Thesis Simulation Document for Chapter 4

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Contents

This file is intended to contain all the code and information to set up the simulation study and supplement Chapter 4.

Data Generation Mechanism

We're interested in creating a data set that has 50-50 class balance, even across the demographic group, and also has better predictive performance than the COMPAS tool. For this set-up, we will only use 2 variables from the COMPAS data set: 1 continuous variable and 1 categorical variable.

Reading in the Data

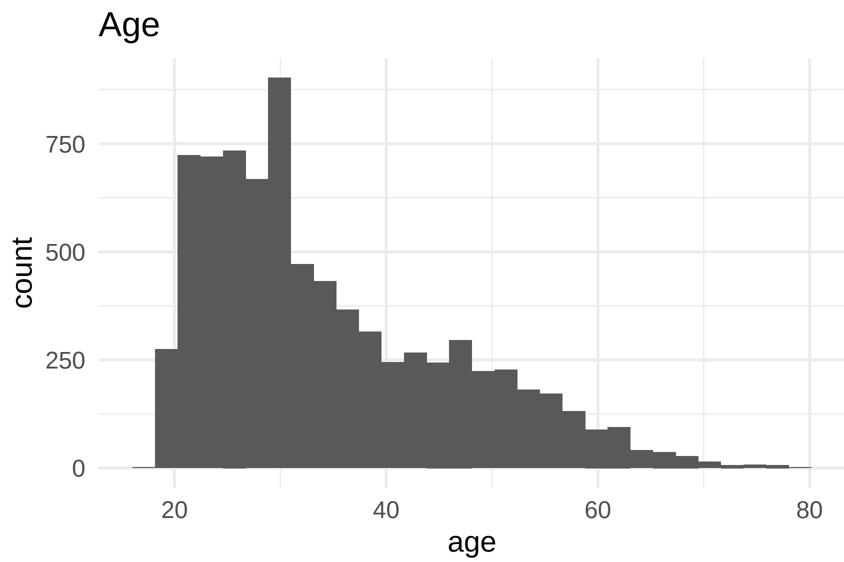
First, let's read in the data.

```
compas_path <- "/home/dasienga24/Statistics-Senior-Honors-Thesis/Data Sets/COMPAS/compas_seldonian_bw.cs
compas_sim <- read.csv(compas_path)
```

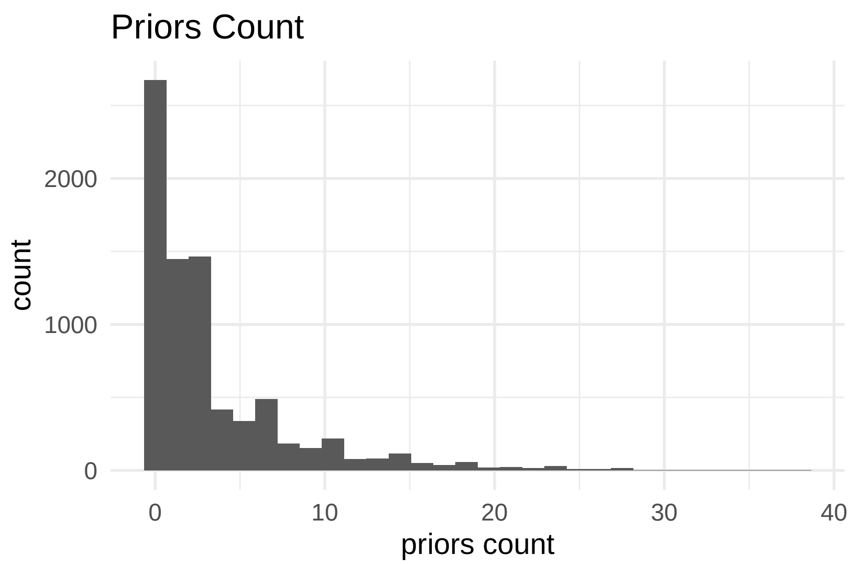
Data Subsetting

Next, let's plot the distributions of the continuous variables to choose which one we'll proceed with.

```
compas_sim %>%
  ggplot(mapping = aes(x = age)) +
  geom_histogram() +
  theme_minimal() +
  labs(title = "Age")
```




```
compas_sim %>%
  ggplot(mapping = aes(x = priors_count)) +
  geom_histogram() +
  theme_minimal() +
  labs(title = "Priors Count",
       x = "priors count")
```



Because age has more variation, we'll use it as our continuous variable. We'll convert `priors_count` into a categorical variable.

```
compas_sim <- compas_sim %>%
  mutate(prior_offense = ifelse(priors_count > 0, 1, 0)) %>%
  dplyr::select(c(race, prior_offense, age, is_recid))
```

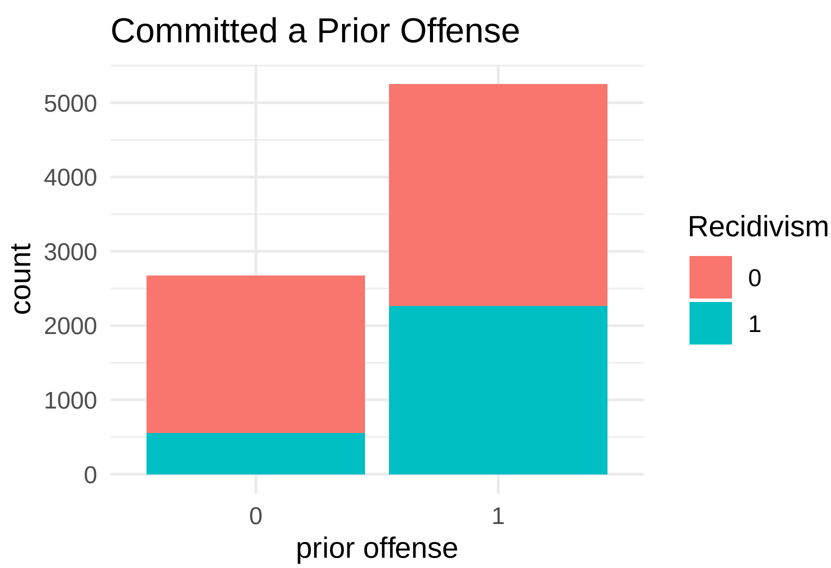
`age` seems to be a useful predictor for recidivism.

```
favstats(age ~ is_recid, data = compas_sim)
```

```
##   is_recid min Q1 median Q3 max     mean       sd    n missing
## 1        0  18 26     33 44  80 35.92591 12.24397 5102       0
## 2        1  18 24     29 37  78 32.25797 10.57842 2822       0
```

Whether a defendant has committed a prior offense or not appears to be a useful predictor for recidivism as well.

```
compas_sim %>%
  ggplot(mapping = aes(x = as.factor(prior_offense), fill = as.factor(is_recid))) +
  geom_bar() +
  theme_minimal() +
  labs(title = "Committed a Prior Offense",
       fill = "Recidivism",
       x = "prior offense")
```



We'll proceed with these 2 variables – `age` and `prior_offense` for the simulation study. A glimpse of the data is shown below.

```
compas_sim <- compas_sim %>%
  mutate(prior_offense = as.factor(prior_offense),
         is_recid = as.factor(is_recid))

glimpse(compas_sim)
```

```
## Rows: 7,924
## Columns: 4
## $ race          <chr> "African-American", "African-American", "Caucasian", "Ca~
## $ prior_offense <fct> 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0,~
## $ age           <int> 34, 24, 41, 39, 20, 26, 27, 23, 37, 22, 41, 47, 31, 25, ~
## $ is_recid      <fct> 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1,~
```

```r
head(compas_sim)
```

```
##               race prior_offense age is_recid
## 1 African-American             0  34        1
## 2 African-American             1  24        1
## 3        Caucasian             1  41        1
## 4        Caucasian             0  39        0
## 5        Caucasian             0  20        0
## 6        Caucasian             0  26        0
```

Generating the Parent Simulation Data Set

We want a setting with 50-50 class balance for each combination of race and recidivism status. To achieve that, we'll perform sample observations with replacement. Let's create a data set with 1250 observations in each of these 4 groups, hence, 5000 observations total.

First, let's subset these 4 groups.

```r
compas_b_y <- compas_sim %>%
  filter(race == "African-American" & is_recid == 1)

compas_b_n <- compas_sim %>%
  filter(race == "African-American" & is_recid == 0)

compas_w_y <- compas_sim %>%
  filter(race == "Caucasian" & is_recid == 1)

compas_w_n <- compas_sim %>%
  filter(race == "Caucasian" & is_recid == 0)
```

Next, let's randomly sample 1250 observations from each of these groups.

```r
compas_b_y_balanced <- compas_b_y[sample(nrow(compas_b_y), 1250, replace = TRUE),]
compas_b_n_balanced <- compas_b_n[sample(nrow(compas_b_n), 1250, replace = TRUE),]
compas_w_y_balanced <- compas_w_y[sample(nrow(compas_w_y), 1250, replace = TRUE),]
compas_w_n_balanced <- compas_w_n[sample(nrow(compas_w_n), 1250, replace = TRUE),]
```

Finally, let's union all these together into a single data set.

```r
compas_sim_balanced <- rbind(compas_b_y_balanced,
                             compas_b_n_balanced,
                             compas_w_y_balanced,
                             compas_w_n_balanced)
```

Let's also shuffle the data set row orderings to aid the machine learning algorithms later.

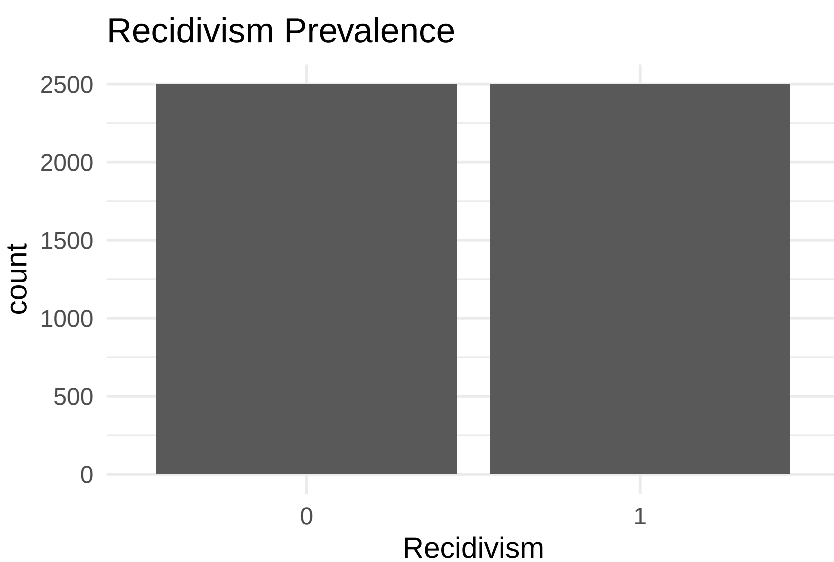
```
compas_sim_balanced <- compas_sim_balanced[sample(nrow(compas_sim_balanced),
                                                  5000,
                                                  replace = FALSE),]
```

The parent data set is now ready.

Examining Distributions of the Recidivism in the Parent Data Set

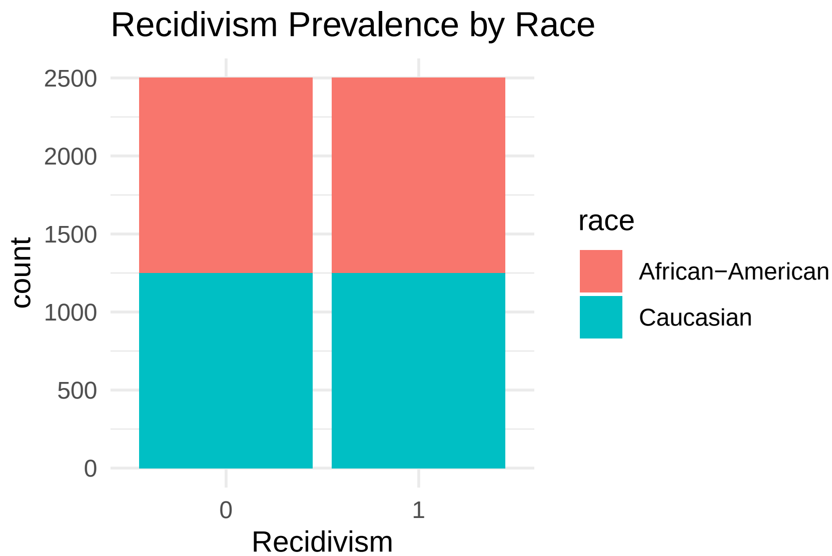
The bar plot below shows that we've achieve perfect class balance.

```
compas_sim_balanced %>%
  ggplot(mapping = aes(x = is_recid)) +
  geom_bar() +
  theme_minimal() +
  labs(x = "Recidivism",
       title = "Recidivism Prevalence")
```



The bar plot below reveals that the balance is preserved by race as well.

```
compas_sim_balanced %>%
  ggplot(mapping = aes(x = is_recid, fill = race)) +
  geom_bar() +
  theme_minimal() +
  labs(x = "Recidivism",
       title = "Recidivism Prevalence by Race")
```



Assessing Baseline Predictive Performance of the Parent Data Set

We want to make sure that our data set also has good predictive performance. We'll fit a logistic regression and assess baseline accuracy.

```
glm1 <- glm(is_recid ~ age + prior_offense,
            data = compas_sim_balanced,
            family = binomial(logit))

msummary(glm1)
```

```
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)      0.036825   0.099271   0.371    0.711
## age             -0.022743   0.002552  -8.910   <2e-16 ***
## prior_offense1   1.081245   0.064619  16.733   <2e-16 ***
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6931.5  on 4999  degrees of freedom
## Residual deviance: 6569.0  on 4997  degrees of freedom
## AIC: 6575
##
## Number of Fisher Scoring iterations: 4
```

```
glm1augment <- glm1 %>%
  broom::augment(type.predict = "response")
glm1augment <- mutate(glm1augment, binprediction = round(.fitted, 0))
with(glm1augment, table(is_recid, binprediction))
```

```
##         binprediction
## is_recid    0    1
##        0 1304 1196
##        1  757 1743
```

```
(1334 + 1713)/5000
```

```
## [1] 0.6094
```

This model has 61% accuracy.