STAT 7995 Prof. Dodson

Dominic Matriccino

2022-11-09

1 Executive Summary

In our analysis of suspect identification, we were able to receive an overall accuracy rate of 65.84%. We used several variables in this logistic regression model, such as Age, Gender and Crossrace. We were able to receive an accuracy rate due to the fact that several of these predictors were significant in our logistic regression model. Crossrace was a variable that Prof. Dodson alerted us to due to the fact that it has the potential to decrease the identification ability of participants. We were able to confirm this hypothesis by running a two sample t-test on the prediction accuracy of same race vs cross race situations. We received a significant result, and thus, we can conclude that cross race situations do decrease the prediction accuracy of an average participant. We can see how some of the covariates relate to accuracy by looking at the coefficients of our logistic regression models.For Crossrace we received a coefficient of -0.1059, which again shows us that in cross race situations, the probability of receiving an accurate identification decreases. With respect to the demographic variables of the participants, such as age and gender, the coefficients of these variables were much closer to zero, which suggests that they do not play a large role in correctly identifying suspects. We determined that the confidence variable is also significant. This suggests that on average, people who feel more confident in their selection are being honest and are more accurate than people who reported having a lower confidence level. For each increase in the confidence factor, there is an increase in the prediction accuracy from approximately 26% at 0% confidence to 58% at 100% confidence.

2 Introduction

2.1 General Background

Often in a criminal investigation, eyewitnesses of a crime may be called upon to try to identify a suspect from a "lineup" of multiple people to see if the witness can choose the suspect. The criminal justice system in America is far from perfect, and one example of its imperfection is the prevalence of wrongful convictions of innocent people. In a study by the Innocence Project, 69% of wrongful convictions later overturned by DNA evidence involved eyewitness misidentification. In order to ensure that witness identifications help convict true offenders and do not convict innocent people, the police need to know how accurate a given witness should be expected to be. Dr. Chad Dodson conducted an experiment to investigate this problem. Participants were first asked to watch a short video depicting a mock robbery. After this, participants had to identify the "robber" in the video when presented with a lineup that may or may not include the "robber". The video, type of lineup, presence of weapon, and time between watching the video and choosing from the lineup were all randomized among the participants.

2.2 Objectives

Our project revolves around understanding the nature of accuracy in eyewitness suspect identification. This is a rather broad question so we will break it down into 3 parts:

1. Overall accuracy (witness made correct choice)
2. Chooser accuracy (witness correct given they picked someone)
3. Nonchooser accuracy (witness correct given they picked nobody)

Beyond this we would like to understand which variables determine how likely an eyewitness is to correctly identify the suspect (if any) in a lineup?

3 Approach to Project

In terms of data cleaning, we only have a few missing values. There are three missing values in the gender column and eight missing values in age column.

We can take a look at some of the variables that we would assume are correlated with having higher accuracy rates. One of these variables is the numeric confidence level of their ability to correctly identify the suspect. We can see how these variables relate by creating a table that shows each confidence level along with the average accuracy that everyone was able to achieve within that level.

```
tapply(data$Accuracy, data$`Confidence (0, 20, 40, 60, 80, 100)`, mean)
```

```
##         0        20        40        60        80       100
## 0.2627119 0.3143564 0.3745455 0.3866667 0.4685315 0.5809524
```

We can see from the table that there is a clear increase in accuracy for every increase in confidence level. People who felt confident in their ability to correctly identify the suspect were generally correct. Although, people that were 100% confident only received an accuracy rate of roughly 58%, This task of identifying the suspect is not easy, and perhaps some individuals were overconfident in their abilities, which would explain why people who were 100% confident only received an accuracy rate of 58%.

Another potentially interesting variable in our analysis is the effect of cross race predictions. These occur when the suspect's race and the race of the participant do not match. We would expect that the accuracy of cross race identification would be lower than the accuracy of same race identification. We can create another table to understand the difference in accuracy with respect to cross race situations.

```
##         0         1
## 0.4884152 0.4546066
```

```
##
##  Welch Two Sample t-test
##
## data:  cr$Accuracy and sr$Accuracy
## t = -2.0107, df = 3614.3, p-value = 0.04443
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.0646787754 -0.0008157235
## sample estimates:
## mean of x mean of y
## 0.3907514 0.4234987
```

We can see from this table that cross race instances do have a lower accuracy rate, but before we make this inference, we can run a two-sample t-test to determine if this difference is significant. After running the t-test, we can see that we received a p-value of approximately 0.044, which is below our significance level of 0.05. We have sufficient evidence to say that the cross race effect does provide a significant difference in variation in accuracy.

Lastly, we should break down accuracy based on whether the participant chose a person in the lineup. This will give us a better understanding of whether the fact that a participant ended up choosing a person in a lineup has any implications with respect to accuracy.

```
##        No       Yes
## 0.5767357 0.2695956
```

We can see that when people pick someone out of the lineup that the accuracy of that prediction is approximately 30 percentage points lower. This is surprising because this shows that the participants are a lot more accurate when the suspect is not in the lineup.

Going forward we can use a logistic regression model to determine the significance of some of the covariates as well as gain an understanding of the coefficients of our predictors and how they relate to the response variable accuracy.

4 Results

We can run three logistic regression models to find out more regarding what impacts accuracy in a model. The first of our three models will include all the data and we can simply look at the predictor coefficients to understand how our model believes accuracy relates to the covariates.

In the second model we will only include the instances where the participant chose anyone within the lineup that they were given. This will give us an idea of how these individuals relate to accuracy.

In our last model we will only include the instances where the participant did not choose anyone in the lineup that they were given. This will give us an idea of how these individuals relate to accuracy.

```
##                          (Intercept)
##                          0.045141366
## `Confidence (0, 20, 40, 60, 80, 100)`
##                          0.010136728
##                            crossrace
##                         -0.105945016
##                           ChooserYes
##                         -1.270012043
##                                  Age
##                         -0.008637029
##                           GenderMale
##                          0.084432819
```

We can see here the coefficients of the complete model. The variables with negative coefficients indicate that the presence of the predictor decreases the probability of an accurate suspect identification. Two of the three predictors are negative with ChooserYes being the predictor with the largest magnitude. We can understand this to mean that if someone ends us picking someone they are most likely to be wrong. This is likely due to the fact that in a lineup there are usually 6 or more people, so based solely on that if you do decide to pick a suspect randomly you are likely to be wrong.

```
##                          (Intercept)
##                          -1.66645986
## `Confidence (0, 20, 40, 60, 80, 100)`
```

```
##                             0.01907703
##                              crossrace
##                            -0.20967204
##                                    Age
##                            -0.01093117
##                             GenderMale
##                             0.20308171
```

We have here the coefficients of our model when we only include the participants that decided to pick someone out of their lineup. We can see here that both Age and crossrace are negative, while the confidence level that each participant decided on is positive. We can also compare the coefficients of crossrace between this model and the previous model. The magnitude of crossrace increases to -0.2064 from -0.1099. This implies that the cross race effect is more pronounced when the participant chooses someone versuses when the participant does not pick anyone.

```
##                            (Intercept)
##                            0.351305954
## `Confidence (0, 20, 40, 60, 80, 100)`
##                            0.003882746
##                              crossrace
##                           -0.032869834
##                                    Age
##                           -0.006291522
##                             GenderMale
##                           -0.040387676
```

Our last model has coefficients that have much smaller magnitude. The cross race effect is much closer to zero and the confidence level predictor and age are practically zero. This is not surprising because the participants that did not choose a suspect within the lineup are most likely to be wrong given how difficult it is to identify someone even after a short period of time. In our other two models the confidence variable was much more significant than it is now, which indicates that the participants are not very certain when deciding that the suspect is not present in the lineup.

Lastly, we can see the confusion matrices for all three models and compare the accuracy between the models.

```
confusion.matt1
```

```
##
##     FALSE TRUE
##   0  1579  571
##   1   664  821
```

```
confusion.matt2
```

```
##
##     FALSE TRUE
##   0  1450    8
##   1   523   16
```

```
confusion.matt3
```

```
##
##     FALSE TRUE
##   0    13  679
##   1     8  938
```

5 Conclusions and Appropriate Recommendations

Our analysis showed us that there are a few variables that are strongly associated with accurate suspect identification. The confidence level that a participant has is significant, and it does show that the participants who felt more confident tend to be more accurate. While this is fairly obvious, this variable is self-reported, so it could be susceptible to bias. Prof. Dodson can be fairly confident that the participants who feel more confident are more likely to be accurate.

The cross-race effect that Prof. Dodson mentioned is a significant predictor in the complete model. The coefficient that we were given from model 1 is -0.1059. This tells us that the probability of correctly identifying a suspect decreases in cross race situations. This predictor is statistically significant. Even though this is just one study with 3645 observations, we still have evidence that the crossrace effect exists. Crossrace negatively affects the ability of people of different races to identify suspects compared to when the participant and suspect are of the same race.

Lastly, when the participant chooses someone out of the suspect lineup, our full model agrees that the probability of receiving an accurate identification decreases significantly. Individuals are more likely to select someone if they feel somewhat confident in their memory. If they do not feel confident in their ability to remember what the suspect looks like, they may just choose ‘not present’ to be safe and not falsely accuse someone.

Our full model received an accuracy rate of 65.84% with the predictors of confidence, crossrace, chooser, age, and gender. Our second model received an accuracy rate of 72.99% and the third model has an accuracy rate of 57.92%. The models, however, are heavily unbalanced, and the high accuracy rates are mostly due to predictions in the majority class. Even though our accuracy rates are not the most important aspect of our analysis, it is important to see that the variables in our model are significant enough to receive accuracy rates that are well above 50%.

6 Appendix

```
summary(model1)
```

```
##
## Call:
## glm(formula = Accuracy ~ `Confidence (0, 20, 40, 60, 80, 100)` +
##     crossrace + Chooser + Age + Gender, family = "binomial",
##     data = data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5996  -0.8739  -0.7149   1.0681   1.9072
##
## Coefficients:
##                                         Estimate Std. Error z value
## (Intercept)                             0.045141   0.156033   0.289
## `Confidence (0, 20, 40, 60, 80, 100)`  0.010137   0.001471   6.889
## crossrace                              -0.105945   0.071831  -1.475
## ChooserYes                             -1.270012   0.071710 -17.710
## Age                                    -0.008637   0.002949  -2.929
## GenderMale                              0.084433   0.072272   1.168
##                                        Pr(>|z|)
## (Intercept)                              0.7723
## `Confidence (0, 20, 40, 60, 80, 100)` 5.61e-12 ***
## crossrace                                0.1402
## ChooserYes                              < 2e-16 ***
## Age                                      0.0034 **
## GenderMale                               0.2427
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 4916.8  on 3634  degrees of freedom
## Residual deviance: 4498.7  on 3629  degrees of freedom
##   (10 observations deleted due to missingness)
## AIC: 4510.7
##
## Number of Fisher Scoring iterations: 4
```

```
summary(model2)
```

```
##
## Call:
## glm(formula = Accuracy ~ `Confidence (0, 20, 40, 60, 80, 100)` +
##     crossrace + Age + Gender, family = "binomial", data = cho)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.2604  -0.8305  -0.6832   1.2775   2.1762
```

```
##
## Coefficients:
##                                      Estimate Std. Error z value
## (Intercept)                         -1.666460   0.225611  -7.386
## `Confidence (0, 20, 40, 60, 80, 100)`  0.019077   0.002357   8.094
## crossrace                           -0.209672   0.103497  -2.026
## Age                                 -0.010931   0.004351  -2.512
## GenderMale                           0.203082   0.104046   1.952
##                                     Pr(>|z|)
## (Intercept)                         1.51e-13 ***
## `Confidence (0, 20, 40, 60, 80, 100)` 5.76e-16 ***
## crossrace                             0.0428 *
## Age                                   0.0120 *
## GenderMale                            0.0510 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2329.2  on 1996  degrees of freedom
## Residual deviance: 2242.8  on 1992  degrees of freedom
##   (6 observations deleted due to missingness)
## AIC: 2252.8
##
## Number of Fisher Scoring iterations: 4
```

```
summary(model3)
```

```
##
## Call:
## glm(formula = Accuracy ~ `Confidence (0, 20, 40, 60, 80, 100)` +
##     crossrace + Age + Gender, family = "binomial", data = nocho)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.4269  -1.2965   0.9915   1.0491   1.2242
##
## Coefficients:
##                                      Estimate Std. Error z value
## (Intercept)                          0.351306   0.207811   1.691
## `Confidence (0, 20, 40, 60, 80, 100)`  0.003883   0.001920   2.023
## crossrace                           -0.032870   0.100729  -0.326
## Age                                 -0.006292   0.004059  -1.550
## GenderMale                          -0.040388   0.100734  -0.401
##                                     Pr(>|z|)
## (Intercept)                           0.0909 .
## `Confidence (0, 20, 40, 60, 80, 100)`   0.0431 *
## crossrace                             0.7442
## Age                                   0.1211
## GenderMale                            0.6885
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
```

```
##
##     Null deviance: 2231.2  on 1637  degrees of freedom
## Residual deviance: 2224.7  on 1633  degrees of freedom
##   (4 observations deleted due to missingness)
## AIC: 2234.7
##
## Number of Fisher Scoring iterations: 4
```

7 Bibliography

Administrator. "Cross-Race Effect - Iresearchnet." Psychology, 30 May 2016, https://psychology.iresearchnet.com/forensic-psychology/eyewitness-memory/cross-race-effect/.