# Predicting Probability of Recidivism for Current Texas Inmates

Is an inmate's initial crime and their age at the time it was committed predictive of recidivism?

# Why do we want to know?

This work is done in an attempt to support any entity that provides services to previously incarcerated individuals.

# Recidivism

The tendency of a convicted criminal to reoffend.

# The Process:



- 1. Research
- 2. Data Collection
- 3. Cleaning, Feature Engineering, & EDA
- 4. Model Fittings & Metrics
- 5. Model Selection& Application
- 6. Summary Statistics

# The Process:



- 1. Research
- 2. Data Collection
- 3. Cleaning, Feature
  - Engineering, & EDA
- 4. Model Fittings & Metrics —
- 5. Model Selection
  - & Application
- 6. Summary Statistics

 Available government datasets.

### 29 datasets found

Survey of Inmates in State and Federal Correctional Facilities, 2004

 $\label{lem:presentative} Department of \textit{Justice} - This survey provides nationally representative data on inmates held in state prisons and federally-owned and operated prisons. Through personal interviews conducted...$ 



Average Daily Inmate Population

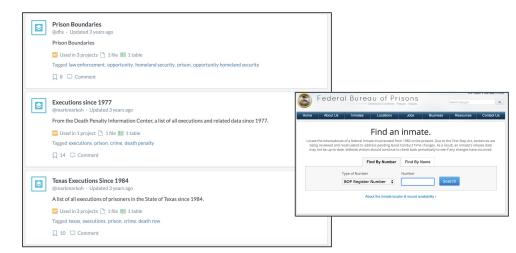
City of New York — Average daily inmate population by fiscal year Note: The data for each of these indicators is based upon year of report, not year of occurrence.



Deaths in Custody Reporting Program: State Prisons 2001 - 2009

 $\label{eq:decomposition} \textit{Department of Justice} - \text{The Deaths in Custody Reporting Program (DCRP) is an annual data collection conducted by the Bureau of Justice Statistics (BJS). The DCRP began in 2000 under the...$ 





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2. The COMPAS algorithm, and ProPublica's work in exposing bias.

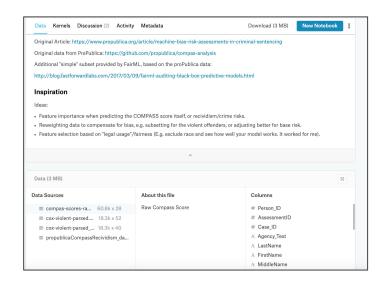
So ProPublica did its own analysis.

#### How We Acquired the Data

We chose to examine the COMPAS algorithm because it is one of the most popular scores used nationwide and is increasingly being used in pretrial and sentencing, the so-called "front-end" of the criminal justice system. We chose Broward County because it is a large jurisdiction using the COMPAS tool in pretrial release decisions and Florida has strong open-records laws.

Through a public records request, ProPublica obtained two years worth of COMPAS scores from the Broward County Sheriff's Office in Florida. We received data for all 18,610 people who were scored in 2013 and 2014.

Because Broward County primarily uses the score to determine whether to release or detain a defendant before his or her trial, we discarded scores that were assessed at parole, probation or other stages in the criminal justice system. That left us with <a href="https://example.com/11,757">11,757</a> people who were assessed at the pretrial stage.



#### **Compas Analysis**

What follows are the calculations performed for ProPublica's analaysis of the COMPAS Recidivism Risk Scores. It might be helpful to open the methodology in another tab to understand the following.

#### Loading the Data

In [1]: # filter dplyr warnings

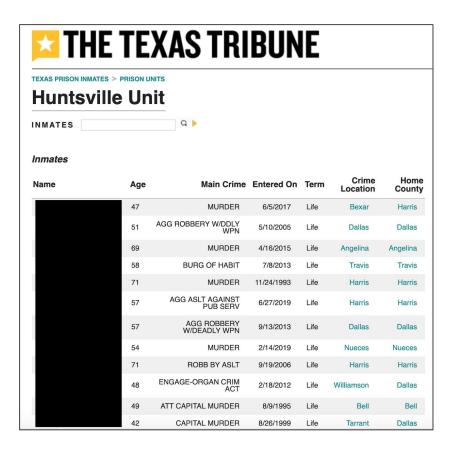
We select fields for severity of charge, number of priors, demographics, age, sex, compas scores, and whether each person was accused of a crime within two years.

```
%load_ext rpy2.ipython
import warnings
warnings.filterwarnings('ignore')

In [2]: %%R
library(dplyr)
library(ggplot2)
   raw_data <- read.csv("./compas-scores-two-years.csv")
   nrow(raw_data)
[1] 7214</pre>
```

3. The Huntsville State Prison





4. The Texas Tribune



# **THE TEXAS TRIBUNE**

**TEXAS PRISON INMATES** 

#### **Prison Units**

Q > INMATES Type + Prisoners + Name Operator \$ Correctional Institutions Allred Prison 3677 Division Correctional Institutions Beto Prison 3315 Division Correctional Institutions Boyd Prison 1332 Division Corrections Corporation of Bradshaw State Jail 1849 America Global Expertise in Outsourcing Bridgeport Prison 520 Correctional Institutions Briscoe Prison 1369 Division Correctional Institutions Byrd 1016 Prison Division Correctional Institutions Chase Field Wilderness Work Program 383 Division Correctional Institutions Clemens Prison 1137 Division Correctional Institutions Prison 3738 Clements Division Global Expertise in Outsourcing Cleveland Prison 513 Correctional Institutions Coffield Prison 4127 Division Correctional Institutions Cole 809 State Jail Division

# **Data Collection**

Web Scraping:

- 1. Beautiful Soup
- 2. Amazon Web Services





Oh, you didn't understand how it worked and you terminated your session, losing all your functions...

Oh, you forgot useful print statements, and you're lost in the abyss of the \* ...

Oh, you didn't embed saving to a .csv within the function, so you have to wait until the entire thing is finished before you can do any work...



Oh, the website updated, adding a prison and reducing the number of inmates by over 1000 during your scrape...

Oh, you didn't incorporate try and except statements for every possible place data could be missing...

Oh, you didn't get overlapping information to validate the merge for each dataset you were scraping...



# What was collected



- Name, TDCJ ID
- The current offense and three most recent priors
- Dates, term lengths, and crimes for each
- Home county, prison unit, DOB, age, race, sex, projected release date

- Only 4 most recent crimes committed per inmate, rather than all crimes for each.
- Only current inmates, not former inmates that have not reoffended.
- Multiple types of facilities, not exclusively prisons.
- No additional inmate information (home zipcode, occupation, family, etc.)
  - \*ethical considerations with this additional information



# Limitations of the data



- 1. Merging the datasets(on a *unique identifier* TDCJ ID)
- 2. Removing nulls for relevant columns
- 3. Finding the first crime committed, and the information connected with this crime for each inmate

```
def find crime(row):
        if row['pr crime 3'] != 'No data':
            return row['pr crime 3']
        elif row['pr crime 2'] != 'No data':
            return row['pr crime 2']
10
11
        elif row['pr crime 1'] != 'No data':
            return row['pr crime 1']
12
13
14
        else:
            return row['pr crime 0']
15
1 df['feature crime'] = df.apply(find crime, axis=1)
```

 Calculating the age of each person at the time of their \*first crime.

feature_term	commit_age	feature_commit_date	DOB
60 years	32.003395	1980-03-03	1948-03-02
60 years	27.294195	1984-08-06	1957-04-21
55 years	16.895624	1994-02-02	1977-03-12
55 years	26.100467	1982-11-28	1956-10-22
55 years	23.359823	1991-09-22	1968-05-13
55 years	54.410426	1994-04-10	1939-11-12



commit\_age = feature\_commit\_date - DOB

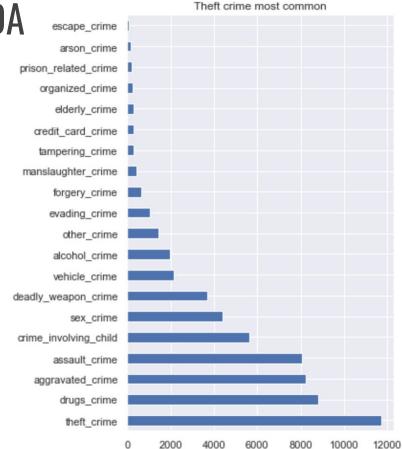
 Converting term lengths of feature crime to floats.

2. Filtered out any observations where the projected release date was more than 30 years from now.

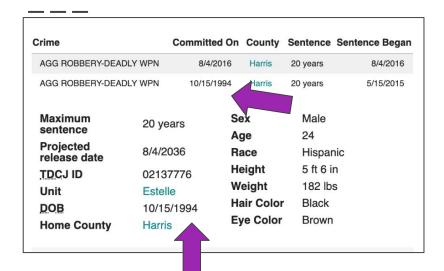
featu	re_term_flt	feature_term
	2.000000	2 years
	30.000000	30 years
	8.000000	8 years
	2.000000	2 years
	30.000000	30 years
	8.000000	8 years
	0.500000	6 months
	1.500000	1 year, 6 months
7	1.416667	1 year, 5 months
	25.000000	25 years
	30.000000	30 years
	1.500000	1 year, 6 months

 Categorical columns for types of crimes

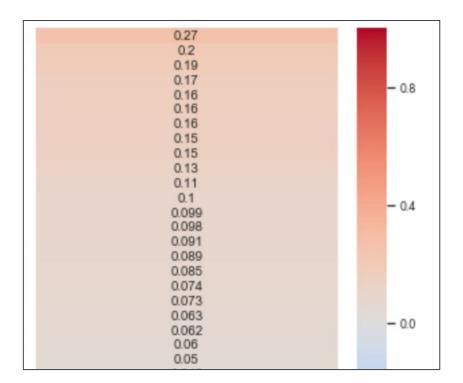
2. Binned age and length of term, also kept as floats for comparison



# **Challenges Discovered**



- .27 highest correlation with target.
- Only 12 features above .10 correlation.
- Incorrect data on the website.
- Target imbalanced classes.



```
1 y.value_counts(normalize=True)

1 0.745561
0 0.254439
Name: final_target, dtype: float64
```

# **Model Selection**

#### Classification Models:

- 1. Support Vector Classifier
- 2. Random Forest
- 3. Logistic Regression

Research for model selection in consideration of imbalanced classes led to the selection of SVC and random forest. I also wanted to do logistic regression to have access to the coefficients.

\*research article <u>link</u>

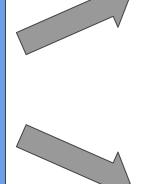
#### For Each Model

### 80% of data

30,160 observations

\*Model instantiated with best params from gridsearch and scored.





22,620 observations

\*Gridsearch on model.

**Internal Train** 

7540 observations

16% of data
Holdout

64% of data

### 20% of data

\*Preds and probas applied.

10,054 Summary statistics.

observations

**Total observations: 40,214** 

# Support Vector Classifier

- Fit model overnight on <u>paid</u> AWS
- Kernel: 'linear'
- Probability: True

- Best score approx .75
- Accidental termination without downloading, I have no proof.



# Random Forest Classifier

- Fit model <= 25 mins</p>
- Best score: .775
- Best params:
  - max\_depth = 10
  - min\_samples\_leaf = 1
  - min\_samples\_split = 4
  - N\_estimators = 150

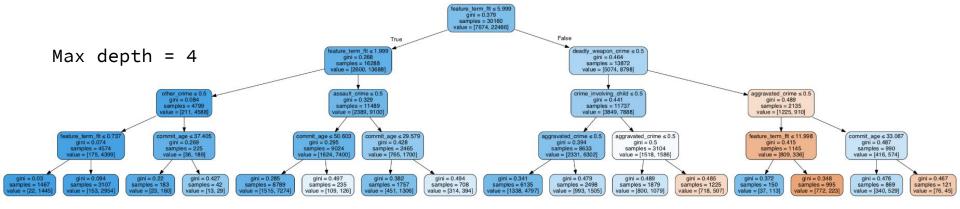
Complete proof on my machine.



	Features
feature_term_flt	0.313261
commit_age	0.171880
deadly_weapon_crime	0.125341
aggravated_crime	0.104854
crime_involving_child	0.076614
assault_crime	0.045037
sex_crime	0.036206
theft_crime	0.035315
manslaughter_crime	0.032380
drugs_crime	0.028337
alcohol_crime	0.006767
vehicle_crime	0.006604
forgery_crime	0.005470

model.feature\_importances\_

# Random Forest - One Decision Tree



Max depth = 10

# Logistic Regression

- Fit model <= 3 mins</pre>
- Best score: .768
- Best params:
  - C = 0.1

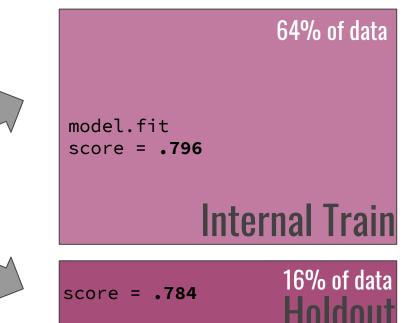
Complete proof on my machine.



	Coefficients	Abs Value
manslaughter_crime	-1.667695	1.667695
forgery_crime	1.575078	1.575078
credit_card_crime	1.072515	1.072515
deadly_weapon_crime	-0.798021	0.798021
vehicle_crime	0.759078	0.759078
drugs_crime	0.691760	0.691760
escape_crime	0.634955	0.634955
theft_crime	0.585717	0.585717
aggravated_crime	-0.571045	0.571045
tampering_crime	0.555448	0.555448
prison_related_crime	0.488335	0.488335
crime_involving_child	-0.429678	0.429678
elderly_crime	-0.304356	0.304356
arson_crime	-0.246226	0.246226
alcohol_crime	0.148257	0.148257
other_crime	0.124011	0.124011
sex_crime	-0.121948	0.121948
evading_crime	0.119084	0.119084
assault_crime	0.117495	0.117495
organized_crime	0.038085	0.038085

### **Random Forest Selected**

```
80% of data
model.fit
score = .794
                       Full Train
```

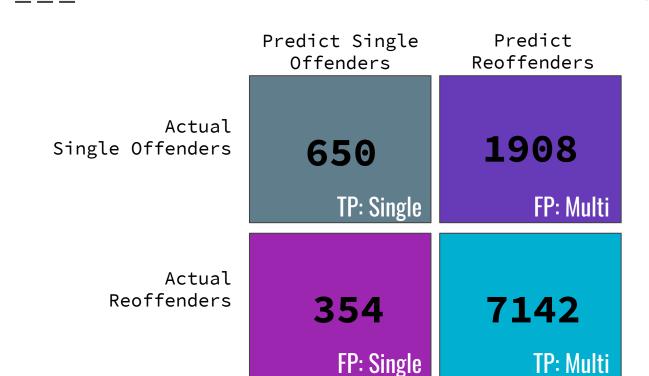


20% of data
internal model.score = .774
full train model.score = .775
Tect

model.score == accuracy

# **Random Forest - Metrics**





2,558

+ 7,496

Total: 10,054

\*confusion matrix <a href="inspo">inspo</a>

## **Random Forest - Metrics**

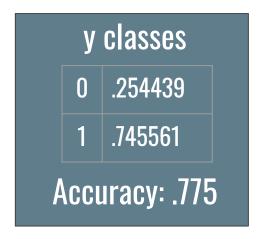
80% of data

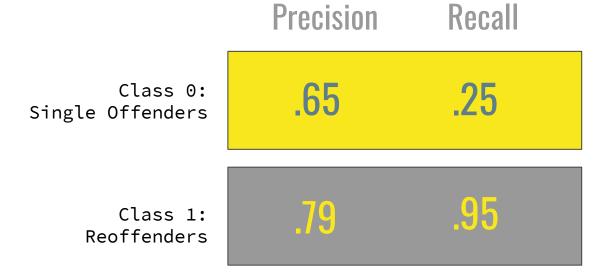
model.fit
score = .794

Full Train

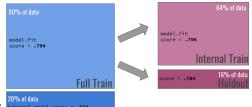
20% of data
internal model.score = .774
full train model.score = .775
full train model.score = .775

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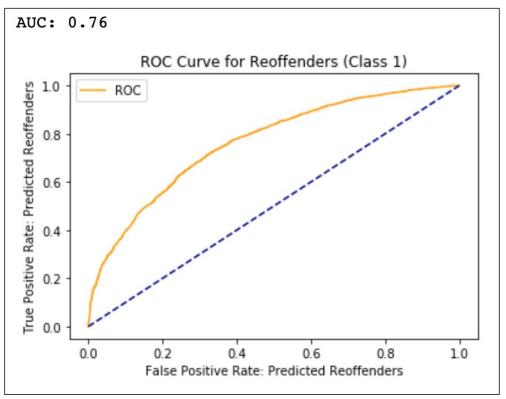




# **Random Forest - Metrics**







# Test Data Set Statistics

Predictions and the people:

- 1. Looking at the numbers
- 2. Range of probability
- 3. Gender/Racial distributions
- 4. Noteworthy findings

# Looking at the Numbers

80% of data

model.fit
score = .794

Full Train

20% of data
internal model.score = .774
full train model.score = .775
Test

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**Probabilities** 

Age (at time crime occurred)

**Projected Release Date** 

Minimum Value Maximum

12

11.4

Aug 2019

Maximum Value

.98

76.5

Aug 2049

# Looking at the Numbers



DCJ Criminal History	,				
Crime		mmitted On	County	Sentence	Sentence Began
FAILURE TO COMPLY W/RE	EG REQ	3/22/2019	Bowie	1 year, 4 months	3/26/2019
HARASS PER CORR FAC	9/12/2008	Anderson	6 years	1/23/2013	
INDEC W/CHILD		5/30/2002	Dallas	10 years	2/8/2004
Maximum sentence	1 years, 4 months		Sex Age	Male 28	
Projected release date	7/22/2020		Race	White	
TDCJ ID Unit DOB Home County	02265728 Jester IV 1/1/1991 Bowie		Height Weight Hair Color Eye Color	5 ft 8 in 162 lbs Red Blue	

## Age (at time crime occurred)

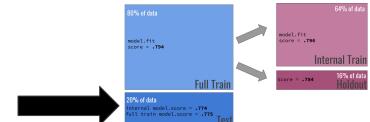
Minimum Value

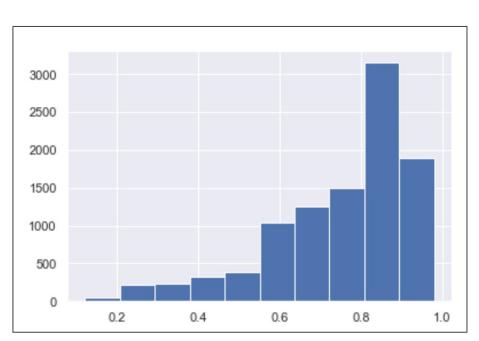
Maximum Value

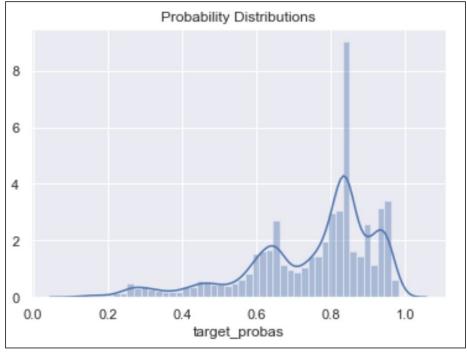
11.4

76.5

# **Probability Distributions**



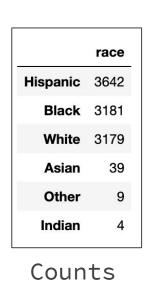


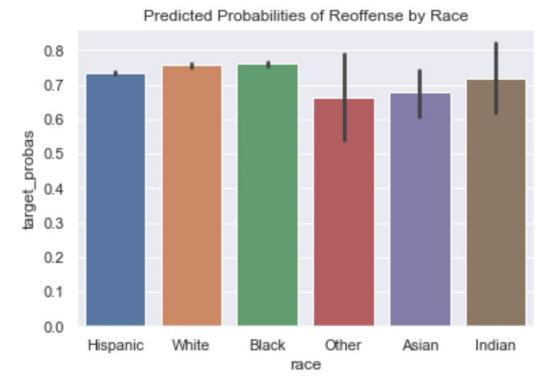


# **Probability Distributions**





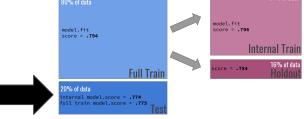




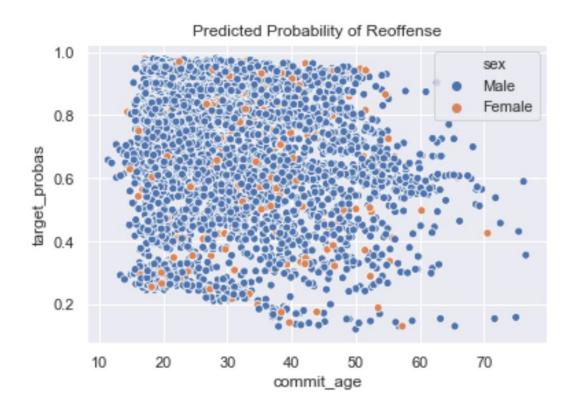
	target_probas
race	
Black	0.759784
White	0.755775
Hispanic	0.734207
Indian	0.718471
Asian	0.677388
Other	0.661585

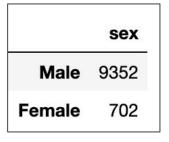
Averages

# **Probability Distributions**



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Counts

# Conclusions

- 1. Practical Application
- 2. Additional considerations

# **Practical Application - Example with Test Dataset**

1. Apply model to complete dataset of interest (ie by prison)

Total observations: 10,054 inmates
Probability Range: .12 - .98

2. Filter by probabilities of interest

Total observations: 3003 Probability Range: .30 - .70

3. Filter by projected release dates

Total observations: 504
Project Release Date Range: 2 years

# Additional Considerations

- Incorporation of other features
- Learning more about options for feature engineering