# Criminal Justice - Recidivism

### DeBoris Leonard

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#### INTRODUCTION:

Recidivism is the \$10,000 word for the likely hood of a convicted criminal to repeat offend. In recent in this project we are going to look at data on recidivism from Broward County and ProPublica to see if

#### **OBSERVATIONS:**

Total Count of Defendents:

## [1] 6011

Age Range of Defendants:

## 25 - 45 Greater than 45 Less than 25 ## 3384 1172 1455

Based on the data most defendants in fall between 25-45 years of age which aligns with the average age

Total Defendants by Race:

## African-American Asian Caucasian Hispanic ## 3342 21 1933 403 ## Native American Other

## 8 304

print("Black: %.2f%%" % (3342 / 6011 \* 100))

## Black: 55.60%

print("White: %.2f%%" % (1933 / 6011 \* 100))

## White: 32.16%

print("Hispanic: %.2f%%" % (403 / 6011 \* 100))

## Hispanic: 6.70%

print("Other: %.2f%%" % (304 / 6011 \* 100))

## Other: 5.06%

print("Asian: %.2f%%" % (21 / 6011 \* 100))

## Asian: 0.35%

print("Native American: %.2f%%"% (8 / 6011 \* 100))

## Native American: 0.13%

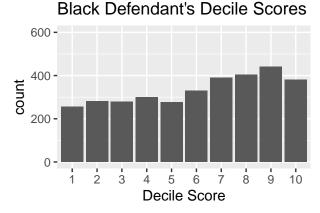
The percentage of defendants broken down by race shows that Black or African American individuals compr

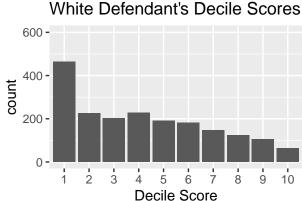
Total Poluation by Gender:

## Female Male ## 936 5075

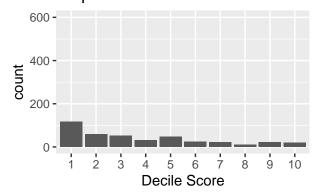
Total Population by Gender and Race:

## race ## sex African-American Asian Caucasian Hispanic Native American Other ## 431 57 30 416 Female 2926 21 1502 346 274 ## Male





# Hispanic Defendant's Decile Scores



The Decile Score is the measurement of the likelihood of recidivism. The higher the Decile Score the mo But what if there is bias built in the algorithm? Could COMPAS' built in bias create a system that rate

4

Decile Score by Race:

```
##
               race
## decile_score African-American Asian Caucasian Hispanic Native American Other
             1
                             255
                                     8
                                              464
                                                       116
             2
                             282
                                              226
                                                                          2
                                                                               52
##
                                     1
                                                        59
##
             3
                             280
                                     3
                                              203
                                                        51
                                                                          1
                                                                               34
##
             4
                             299
                                     0
                                              228
                                                        32
                                                                               33
##
             5
                             277
                                     1
                                              191
                                                        48
                                                                         0
                                                                               22
                                     2
##
             6
                             330
                                              182
                                                        25
                                                                         0
                                                                               27
##
             7
                             391
                                     2
                                              146
                                                        21
                                                                         1
                                                                              17
##
             8
                             405
                                     4
                                              123
                                                        10
                                                                         0
                                                                               11
                                                                         2
##
             9
                             442
                                     0
                                              106
                                                        22
##
             10
                             381
                                     0
                                               64
                                                        19
                                                                               12
##
## glm(formula = score_factor ~ gender_factor + age_factor + race_factor +
       priors_count + crime_factor + two_year_recid, family = "binomial",
##
       data = compas_df)
## Deviance Residuals:
       Min
                 1Q
                      Median
                                   3Q
                                            Max
## -3.0611
                      0.2124
           -0.7597
                               0.7538
                                         2.6312
##
## Coefficients:
##
                               Estimate Std. Error z value Pr(>|z|)
## (Intercept)
                               -1.57471
                                            0.08915 -17.663 < 2e-16 ***
                                                      2.076
## gender_factorFemale
                                0.18448
                                            0.08885
                                                              0.0379 *
## age_factorGreater than 45
                               -1.48482
                                            0.10210 -14.543 < 2e-16 ***
## age_factorLess than 25
                                1.29450
                                            0.07917 16.352 < 2e-16 ***
## race_factorAfrican-American 0.43348
                                            0.07233
                                                     5.993 2.06e-09 ***
## race_factorAsian
                                            0.49806
                                                     1.541
                                0.76737
                                                              0.1234
## race_factorHispanic
                               -0.31006
                                            0.13930 -2.226
                                                              0.0260 *
## race_factorNative American 0.82142
                                            0.88861
                                                      0.924
                                                              0.3553
## race_factorOther
                               -0.75951
                                            0.15646
                                                    -4.854 1.21e-06 ***
## priors_count
                                0.26984
                                                     24.754 < 2e-16 ***
                                            0.01090
## crime_factorM
                               -0.33000
                                            0.07025
                                                    -4.697 2.63e-06 ***
## two_year_recid
                                0.95981
                                            0.07028 13.657 < 2e-16 ***
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## (Dispersion parameter for binomial family taken to be 1)
##
       Null deviance: 8279.1 on 6010 degrees of freedom
## Residual deviance: 5768.3 on 5999 degrees of freedom
## AIC: 5792.3
##
## Number of Fisher Scoring iterations: 5
```

```
## [1] 1.427987
```

Based on the Broward County data Black or African American individuals are almost 43% more likely to re

```
exp(0.118109) / (1 - control + (control * exp(0.118109)))
```

```
## [1] 1.098859
```

Women are almost 10% more likely to receive a higher score than their male counterparts.

```
from sys import stdout
from csv import DictReader, DictWriter
class PeekyReader:
   def __init__(self, reader):
       self.peeked = None
        self.reader = reader
   def peek(self):
        if self.peeked is None:
            self.peeked = next(self.reader)
        return self.peeked
   def __iter__(self):
        return self
   def __next__(self):
        if self.peeked is not None:
            ret = self.peeked
            self.peeked = None
            return ret
        try:
            return next(self.reader)
        except StopIteration:
            self.peeked = None
            raise StopIteration
class Person:
   def __init__(self, reader):
        self.__rows = []
        self.__idx = reader.peek()['id']
            while reader.peek()['id'] == self.__idx:
                self.__rows.append(next(reader))
        except StopIteration:
            pass
   @property
   def lifetime(self):
       memo = 0
       for it in self.__rows:
```

```
memo += int(it['end']) - int(it['start'])
   return memo
@property
def recidivist(self):
    return (self.__rows[0]['is_recid'] == "1" and
            self.lifetime <= 730)</pre>
@property
def violent_recidivist(self):
   return (self.__rows[0]['is_violent_recid'] == "1" and
            self.lifetime <= 730)</pre>
@property
def low(self):
    return self.__rows[0]['score_text'] == "Low"
@property
def high(self):
   return not self.low
@property
def low_med(self):
   return self.low or self.score == "Medium"
@property
def true_high(self):
    return self.score == "High"
@property
def vlow(self):
   return self.__rows[0]['v_score_text'] == "Low"
@property
def vhigh(self):
   return not self.vlow
@property
def vlow_med(self):
   return self.vlow or self.vscore == "Medium"
@property
def vtrue_high(self):
    return self.vscore == "High"
@property
def score(self):
   return self.__rows[0]['score_text']
@property
def vscore(self):
   return self.__rows[0]['v_score_text']
```

```
@property
   def race(self):
       return self. rows[0]['race']
   @property
   def valid(self):
       return (self.__rows[0]['is_recid'] != "-1" and
                (self.recidivist and self.lifetime <= 730) or
                self.lifetime > 730)
   @property
   def compas_felony(self):
       return 'F' in self.__rows[0]['c_charge_degree']
   @property
   def score_valid(self):
       return self.score in ["Low", "Medium", "High"]
   @property
   def vscore_valid(self):
       return self.vscore in ["Low", "Medium", "High"]
   @property
   def rows(self):
       return self.__rows
def count(fn, data):
   return len(list(filter(fn, list(data))))
def t(tn, fp, fn, tp):
    surv = tn + fp
   recid = tp + fn
   print("
                      \tLow\tHigh")
   print("Survived \t%i\t%i\t%.2f" % (tn, fp, surv / (surv + recid)))
   print("Recidivated\t%i\t%i\t%.2f" % (fn, tp, recid / (surv + recid)))
   print("Total: %.2f" % (surv + recid))
   print("False positive rate: %.2f" % (fp / surv * 100))
   print("False negative rate: %.2f" % (fn / recid * 100))
   spec = tn / (tn + fp)
   sens = tp / (tp + fn)
   ppv = tp / (tp + fp)
   npv = tn / (tn + fn)
   prev = recid / (surv + recid)
   print("Specificity: %.2f" % spec)
   print("Sensitivity: %.2f" % sens)
   print("Prevalence: %.2f" % prev)
   print("PPV: %.2f" % ppv)
   print("NPV: %.2f" % npv)
   print("LR+: %.2f" % (sens / (1 - spec)))
   print("LR-: %.2f" % ((1-sens) / spec))
```

```
def table(recid, surv, prefix=''):
   tn = count(lambda i: getattr(i, prefix + 'low'), surv)
   fp = count(lambda i: getattr(i, prefix + 'high'), surv)
   fn = count(lambda i: getattr(i, prefix + 'low'), recid)
   tp = count(lambda i: getattr(i, prefix + 'high'), recid)
   t(tn, fp, fn, tp)
def hightable(recid, surv, prefix=''):
   tn = count(lambda i: getattr(i, prefix + 'low_med'), surv)
   fp = count(lambda i: getattr(i, prefix + 'true_high'), surv)
   fn = count(lambda i: getattr(i, prefix + 'low_med'), recid)
   tp = count(lambda i: getattr(i, prefix + 'true_high'), recid)
   t(tn, fp, fn, tp)
def vtable(recid, surv):
   table(recid, surv, prefix='v')
def vhightable(recid, surv):
   hightable(recid, surv, prefix='v')
def is_race(race):
   return lambda x: x.race == race
def write_two_year_file(f, pop, test, headers):
   headers = list(headers)
   headers.append('two_year_recid')
   with open(f, 'w') as o:
        writer = DictWriter(o, fieldnames=headers)
        writer.writeheader()
        for person in pop:
            row = person.rows[0]
            if getattr(person, test):
                row['two year recid'] = 1
            else:
                row['two_year_recid'] = 0
            if person.compas_felony:
                row['c_charge_degree'] = 'F'
            else:
                row['c_charge_degree'] = 'M'
            writer.writerow(row)
            stdout.write('.')
def create_two_year_files():
   people = []
   headers = []
   with open("C:/Users/debor/Documents/GitHub/dsc520/Final Project/cox-violent-parsed.csv") as f:
```

```
reader = PeekyReader(DictReader(f))
        try:
            while True:
                p = Person(reader)
                if p.valid:
                    people.append(p)
        except StopIteration:
           pass
       headers = reader.reader.fieldnames
   pop = list(filter(lambda i: (i.recidivist and i.lifetime <= 730) or
                      i.lifetime > 730,
                      filter(lambda x: x.score_valid, people)))
   vpop = list(filter(lambda i: (i.violent_recidivist and i.lifetime <= 730) or</pre>
                       i.lifetime > 730,
                       filter(lambda x: x.vscore_valid, people)))
   write_two_year_file("./compas-scores-two-years.csv", pop,
                        'recidivist', headers)
   write_two_year_file("./compas-scores-two-years-violent.csv", vpop,
                        'violent_recidivist', headers)
if __name__ == "__main__":
   create_two_year_files()
```

## .....

```
people = []
with open("C:/Users/debor/Documents/GitHub/dsc520/Final Project/cox-violent-parsed.csv") as f:
   reader = PeekyReader(DictReader(f))
   try:
        while True:
            p = Person(reader)
            if p.valid:
                people.append(p)
    except StopIteration:
        pass
pop = list(filter(lambda i: ((i.recidivist == True and i.lifetime <= 730) or
                              i.lifetime > 730), list(filter(lambda x: x.score_valid, people))))
recid = list(filter(lambda i: i.recidivist == True and i.lifetime <= 730, pop))
rset = set(recid)
surv = [i for i in pop if i not in rset]
print("All Defendants:\n")
```

## All Defendants:

```
table(list(recid), list(surv))
##
                Low High
## Survived
                1822
                        803 0.37
## Recidivated 1423
                        3140
                              0.63
## Total: 7188.00
## False positive rate: 30.59
## False negative rate: 31.19
## Specificity: 0.69
## Sensitivity: 0.69
## Prevalence: 0.63
## PPV: 0.80
## NPV: 0.56
## LR+: 2.25
## LR-: 0.45
The test reveals that there is an overall false positive rate of 30.6% for all defendants when comparing
print("Black Defendants:\n")
## Black Defendants:
is_afam = is_race("African-American")
table(list(filter(is_afam, recid)), list(filter(is_afam, surv)))
##
                Low High
## Survived
                684 502 0.30
## Recidivated 638 2138
## Total: 3962.00
## False positive rate: 42.33
## False negative rate: 22.98
## Specificity: 0.58
## Sensitivity: 0.77
## Prevalence: 0.70
## PPV: 0.81
## NPV: 0.52
## LR+: 1.82
## LR-: 0.40
print("\nWhite Defendants:\n")
## White Defendants:
is_white = is_race("Caucasian")
table(list(filter(is_white, recid)), list(filter(is_white, surv)))
##
                Low High
## Survived
               762 208 0.42
## Recidivated 572 775 0.58
```

```
## Total: 2317.00
## False positive rate: 21.44
## False negative rate: 42.46
## Specificity: 0.79
## Sensitivity: 0.58
## Prevalence: 0.58
## PPV: 0.79
## NPV: 0.57
## LR+: 2.68
## LR-: 0.54
print("\nHispanic Defendants:\n")
##
## Hispanic Defendants:
is_hisp = is_race("Hispanic")
table(list(filter(is_hisp, recid)), list(filter(is_hisp, surv)))
##
                Low High
## Survived
                230 60 0.55
## Recidivated 99 134 0.45
## Total: 523.00
## False positive rate: 20.69
## False negative rate: 42.49
## Specificity: 0.79
## Sensitivity: 0.58
## Prevalence: 0.45
## PPV: 0.69
## NPV: 0.70
## LR+: 2.78
## LR-: 0.54
```

It would be easy to assume that COMPAS is biased based on these numbers. However, taking look at the number of cannot conclude based on this that COMPAS is biased against Black people. These numbers do, however,

After reviewing the data for the top 3 population groups it was determined that Black or African Americ