Algorithmic Fairness in Practice - Solutions

Now that we've discussed algorithmic fairness and bias, let's work through a real example and see how an algorithm can be biased.

In May 2016, Jeff Larson and others from ProPublica published a story about algorithmic bias in criminal justice risk assessment scores. These scores are used to inform decisions about who can be set free at every stage of the criminal justice system, from assigning bond amounts to even more fundamental decisions about defendants' freedom. In Arizona, Colorado, Delaware, Kentucky, Louisiana, Oklahoma, Virginia, Washington and Wisconsin, the results of such assessments are given to judges during criminal sentencing.

In 2014, then U.S. Attorney General Eric Holder warned that the risk scores might be injecting bias into the courts. He called for the U.S. Sentencing Commission to study their use. "Although these measures were crafted with the best of intentions, I am concerned that they inadvertently undermine our efforts to ensure individualized and equal justice," he said, adding, "they may exacerbate unwarranted and unjust disparities that are already far too common in our criminal justice system and in our society." The sentencing commission did not, however, launch a study of risk scores. So, ProPublica did, as part of a larger examination of the powerful, largely hidden effect of algorithms in American life.

ProPublica obtained the risk scores assigned to more than 7,000 people arrested in Broward County, Florida, in 2013 and 2014 and checked to see how many were charged with new crimes over the next two years. The score proved remarkably unreliable in forecasting violent crime. In addition, ProPublica was able to show the algorithm was racially biased.

ProPublica completed a thorough analysis involving logistic regression, survival analysis and other statistical methods (check out more details here if interested), but here we will be exploring how the algorithm is biased and communicating this bias.

The data for ProPublica's analysis is contained in the file `compas-scores-two-years.csv`. Below are the variables we will be using:

- `race`: Race of the individual (we will only focus on `African-American` and `Caucasian` race categories).
- `two_year_recid`: Indicator if the individual reoffended (commited another crime) within 2 years.
- `decile_score`: Risk score, 1-10, 1 being low and 10 being high.
- `score_text`: score group, "Low": `decile_score` = 1-3, "Medium": `decile_score` = 4-7, "High": `decile_score` = 8-10.

Question 1

While there are several race/ethnicity categories represented in this dataset, we will limit our analyses to those who self-identified as Caucasian or African-American. Read in the data and filter the data frame to only include Caucasian and African-American individuals. How many African-American individuals are represented in this dataset and how many Caucasian individuals are represented?

```
library(tidyverse)
library(ggplot2)
library(readr)
```

```
scores <- read_csv("compas-scores-two-years.csv")

races <- c("African-American", "Caucasian")
```

```r
data <- scores %>% filter(race %in% races)

table(data$race)
```

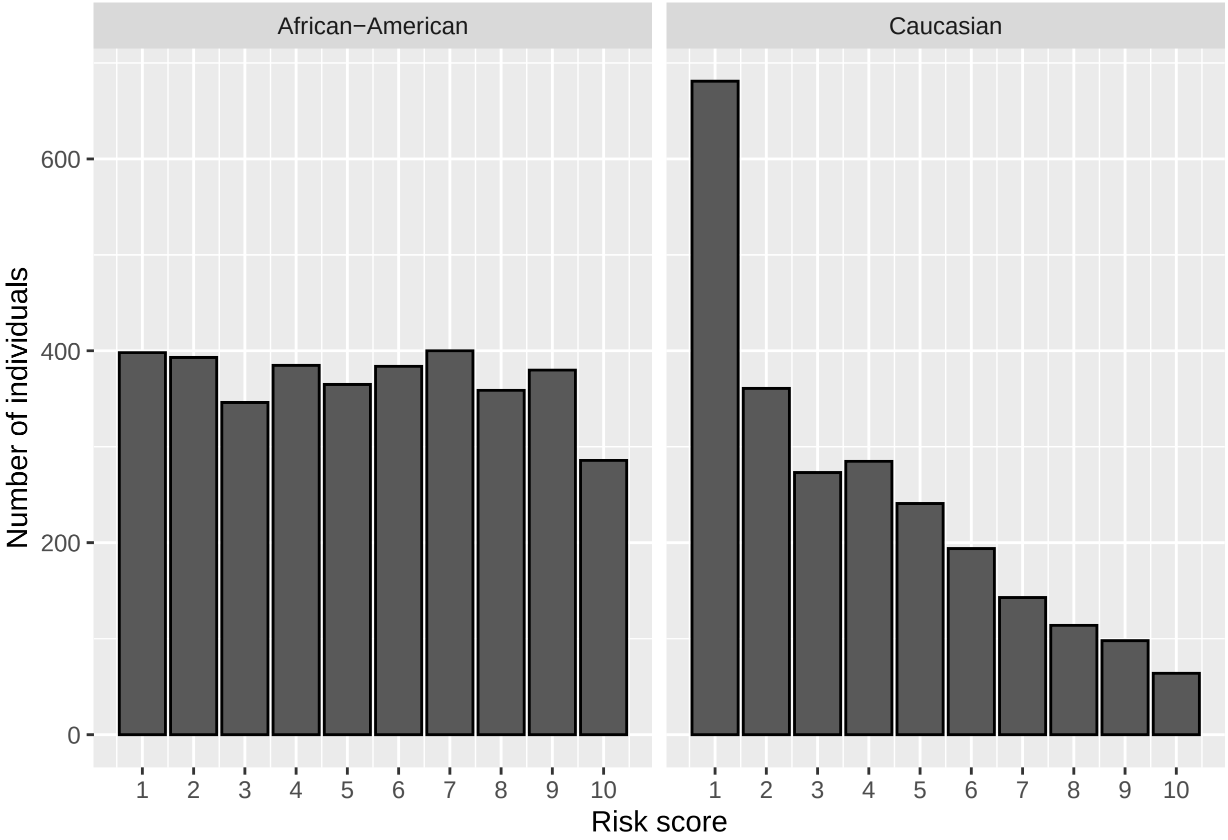
```
##
## African-American        Caucasian
##             3696             2454
```

There are 3,696 African-Americans and 2,454 Caucasians.

Question 2

Make 2 bar charts of `decile_score`, one for each race group. What do you notice about the distributions of scores for the two groups?

```r
data %>% ggplot(aes(decile_score)) +
  geom_bar(color = "black") +
    xlab("Risk score") +
    scale_x_continuous(breaks = seq(1,10)) +
    ylab("Number of individuals") +
  facet_grid(~race)
```



The scores are right-skewed for Caucasians and uniformly distributed for African-Americans. In other words, most Caucasians have lower risk scores (the number of individuals in each risk score decreases as score increases) while the number of African-Americans in each score group are about equal.

Question 3

Is the risk score a good predictor of two-year recidivism (i.e., committing another crime within 2 years)? Create a new variable called `binary_score` that is equal to 0 if `score_text` is equal to "Low" (this will be the "low-risk" group) and 1 otherwise (this will be the "high-risk" group). Create a 2x2 table of `binary_score` and `two_year_recid` using the `table` function. Calculate accuracy, sensitivity, specificity, false positive rate and false negative rate by hand. What is the accuracy? Are the sensitivity and specificity balanced? Are the false positive rate and false negative rate balanced?

- Here, false positive rate is the number of false positives over the total number of true negatives, and false negative rate is the number of false negatives over the total number of true positives.

```
data <- data %>% mutate(binary_score = ifelse(score_text == "Low", 0, 1))
with(data, table(binary_score, two_year_recid))
```

```
##              two_year_recid
## binary_score    0    1
##            0 2129  993
##            1 1154 1874
```

```
n = 1874 + 2129 + 993 + 1154
acc = (1874 + 2129)/n
TP = sum(data$binary_score == 1 & data$two_year_recid == 1)
FP = sum(data$binary_score == 1 & data$two_year_recid == 0)
TN = sum(data$binary_score == 0 & data$two_year_recid == 0)
FN = sum(data$binary_score == 0 & data$two_year_recid == 1)
sens = TP/(TP+FN)
spec = TN/(TN+FP)
FP_rate = FP/(FP+TN)
FN_rate = FN/(FN+TP)

results = data.frame("Accuracy" = acc,
                                         "Sensitivity" = sens,
                                         "Specificity" = spec,
                                         "FP_Rate" = FP_rate,
                                         "FN_Rate" = FN_rate)
results
```

```
##    Accuracy Sensitivity Specificity   FP_Rate   FN_Rate
## 1 0.6508943   0.6536449   0.6484922 0.3515078 0.3463551
```

The overall accuracy is 65% - not much better than flipping a coin. The sensitivity and specificity are balanced. This means the scoring algorithm is equally as good at correctly classifying someone as high-risk who subsequently reoffends within two years, as correctly classifying someone as low-risk who subsequently does not reoffend within two years. The false positive rate and false negative rate are also balanced.

Question 4

Now calculate the accuracy, sensitivity, specificity, false positive rate and false negative rate for each race group. Does the algorithm perform better for one group over the other? Describe how the model is biased.

- Hint: think about what false positives, false negatives, false positive rate and false negative rate mean in this context.

```
data %>% group_by(race) %>%
                 summarize(acc = sum(binary_score == two_year_recid)/n(),
                                    TP = sum(binary_score == 1 & two_year_recid == 1),
                                    FP = sum(binary_score == 1 & two_year_recid == 0),
                                    TN = sum(binary_score == 0 & two_year_recid == 0),
                                    FN = sum(binary_score == 0 & two_year_recid == 1),
                                    sens = TP/(TP+FN),
                                    spec = TN/(TN+FP),
                                    FP_rate = FP/(FP+TN),
                                    FN_rate = FN/(FN+TP))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 2 x 10
##   race               acc    TP    FP    TN    FN  sens  spec FP_rate FN_rate
##   <chr>            <dbl> <int> <int> <int> <int> <dbl> <dbl>   <dbl>   <dbl>
## 1 African-American 0.638  1369   805   990   532 0.720 0.552   0.448   0.280
## 2 Caucasian        0.670   505   349  1139   461 0.523 0.765   0.235   0.477
```

These contingency tables reveal that the algorithm is more likely to misclassify an African-American defendant as higher risk than a Caucasian defendant. African-American defendants who do not recidivate were nearly twice as likely to be classified as higher risk compared to their Caucasian counterparts (45 percent vs. 23 percent).

The algorithm tended to make the opposite mistake with Caucasians, meaning that it was more likely to wrongly predict that Caucasian people would not commit additional crimes if released compared to African-American defendants. The algorithm under-classified Caucasian reoffenders as low risk 70.5 percent more often than African-American reoffenders (48 percent vs. 28 percent).