

Criminal_sentencing

Algorithmic Bias in Criminal Sentencing

Following is an example of data science in Journalism. The purpose of the project is to shed light on how the criminal sentencing by **Correctional Offender Management Profiling for Alternative Sanctions (COMPAS)** is racially biased. The purpose of Journalism is to give voice and by use of such projects it exactly does that.

```
#loading libraries
library(tidyverse)

-- Attaching packages ----- tidyverse 1.3.2 --
v ggplot2 3.3.6      v purrr   0.3.4
v tibble  3.1.8      v dplyr   1.0.10
v tidyr   1.2.0      v stringr 1.4.0
v readr   2.1.2      v forcats 0.5.1
-- Conflicts ----- tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()

library(readr)
library(dplyr)
library(ggplot2)
library(grid)
library(gridExtra)
```

Attaching package: 'gridExtra'

The following object is masked from 'package:dplyr':

combine

```
library(caTools)
```

Warning: package 'caTools' was built under R version 4.2.2

```
library(pROC)
```

Type 'citation("pROC")' for a citation.

Attaching package: 'pROC'

The following objects are masked from 'package:stats':

cov, smooth, var

```
library(caret)
```

Warning: package 'caret' was built under R version 4.2.2

Loading required package: lattice

Attaching package: 'caret'

The following object is masked from 'package:purrr':

lift

```
library(psych)
```

Warning: package 'psych' was built under R version 4.2.2

Attaching package: 'psych'

The following objects are masked from 'package:ggplot2':

%+%, alpha

For the purpose of the project I have taken the dataset from **ProPublica of criminal justice records from Broward County, Florida** and created own risk assessment model.

```
crime<-read.csv("https://raw.githubusercontent.com/propublica/compas-analysis/master/compa
```

```
head(crime)
```

	id		name	first	last	compas_screening_date	sex
1	1	miguel	hernandez	miguel	hernandez	2013-08-14	Male
2	3	kevon	dixon	kevon	dixon	2013-01-27	Male
3	4	ed	philo	ed	philo	2013-04-14	Male
4	5	marcu	brown	marcu	brown	2013-01-13	Male
5	6	bouthy	pierrelouis	bouthy	pierrelouis	2013-03-26	Male
6	7	marsha	miles	marsha	miles	2013-11-30	Male
	dob	age	age_cat		race	juv_fel_count	decile_score
1	1947-04-18	69	Greater than 45		Other	0	1
2	1982-01-22	34	25 - 45	African-American		0	3
3	1991-05-14	24	Less than 25	African-American		0	4
4	1993-01-21	23	Less than 25	African-American		0	8
5	1973-01-22	43	25 - 45	Other		0	1
6	1971-08-22	44	25 - 45	Other		0	1
	juv_misd_count	juv_other_count	priors_count	days_b_screening_arrest			
1	0	0	0	-1			
2	0	0	0	-1			
3	0	1	4	-1			
4	1	0	1	NA			
5	0	0	2	NA			
6	0	0	0	0			
	c_jail_in	c_jail_out	c_case_number	c_offense_date			
1	2013-08-13 06:03:42	2013-08-14 05:41:20	13011352CF10A	2013-08-13			
2	2013-01-26 03:45:27	2013-02-05 05:36:53	13001275CF10A	2013-01-26			
3	2013-04-13 04:58:34	2013-04-14 07:02:04	13005330CF10A	2013-04-13			
4			13000570CF10A	2013-01-12			
5			12014130CF10A				
6	2013-11-30 04:50:18	2013-12-01 12:28:56	13022355MM10A	2013-11-30			
	c_arrest_date	c_days_from_compas	c_charge_degree				
1			1	F			
2			1	F			
3			1	F			
4			1	F			
5	2013-01-09	76		F			
6		0		M			
	c_charge_desc	is_recid	r_case_number	r_charge_degree			
1	Aggravated Assault w/Firearm	0					
2	Felony Battery w/Prior Convict	1	13009779CF10A	(F3)			

3	Possession of Cocaine	1	13011511MM10A	(M1)
4	Possession of Cannabis	0		
5	arrest case no charge	0		
6	Battery	0		
	r_days_from_arrest	r_offense_date	r_charge_desc	r_jail_in
1	NA			
2	NA	2013-07-05	Felony Battery (Dom Strang)	
3	0	2013-06-16	Driving Under The Influence	2013-06-16
4	NA			
5	NA			
6	NA			
	r_jail_out	violent_recid	is_violent_recid	vr_case_number
1	NA	0		
2	NA	1	13009779CF10A	(F3)
3	2013-06-16	NA		
4	NA	0		
5	NA	0		
6	NA	0		
	vr_offense_date	vr_charge_desc	type_of_assessment	decile_score.1
1			Risk of Recidivism	1
2	2013-07-05	Felony Battery (Dom Strang)	Risk of Recidivism	3
3			Risk of Recidivism	4
4			Risk of Recidivism	8
5			Risk of Recidivism	1
6			Risk of Recidivism	1
	score_text	screening_date	v_type_of_assessment	v_decile_score
1	Low	2013-08-14	Risk of Violence	1
2	Low	2013-01-27	Risk of Violence	1
3	Low	2013-04-14	Risk of Violence	3
4	High	2013-01-13	Risk of Violence	6
5	Low	2013-03-26	Risk of Violence	1
6	Low	2013-11-30	Risk of Violence	1
	v_screening_date	in_custody	out_custody	priors_count.1
1	2013-08-14	2014-07-07	2014-07-14	0
2	2013-01-27	2013-01-26	2013-02-05	0
3	2013-04-14	2013-06-16	2013-06-16	4
4	2013-01-13			1
5	2013-03-26			2
6	2013-11-30	2013-11-30	2013-12-01	0
	start	end	event	
1	0	327	0	
2	9	159	1	
3	0	63	0	
4	0	1174	0	
5	0	1102	0	
6	1	853	0	
	two_year_recid			
1	0			
2	1			
3	1			

4	0
5	0
6	0

Data Cleaning for the final model i have selected features most relevant for analysis that includes Sex,Race,Prior count, Juvenile felony Count, Juvenile misdemeanor count, Juvenile other count, charge degree, and two year recidivism. Age at charge was calculated from difference of their date of birth and date when they went to jail. The age was categorized to five categories and length of stay at jail was counted by subtracting c_jail_out and c_jail_in. All the NA values were dropped.

```
clean<-crime%>%select("sex","race","priors_count","juv_fel_count","juv_misd_count","juv_ot
clean<-clean%>%select(-c("c_jail_out","c_jail_in","dob"))
```

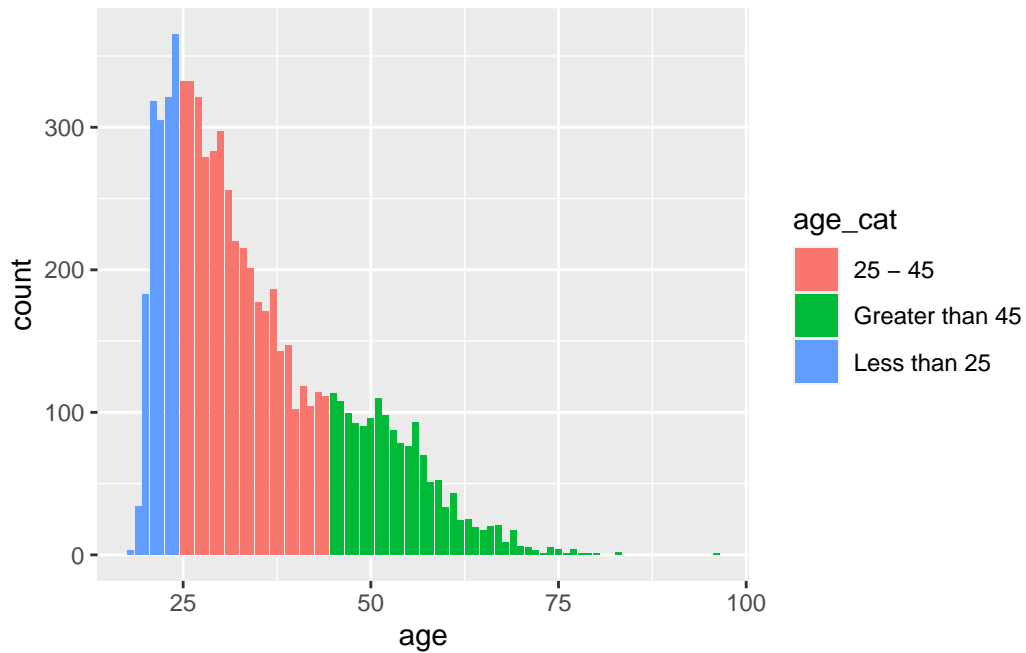
```
for(i in (1:range(nrow(clean)))){
  if (clean$age[i]>16 & clean$age[i]<25){clean$age[i]="[17,24]" }
  if (clean$age[i]>24 & clean$age[i]<32){clean$age[i]="(24,31]" }
  if (clean$age[i]>31 & clean$age[i]<43){clean$age[i]="(31,42]" }
  if (clean$age[i]>42 & clean$age[i]<81){clean$age[i]="(42,80]" }
  if(clean$age[i]>80){clean$age[i]="older"}
}
```

Warning in 1:range(nrow(clean)): numerical expression has 2 elements: only the first used

```
clean<-clean%>%rename(age_cat=age)
```

Exploratory Data Analysis

```
crime%>%ggplot(mapping = aes(x = age, fill=age_cat)) + geom_bar()
```



From the original dataset we can conclude that most recidivism activity was found for 27-40s age group.

```
c1<-clean %>%ggplot(mapping = aes(x = race, fill=as.factor(two_year_recid))) + geom_bar()+
c2<-clean%>%filter(sex=="Female")%>%ggplot(aes(x=race,fill=as.factor(two_year_recid)))+geo
c3<-clean%>%filter(sex=="Male")%>%ggplot(aes(x=race,fill=as.factor(two_year_recid)))+geom_
grid.arrange(c1, c2,c3, ncol = 1,nrow=3)
```

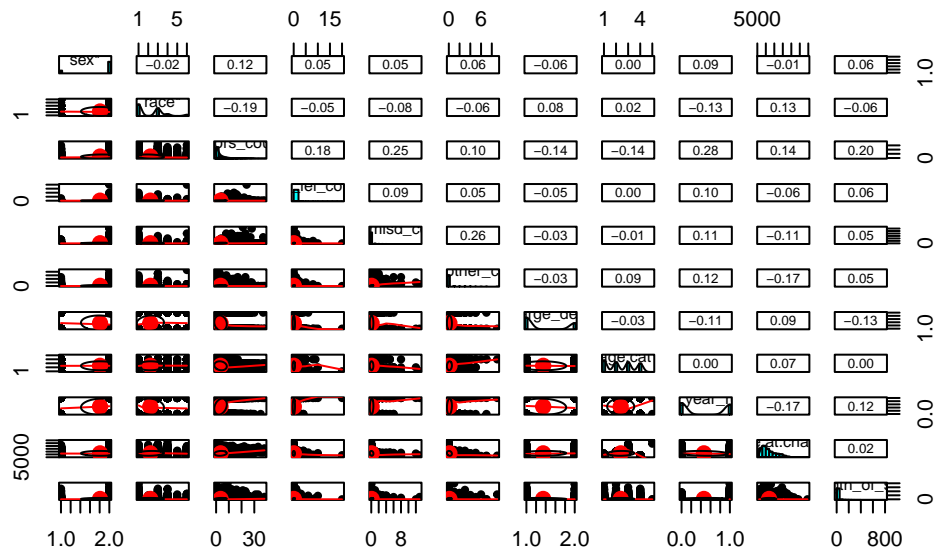


Above graphs represents the analysis of two year recidivism and it is can be clearly concluded that overall more African american have recidivism score than any other races and so is true while doing gender wise analysis. Although difference between second most and first race i.e. Caucasian and African american is less for females when compare to males.

From the above graphs overall recidivism activity was most implicated for people between 24-31 age

Creating correlation matrix

```
pairs.panels(clean)
```



From the correlation matrix we can implicate that the features does not have any significant correlation which is good sign for our model

Creating training and testing datasets Divide train and test in 80-20 ratio

```
index.doc<-sample(x=nrow(crime), size=0.80*nrow(crime))
train_crime<-clean[index.doc,]
test_crime<-clean[-index.doc,]
```

Logistic Regression Model Output variable is taken as two year recidivism score

```
crime_glm<-glm(train_crime$two_year_recid~ .,data=train_crime,family = binomial)
summary(crime_glm)
```

Call:

```
glm(formula = train_crime$two_year_recid ~ ., family = binomial,
     data = train_crime)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.9152	-0.9907	-0.6507	1.0922	2.1251

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	2.284e-01	2.255e-01	1.013	0.311084
sexMale	2.639e-01	7.563e-02	3.490	0.000483 ***
raceAsian	-6.581e-01	4.936e-01	-1.333	0.182417
raceCaucasian	-6.027e-02	6.697e-02	-0.900	0.368120
raceHispanic	-2.402e-01	1.095e-01	-2.194	0.028256 *
raceNative American	1.555e-01	6.505e-01	0.239	0.811017
raceOther	-1.640e-01	1.348e-01	-1.216	0.223878
priors_count	1.503e-01	8.491e-03	17.699	< 2e-16 ***
juv_fel_count	1.934e-01	9.894e-02	1.954	0.050677 .
juv_misd_count	6.885e-02	8.571e-02	0.803	0.421813
juv_other_count	2.365e-01	7.483e-02	3.161	0.001574 **
c_charge_degreeM	-9.238e-02	6.323e-02	-1.461	0.144021
age.cat(31,42]	-2.299e-01	1.049e-01	-2.190	0.028496 *
age.cat(42,80]	6.057e-02	2.095e-01	0.289	0.772504
age.cat[17,24]	2.745e-01	9.292e-02	2.955	0.003132 **
age.catolder	1.433e+01	1.970e+02	0.073	0.942016
age.at.charge	-9.611e-05	2.224e-05	-4.321	1.55e-05 ***
length_of_stay	2.533e-03	6.586e-04	3.846	0.000120 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 7632.4 on 5530 degrees of freedom
Residual deviance: 6742.9 on 5513 degrees of freedom
(240 observations deleted due to missingness)
AIC: 6778.9

Number of Fisher Scoring iterations: 10

Predicting the recidivism score using model on testing dataset

```
predict_crime<-predict(crime_glm,test_crime,type='response')
```

using the sigmoid concept

```
predicted<-ifelse(predict_crime>0.50,1,0)
```

Confusion Matrix

```
confusionMatrix(as.factor(test_crime$two_year_recid),as.factor(predicted))
```

Confusion Matrix and Statistics

	Reference	
Prediction	0	1
0	550	175
1	298	353

Accuracy : 0.6562
95% CI : (0.6305, 0.6814)
No Information Rate : 0.6163
P-Value [Acc > NIR] : 0.00118

Kappa : 0.3038

McNemar's Test P-Value : 2.028e-08

Sensitivity : 0.6486
Specificity : 0.6686
Pos Pred Value : 0.7586
Neg Pred Value : 0.5422
Prevalence : 0.6163
Detection Rate : 0.3997
Detection Prevalence : 0.5269
Balanced Accuracy : 0.6586

'Positive' Class : 0

Sensitivity or True positive rate which is true positive rate the percentage of individuals the model correctly predicted . Here Sensitivity is low that means that model did not correctly predicted the recidivism score i.e. people who should be have high recidivism shouldnt have low recidivism score.

Specificity or true negative rate the percentage of individuals the model correctly predicted would have low risk. For the above model the specificity is low i.e. people who have low recidivism shouldnt have low recidivism score.

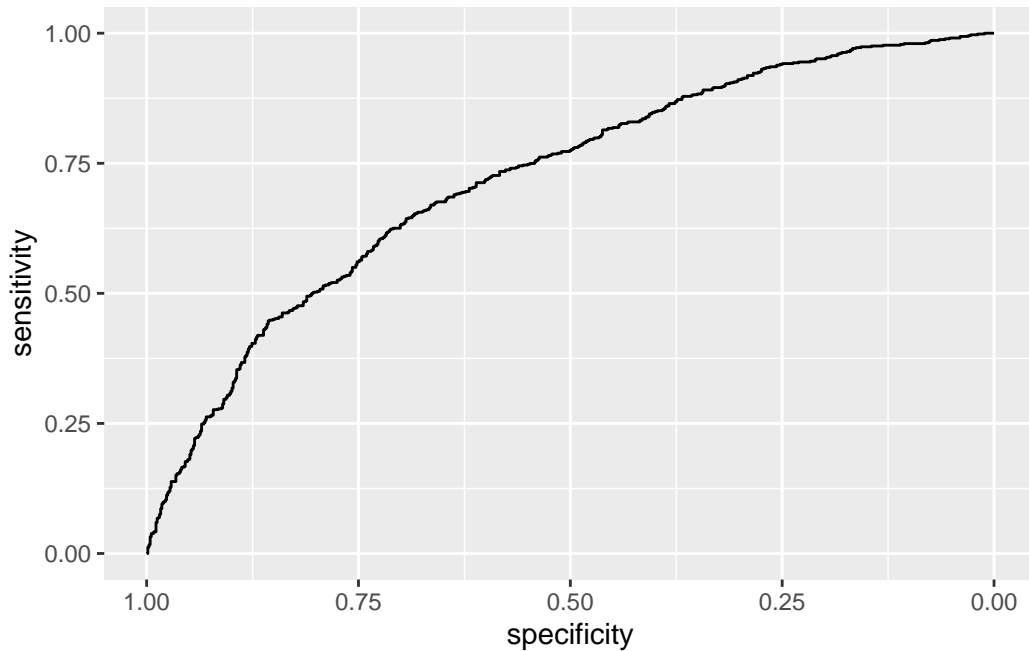
The model also have low accuracy

ROC Curve

```
ggroc(roc(test_crime$two_year_recid,predict_crime))
```

Setting levels: control = 0, case = 1

Setting direction: controls < cases



The ROC Curve of our classification model is bad. A poor classifier will not properly distinguish between the two classes.

Algorithmic Bias

From the evaluation of model it is clearly indicated that the dataset is biased because people of certain race were implicated to higher risk score by model wrongfully, since race and sex are one of the inputs of the dataset as well. To remove the algorithmic bias the basis to train the model should not be such factors.

Conclusion

The model is clearly biased because it takes race and sex as one of its features. As there is a lot of history behind wrongful conviction and suppression of one race by another having such factors in training the model is ethically wrong. Also, the evaluation of model suggests that sizeable people who have low risk score should have high risk score and visa a versa. With

such a model in implementation in real life people can be wrongfully convicted and those who should be convicted just because they belong to certain race are out of consideration.