that from their sample 3,052 juveniles released from the Illinois Department of Juvenile Justice 68 percent of them were re-incarcerated within three years of release (Lindsay Bostwick, 2012). This shows that having a juvenile conviction can represent a higher inclination to reoffend later when they become adults.

The last question concerns the marital status of the defendant. It is a part of the questionnaire as having a spouse gives more stability to the defendant's life, and has a more positive effect on stopping recidivism. Marriage is also important for social integration, and statistics show that married defendants have lower recidivism rates than their single counterparts (Signe Hald Andersen, 2015).

With more data available, especially data about the defendants' life, would mean the questionnaire would contain more questions, which would most probably lead to better results. The nature of this project is to prove that a racial bias exists, and show, given the data available, how another model could work with a reduced racial bias.

3.2 Neural Network

R was the chose programming language for this project mostly because of its vast packages and ease of use. Instead of having to write a few lines of code, built in functions from R were used.

A Neural Network was the best fit for the project. It has the ability to learn and model non-linear and complex relationships (Mahanta, 2017), which is useful in this case as the relationships between the variables are complex and constantly varying. Neural networks also can find hidden relationships in the data that we can't see, potentially increasing the accuracy over more cases.

COMPAS is a decision tree algorithm. Since that was already implemented, a neural network was chosen for this project to also compare which one would be better for this kind of algorithm.

3.3 Contributing Factors of Recidivism

Apart from looking for a racial bias, this project will also take a look at which factors contribute to recidivism. It will especially analyse the role that age, marital status, and sex contribute to reoffending.

There are many studies that show that being married leads to lower recidivism/conviction rates (married defendants have lower recidivism rates than their single counterparts (Signe Hald Andersen, 2015)), being convicted as a juvenile (68 percent of juvenile convicts that were studied were re-incarcerated within three years of release (Lindsay Bostwick, 2012)), and that women are less likely to be convicted than men (see Figure 1 in chapter 2.1)

This project will analyse whether these trends are present in the dataset.

4. Implementation

This chapter will start off with the data pre-processing, extracting the data from the database to a csv file, and then the actions performed on the data. After that there will be a step-by-step explanation of how the neural network was constructed, the different methods used, and how the analysis was conducted.

4.1 Data Pre-processing

The data was stored on a SQLite database. The tables on the database were:

- Case Arrest
- Charge
- Compas
- Jail History
- People
- Prison History
- Summary

Since the data required was not all in one table (i.e. People has the age and race columns while Compas has the scores) combination of inner joins and data manipulation in excel was used.

For **current violent offense**, only felony charges had to be chosen, as none of the misdemeanours were deemed violent. Since the database did not contain a column to indicate whether or not the offense was violent it all had to be done manually. The data was exported (shown below) to excel and gone through manually (unique records only) to indicate violence, then using VBA (Visual Basic for Applications) each conviction was cross referenced with the violent convictions list and given a score of 0 or 1, depending on the offense.

Figure 2 shows the SQL code that was used to retrieve the charge degrees and their descriptions. **SELECT DISTINCT** was used to get only the unique records regarding the charge, so that a list could be made of the charge descriptions. The **INNER JOIN** function is used here to retrieve common data and add constrictions on the retrieved data for each table.

```sql
SELECT DISTINCT charge, charge_degree, person_id, name
FROM charge AS ch
INNER JOIN compas AS c
ON c.person_id = ch.person_id AND ch.charge_degree != "(0)" AND ch.charge_degree != "(CO3)" AND ch.charge_degree != "(CT)"
AND ch.charge_degree != "(X)" AND ch.charge_degree != "XXXXXXXXXX" AND c.screening_date >= ch.offense_date;
```

Figure 2: Charge SQL Code

All the **prior** questions (**prior misdemeanour, felony, and violent conviction**) were determined by using a macro which checked for each defendant if they had a previous conviction (type of conviction was dependent on the question).

Figure 3 shows the main section of the code used to get the data necessary for the question. A while loop was used to make sure that the macro would stop when it reached an empty row (the end of the data). The for loop makes sure each record is searched for each defendant, with the if statement right below it making sure that it is still checking for the same defendant.

The variables mcount, fcount, and vcount stand for misdemeanour count, felony count, and violent count respectively.

The macro checks if the conviction was before the starting conviction date, and then adjusts the above variables accordingly. After all of this the variables are all inserted into the dataset to be processed further.

```vb
Do While Not IsEmpty(range.Offset(1).Value)
  For i = 1 To 100
    If range.Offset(i).Value2 <> range.Value2 Then
      Exit For
    End If

    If range.Offset(i, 3).Value2 < range.Offset(0, 3).Value2 Then
      If range.Offset(i, 2).Value2 = "F" Then
        fcount = fcount + 1
      Else
        mcount = mcount + 1
      End If

      If range.Offset(i, 4).Value2 = 1 Then
        vcount = vcount + 1
      End If
    End If
  Next i
  range.Offset(0, 5).Value2 = mcount
  range.Offset(0, 6).Value2 = fcount
  range.Offset(0, 7).Value2 = vcount
```

Figure 3: Priors figure

4.2 Neural Network

Once all the data pre-processing was completed the neural network was ready to be implemented.

The dataset was normalized to reduce any data redundancy, as there were too many rows to check through manually. It was also normalized so that if the algorithm is used later on with new data it will be scalable. If the data is not normalized then the output from the neural network could remain the same for each row.

Next random sampling was used. Sampling randomly will eliminate systematic bias (Smith, n.d.).

At first a simple split was used, 60-40% for the training set and the test set respectively. After doing some research it was decided that using random sampling would be the best way to go about splitting the data. By using random sampling this gave every defendant and every different conviction a chance for the neural network to be trained and tested on.

Example: All the violent convictions are in the first 20% of the rows of the dataset. In this case if the simple 60-40% split of the dataset had been used then the algorithm would be trained on the violent convictions, but it would not be tested at all, which could lead to the algorithm being trained incorrectly without anyone realising it.

Figure 4 shows the code used to achieve the random sampling. First the sample size is set (60%), to determine the split for training and test sets. The variable **ques_input** is the dataset after it has been normalized. The line **set.seed(80)** is used to set the randomization, 80 is used so that we can get the same results every time it is set to 80.

Inside the index variable being the sample is retrieved from the dataset(ques_input), with the size being set from earlier. The variable **index** is then used to set the training and test sets, with the remainder of the index value used in the second.

```
# Random Sampling
samplesize = 0.60 * nrow(ques_input)
set.seed(80)
index = sample(nrow(ques_input), size = samplesize)

# Training and Test Data
traindata = ques_input[index, ]
testdata = ques_input[-index, ]
```

Figure 4: Random Sampling Code

R offers a simple and easy to use neural network package, the first line in the figure below initiates the package for usage. The package employs backpropagation which is described below:

Backpropagation - Given an artificial neural network and an error function, the method calculates the gradient of the error function with respect to the neural network's weights (John McGonagle, n.d.)

What that means is that the error function (or derivative) is calculated and used to adjust the weights for the algorithm.

Inside the neural network function (**neuralnet**) the first variable (**recidivism**) is the dependent variable, i.e. the one we are trying to predict with the algorithm. The rest are independent variables, and they are all the column names from the questionnaire input.

```
library(neuralnet)

nn <- neuralnet(recidivism ~ age + violent + violentunder + misdemeanour + felony + priorviolent + jail + prison +
                   juvmisdemeanour + juvfelony + marriage, data=traindata)
```

Figure 5: Neural Network

After the neural network is trained, it is then run on the test dataset. The way this was done was by first using the subset function to remove the dependent variable (**recidivism**) since that is what we are testing the accuracy of the algorithm on. Then we compute the neural network and save the results so they can be analysed.

The scores from the algorithm range from 0 to 1, 1 indicating that the defendant will reoffend. Since the scores from the neural network will go up against the COMAPS scores, the scores were changed from decimal numbers to 1, 2, or 3. 1 indicates that the defendant is low risk, 2 is for medium risk, and 3 is for high risk. The scores were changed by using a simple macro in Excel, where the scores below 0.33 were 1, scores between 0.33 and 0.66 were 2, and higher than 0.66 were 3.

```
#Testing
temp_test <- subset(testdata, select = c("age", "violent", "violentunder", "misdemeanour", "felony", "priorviolent",
                                         "jail", "prison", "juvmisdemeanour", "juvfelony", "marriage"))
nn.results <- compute(nn, temp_test)
```

Figure 6: Neural Network Testing

To get a simple accuracy for the neural network the scores were rounded, and then put up against the actual recidivism scores. The resulting table is shown below:

	Prediction	
Actual	0	1
0	6541	856
1	476	344

Table 1: Neural Network Accuracy

The above table is the accuracy for the neural network with one hidden layer. After lengthy testing by using different amounts of layers, when using one hidden layer the accuracy came up to above 83%, whereas using other amounts came up to an average of 73%.

Figure 7 shows a plot of the neural network. The arrows on the left represent each variable from the dataset. The black arrows with the numbers are the nodes weights, showing how much each one contributes to the hidden layer node. The blue lines are the bias weights, the bias weight is an easy way for the algorithm to change the weight and the value at the same time, without having to do each separately. The node in the middle is the hidden layer, and the node on the right is the output layer, which is the recidivism score.

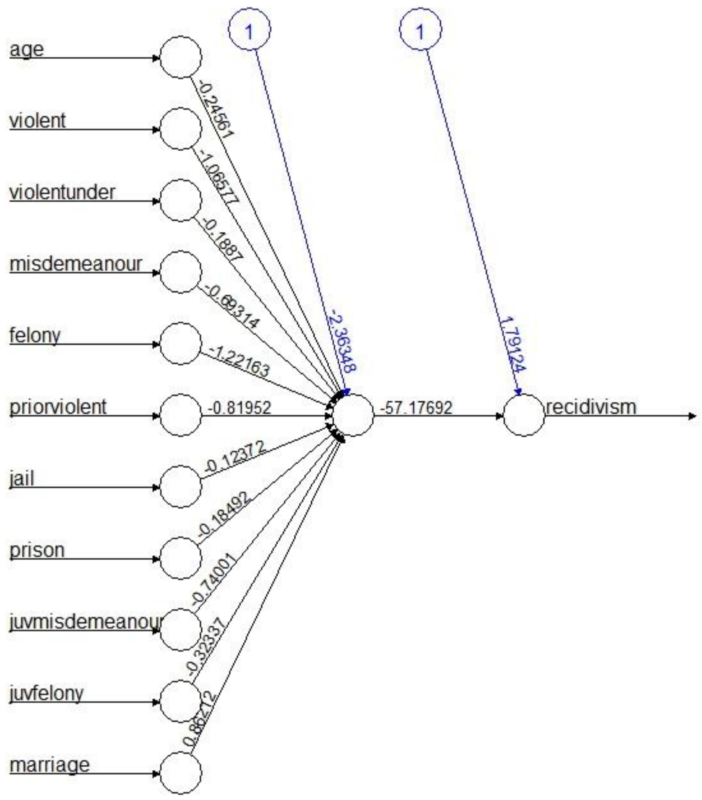

Figure 7: Neural Network Plot

4.3 Analysis

The analysis was completed by using Excel. Formulas, tables, and charts were used. All the results of the analysis will be in the next chapter.

The analysis Excel file together with the Neural Network and all the other pieces of code can be found in the Appendix Material Section.

5. Evaluation

The data that will be analysed in this section will be:

- COMPAS and Neural Network Scores and overall accuracy
- Racial Bias levels in both sets of scores
- The effect marriage has on recidivism
- The difference in sexes when it comes to conviction rates
- Which age group reoffends most and the link between prior juvenile conviction and recidivism
- The connection between prior jail/prison history and reoffending

COMPAS Scores VS Neural Network Scores

One of the objectives of this project was to achieve a higher accuracy rating with the neural network algorithm compared to the COMPAS scores. It is easy to see from the graphs above that both algorithms got around the same scores for low and medium risk. the overall accuracy was around 93.4% for both, while the misclassification scores for the low risk were 6.49% (COMPAS) and 6.68% (Neural Network).

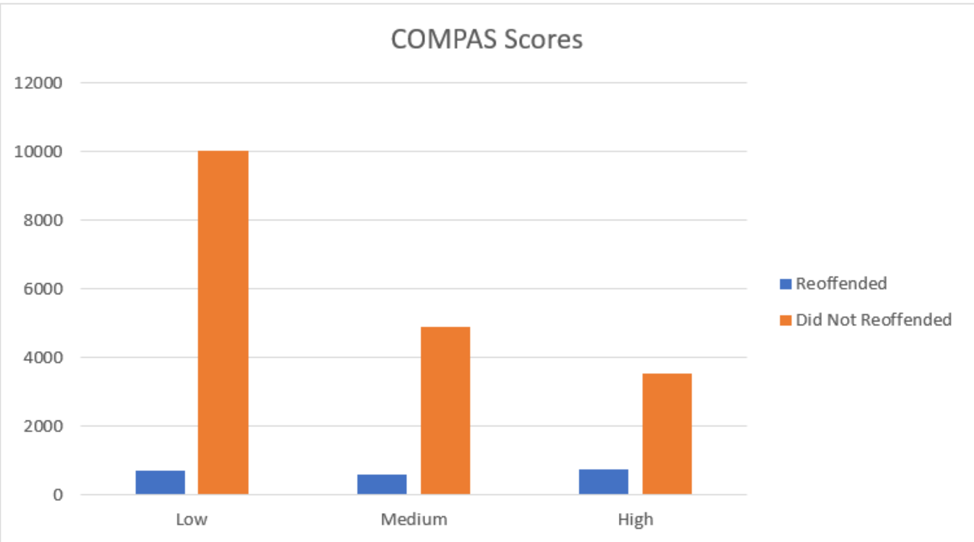

Figure 8: COMPAS Scores

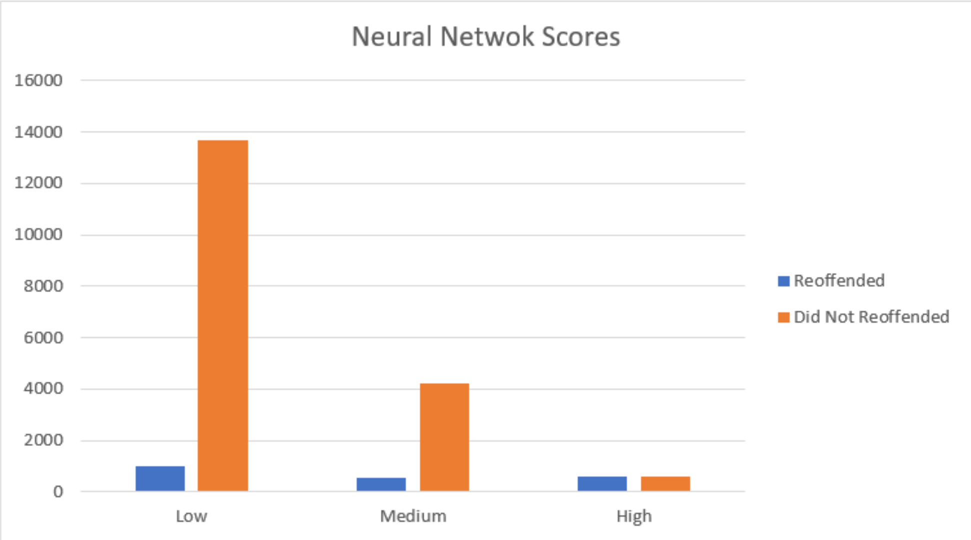

Figure 9: Neural Network Scores

The accuracy of the medium risk scores will be calculated by comparing the number of defendants that did not reoffend to the total of all medium risk scores. All medium risk scores for both COMPAS and the Neural Network were within 1.5 percentage points of each other so that together with the fact that these scores are harder to analyse as they don't provide clear guides as with low and high-risk scores, means that this section will not focus on medium risk scores.

The high-risk scores are when it gets interesting. The neural network had a misclassification rate of 50.44% overall and an accuracy rate of 49.56%. Meanwhile the COMPAS high-risk scores told another story, they had an 82.29% misclassification rate and an accuracy rating of only 17.71%.

This shows that while the low and medium risk scores were fairly similar, high-risk is where COMPAS fails. COMPAS has real life consequences for the defendants as they can face harsher sentences, longer jail/prison time, and all because of an algorithm that has not been tested and studied properly. With an 82% misclassification rate, it makes the COMPAS high-risk scores far worse than a coin toss.

Racial Bias levels in both sets of scores

First the scores from both algorithms for African-American defendants will be analysed, then for white defendants, and then African-American defendants scores will be analysed against the white defendants scores.

African-American Defendants Scores

Figures 10 and 12 show the COMPAS and Neural Network scores for African-American defendants.

As in the overall scores analysis, the accuracy for both algorithms was about the same for both low and medium risk scores (Nearly 92% and 13.5% respectively).

The high-risk scores had a much higher misclassification rate. The Neural Network had a misclassification rate of 48.28%, meanwhile the COMPAS misclassification rate was 82.36%, a lot higher than the neural network. We will go more in depth on these scores when the African-American defendants scores are compared to white defendants scores.

White Defendants Scores

As you can see in figures 11 and 13 the accuracy rates for both COMPAS and the Neural Network were very high, both came in at around 94%.

COMPAS once again fails to perform for the high-risk scores, reaching a misclassification rate of 82.89%, almost half a percent lower than for African-American defendants. The Neural Network misclassification score was 52.94%, almost 5% higher than African-American defendants.

Racial Bias Levels in the Scores

On face value there does not seem to be a racial bias in the COMPAS scores. COMPAS scored relatively bad for high-risk scores for both African-American and white defendants. Each different risk category scored within a few percentage points (largest difference was medium risk, with a difference of 6%).

The reality however is different. The COMPAS scores for white defendants show that the majority (65%) are classified as low-risk and only 12% are classified as high-risk. However, for African-American defendants it’s an entirely different story. 37.5% are classified as low-risk while 30% are classified as high-risk. The difference can be seen clearly between figures 10 and 11.

African-Americans are almost three times as likely to be scored as high-risk compared to white defendants. White defendants are almost twice as likely to be scored as low-risk compared to African-Americans. The accuracy and misclassification rates remain relatively the same for both.

This paints a clear picture. The scores are not reliable based on the misclassification rates for high-risk defendants alone, without even going into the racial bias. All validation studies on COMPAS have only focused on accuracy and misclassification rates, which has masked the racial bias present in the algorithm. Without access to the algorithm it is hard to say where the bias seeps from, whether it is in the algorithm, the training data, or something else altogether. One thing is for certain though, the COMPAS algorithm has a very clear racial bias, and has not put in place enough controls to stop this from happening.

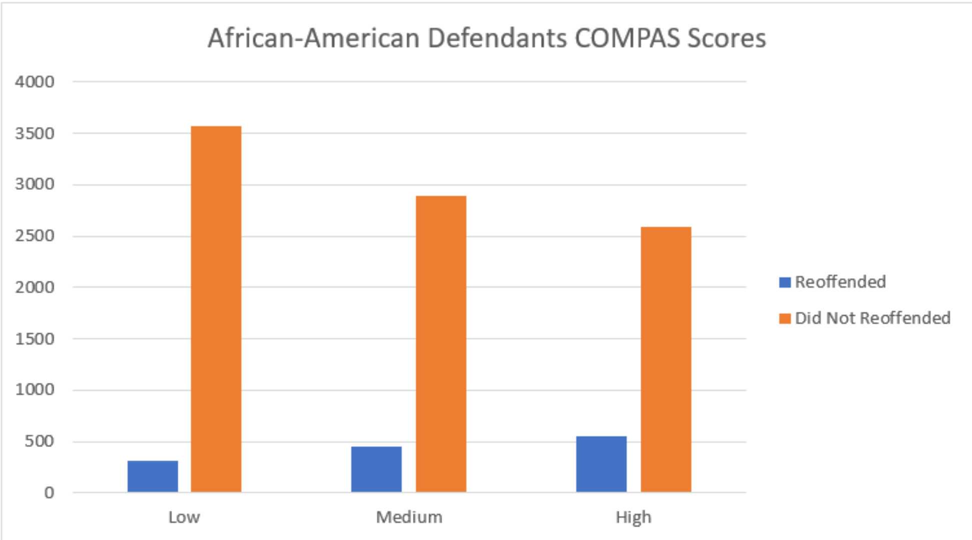

Figure 10: African-American Defendants COMAPS Scores

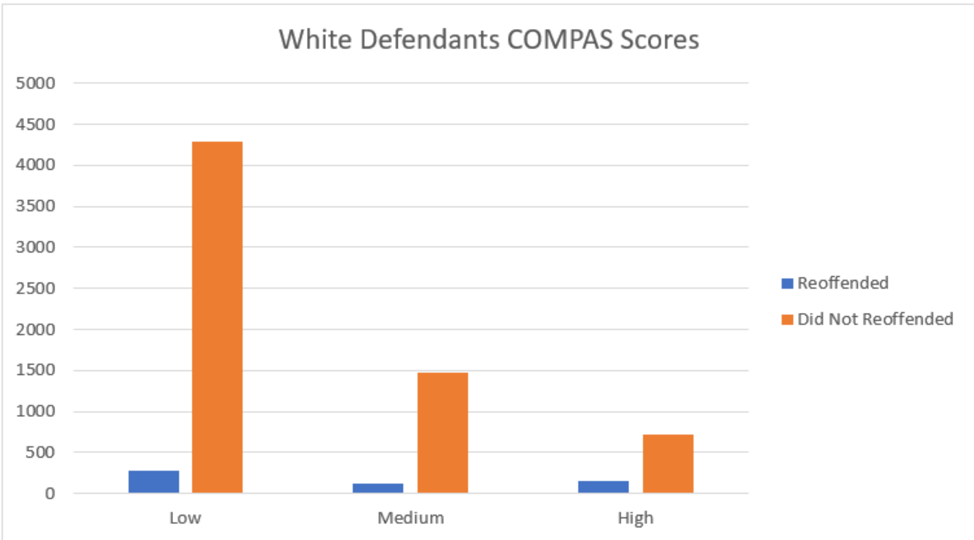

Figure 11: White Defendants COMPAS Scores

While the COMPAS algorithm contained a racial bias, the same cannot be said for the Neural Network. As you can see in the figures below, the algorithm performs relatively similar for both African-American and white defendants.

In both cases the majority of the defendants score as low-risk, with the algorithm boasting about a 3% increase in the misclassification for African-American defendants compared to white defendants.

For medium-risk scores white defendants have almost 5% more in misclassification rates, but since medium-risk could go either way it does not pose a problem.

African-Americans had almost double the numbers in the high-risk scores compared to white defendants, although the accuracy was almost 4% higher for African-Americans. Since AfricanAmerican males are six times more likely to be incarcerated than white males (U.S. Bureau of Justice Statistics, 2012).

As you can see in figures 12 and 13 the distribution remains fairly the same for both African-American and white defendants. This shows that contrary to the COMPAS scores, the Neural Network does not contain a racial bias.

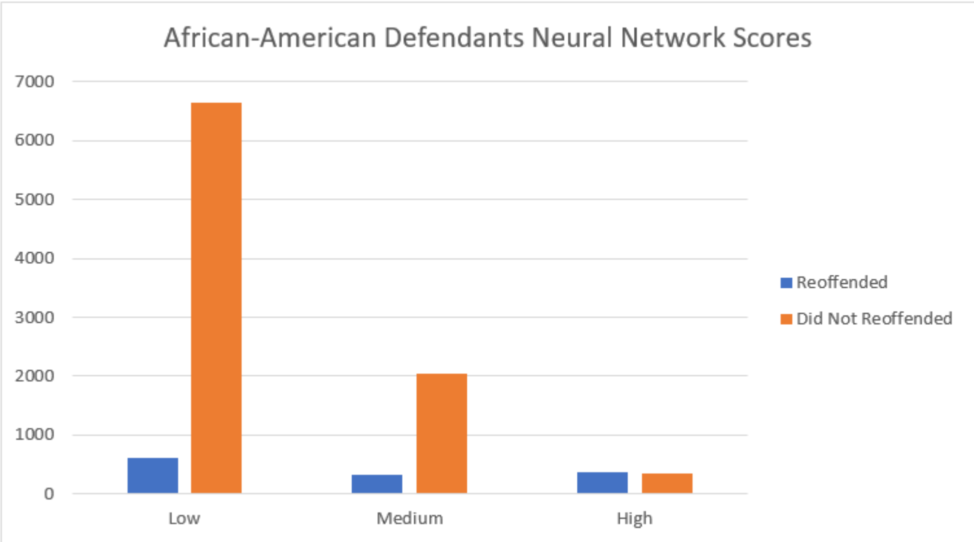

Figure 12: African-American Defendants Neural Network Scores

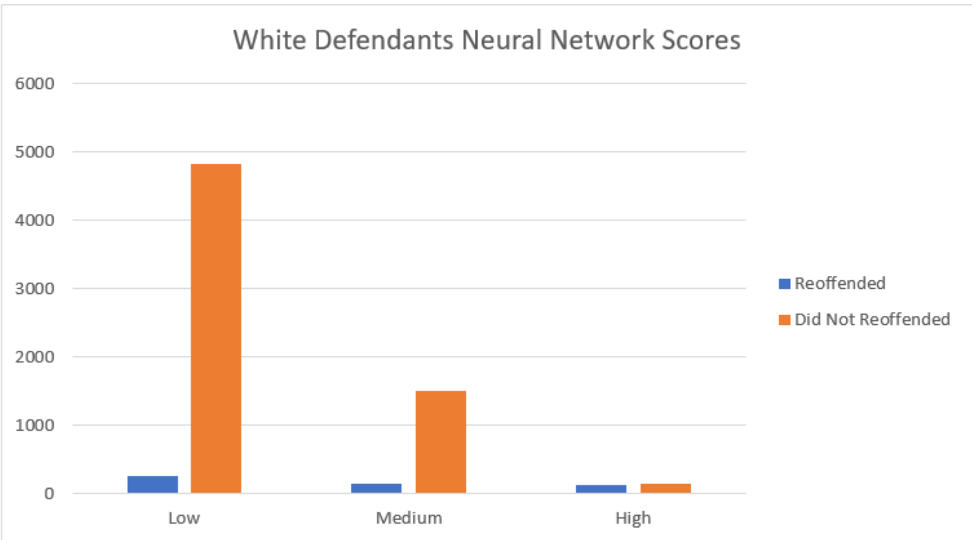

Figure 13: White Defendants Neural Network Scores

The effect marriage has on recidivism

Drawing on the findings from the study shown in the methodology chapter regarding the effect of being married on recidivism (marriage is important for social integration, and statistics show that married defendants have lower recidivism rates than their single counterparts (Signe Hald Andersen, 2015)), this section will look at whether or not that is true for the dataset.

At first look at the figure below it seems as though non-married defendants reoffended much more than married defendants, however that is because there were more non-married defendants. Defendants that were not married reoffended almost 3% more than married defendants (7.81% for married defendants compared to 10.42% for non-married defendants). From 2502 married defendants 212 reoffended, compared to 1858 from 15967 non-married defendants.

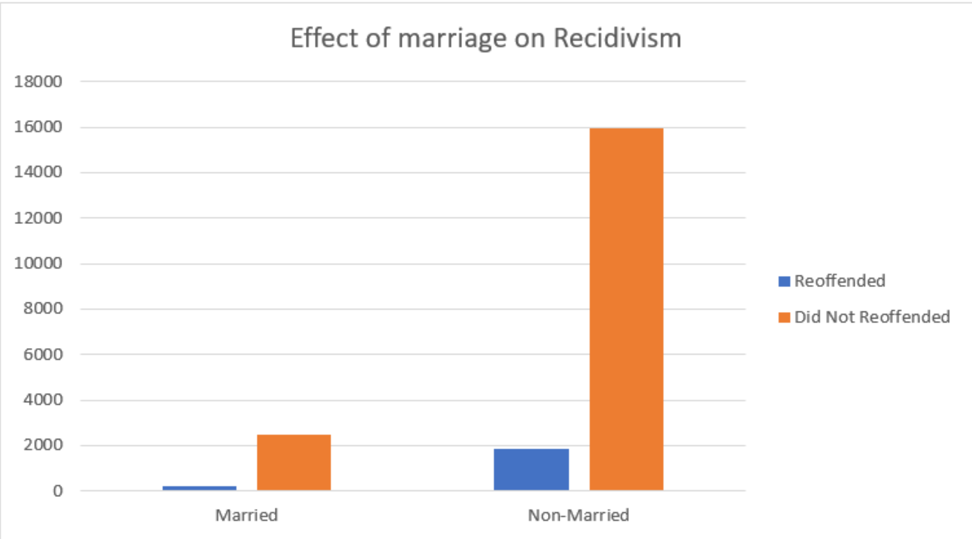

Figure 14: Effect of marriage on recidivism

The difference in sexes when it comes to conviction rates

The analysis agreed with the studies that females are convicted at much lower rates than males. From all the convicted defendants 83% were male compared to almost 17% females. This shows a general consistency between the analysis and studies and statistics conducted on the topic.

Which age group reoffends most

This section will analyse which age group reoffends the most, and the role that prior juvenile convictions play in recidivism.

The analysis found that Under-23s reoffended the most (17%), with 23 to 39 second at almost 10%, and 46 to 60s were close behind in third (7%). 23 to 39s had the highest numbers of convictions, almost 10,000 more than Under-23s.

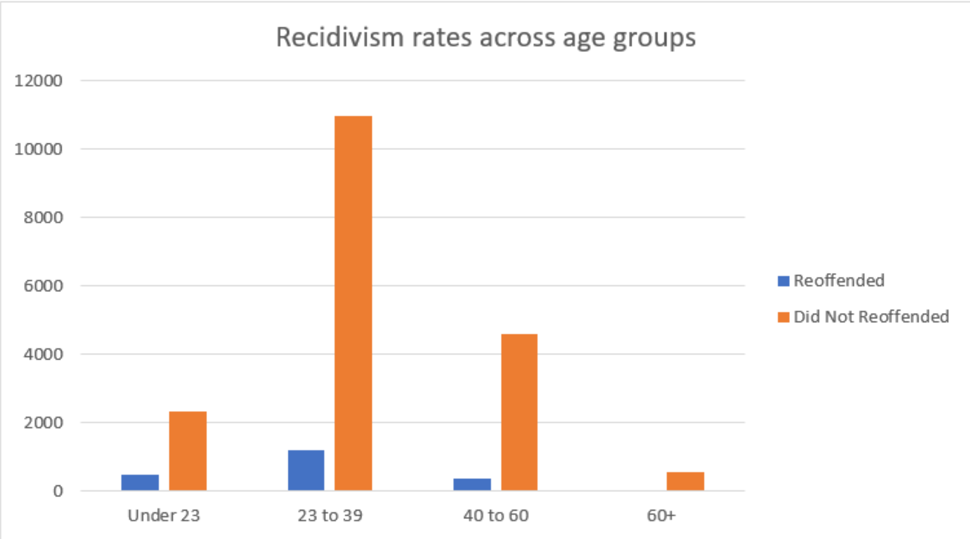

Figure 15: Recidivism Rates across Age Groups

The link between prior juvenile conviction and recidivism

The analysis found a pretty similar rate of reoffending for defendants with prior juvenile convictions and those without. The difference was 0.04% which is miniscule. The biggest difference was for the Under-23 age group, the defendants with prior juvenile convictions had an almost 5% higher recidivism rate. The differences are not large enough to warrant saying that for this dataset prior juvenile convictions lead to higher recidivism rates

The connection between prior jail/prison history and reoffending

In the methodology chapter a statistic about the link between prior jail/prison time and reoffending was mentioned. Based on a report from the United States Sentencing Commission (USSC) nearly half of offenders who served time in federal prisons reoffended within 8 years of their release (Kim Steven Hunt, 2016). Since the dataset only contains records spanning over two years the recidivism rates should not be as large as in the report.

Defendants who had prior jail/prison time reoffended almost three times more than those without any previous jail/prison time. 19% of defendants with prior jail/prison time reoffended compared to only 6.5% of defendants with no prior jail/prison time.

This shows a trend that could go up to a 50% recidivism rate after 8 years, which would be in line with the report.

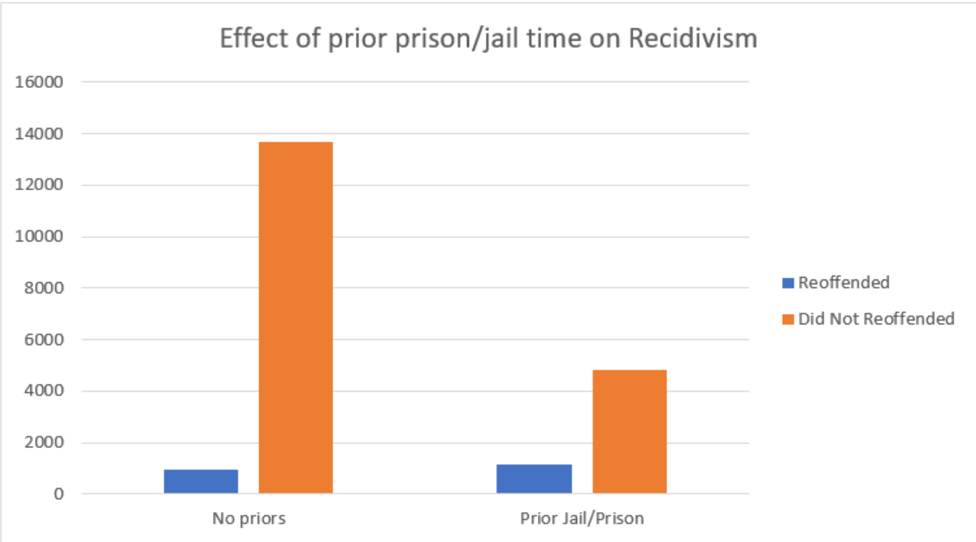

Figure 16: Effect of prior jail/prison time on recidivism

6. Conclusions

Risk Assessment algorithms are supposed to finally give every defendant an equal sentence. This unfortunately is still not the case.

As seen in the analysis section the aim of this project has been fulfilled. A racial bias was found in the COMPAS algorithm. The reasons behind the racial bias being present could not be determined because of a lack of access to the algorithm and its source code. The analysis shows that African-Americans were affected the most by this.

The neural network was implemented to great effect, achieving a better accuracy rate and showing no clear signs of racial bias. The neural network was far from perfect, but considering the limitations faced (time, amount of data, no expertise knowledge, etc.) it was definitely a success.

Other contributing factors to recidivism were also analysed. The findings were in mostly in line with what other studies have concluded. The only analysis that did not have the same findings as studies conducted on the matter was the link between prior juvenile convictions and recidivism. This could have been because of the two-year data period, perhaps if the period was longer a larger difference would have been found.

The Neural Network algorithm developed for this project showed a glimmer of hope. It showed that in this case there was no need to overcomplicate the algorithm. There have been risk assessment algorithms that are taking similar approaches, but none of them are being used as widely as COMPAS.

The Background and Potential Social Outcomes chapter showed that some studies conducted on COMPAS produced similar findings to this project. Others however, found no racial bias in the algorithm. This was most probably due to a lack of in-depth analysis, or could simply have been completed that way to show no racial bias.

The racial bias chapter showed the discrimination still prevails in the US justice system. African-Americans are still more likely to be stopped, searched, and convicted compared to white Americans. Since they are more likely to be convicted, they are more likely to reoffend. Having a criminal conviction makes adjusting to society much more difficult, as it is harder to find a job, friends and family could leave you once you are convicted, and depending on the time spent in jail or prison the world could be a different place compared to before being convicted.

State V. Loomis was a case where the Wisconsin Supreme Court could have sent a clear message that transparency needs to be key for risk assessment algorithms. The case did send a very clear message, it was just not the one that people wanted. It sent the message that these algorithms are allowed to be controlled by private companies with little oversight, and that they are here to stay. It decided that a few warning labels would be enough, whereas in reality the warning labels are the bare minimum that could have been done. The court showed that defendants' rights could be disregarded as long as the score was not the deciding factor for sentencing.

The accuracy rates for COMPAS make it hard to believe that it is still being used on such a large scale and is allowed to have such a big impact on the whole sentencing process. Hopefully this project can help spread awareness about the impacts of risk assessment algorithms being used in the criminal justice system and the racial bias surrounding them. These algorithms were put in place to help stop racial bias being present in the justice system, to ease prison overcrowding. However, the way that they were implemented only further increase the problems. With no real initiatives being taken to solve these problems there does not seem to be much hope for defendants to get a fair and equal trial in the near future.

6.1 Future Work

There is always room for improvement. With more data, time, and expertise knowledge this project could be expanded into a risk assessment algorithm that is ready for use in the justice system. The Neural Network produced an accuracy rate of almost 50% for high-risk scores. Even though it outscored COMPAS by more than 30% for this score, it is still not enough. Further analysis and investigation into this would be required before any kind of real world usage.

The algorithm would have to be changed as the medium-risk scores were not clear enough on what they mean. The accuracy rates for these scores were very low, and could potentially be disregarded completely to leave only low and high-risk scores.

Speaking to defendants who had COMPAS used and the judges during their sentencing could be highly beneficial as they would provide better insight into what they think of the use of these algorithms.

An in-depth analysis would be useful for the questionnaire questions. The analysis would have to be around the kind of questions accurately represent factors that could lead to recidivism or factors that lead away from it. It would also definitely need to include an analysis of how questions could be connected to race to try and lower or eliminate entirely any potential bias.

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Appendix A: Personal Reflection

There were many limitations that I had to face for this project, the biggest being the dataset. With a larger time period the algorithm would be better trained, and might have produce better results. The other big limitation was the lack of access to the COMPAS algorithm. I contacted them about it but they replied that their product is not available for students.

If I had to repeat the project with the knowledge I have now, I would do many things differently. One thing that held me back was a lack of experience dealing with a project of this magnitude and the uncertainties surrounding it. I would have more meetings with my supervisor in the beginning to come up with a structure of how the whole project will be implemented. I would come up with a clear plan for each section, so as to not waste time at the start of each chapter thinking about how to structure it and what to include.

I would reach out to people who have conducted similar research to my topic to see how they went about it, what problems they faced, and how they would have improved it. I think that this would be very beneficial as I could avoid the problems that they encountered and would in turn have more time to work on the project.

With more time I would implement different kinds of algorithms to thoroughly determine the best kind for this project. I would also improve the neural network to try to improve the accuracy for high-risk scores (from 50%).

It would have been beneficial to analyse other risk assessment algorithms other than COMPAS, to either provide a better picture of the racial bias in these algorithms, or to show a successful model that should be followed.

All in all, I think the project went well, it achieved its aim and the neural network had a better accuracy rate than COMPAS. The project is far from perfect, and could be expanded much more. I think that the background chapter provided a good overview of the racial bias that lies in the justice system and has a good explanation of all the points from the State V. Loomis case.

The methodology in my opinion could have been done better had I understood it properly earlier. My confusion surrounding it made me waste time trying to figure out what to include, whereas I could have used that time to improve it further.

Appendix B: More relevant material

Ethics Approval

College of Engineering, Design and Physical Sciences Research Ethics Committee
Brunel University London
Kingston Lane
Uxbridge
UB8 3PH
United Kingdom

www.brunel.ac.uk

21 February 2018

LETTER OF APPROVAL

Applicant: Mr Nol Zulfiu

Project Title: Racial Bias in Risk Assessment Algorithms

Reference: 8055-LR-Feb/2018- 11687-1

Dear Mr Nol Zulfiu

The Research Ethics Committee has considered the above application recently submitted by you.

The Chair, acting under delegated authority has agreed that there is no objection on ethical grounds to the proposed study. Approval is given on the understanding that the conditions of approval set out below are followed:

- The agreed protocol must be followed. Any changes to the protocol will require prior approval from the Committee by way of an application for an amendment.

Please note that:

- Research Participant Information Sheets and (where relevant) flyers, posters, and consent forms should include a clear statement that research ethics approval has been obtained from the relevant Research Ethics Committee.
- The Research Participant Information Sheets should include a clear statement that queries should be directed, in the first instance, to the Supervisor (where relevant), or the researcher. Complaints, on the other hand, should be directed, in the first instance, to the Chair of the relevant Research Ethics Committee.
- Approval to proceed with the study is granted subject to receipt by the Committee of satisfactory responses to any conditions that may appear above, in addition to any subsequent changes to the protocol.
- The Research Ethics Committee reserves the right to sample and review documentation, including raw data, relevant to the study.
- You may not undertake any research activity if you are not a registered student of Brunel University or if you cease to become registered, including abeyance or temporary withdrawal. As a deregistered student you would not be insured to undertake research activity. Research activity includes the recruitment of participants, undertaking consent procedures and collection of data. Breach of this requirement constitutes research misconduct and is a disciplinary offence.

Professor Hua Zhao

Chair

College of Engineering, Design and Physical Sciences Research Ethics Committee
Brunel University London