Title: Discussion on the ethical concerns of COMPASS

Content of the document

1. Problem Statement
2. Data Collection
3. Data Preparation
4. Data Preprocessing
5. Model Assessement (Fairness) & optimization
6. Conclusion
7. References

1. Problem Statement

We are investigating COMPAS, a popular commercial algorithm for predicting reoffending likelihoods (recidivism) for criminal defendants. There has been evidence that the algorithm is biased towards white defendants and against black inmates. Next, use a fairness approach to improve the model.

In order to accomplish this, I need first to explore the data and prepare it, then assess the fairness, then use one of the approaches to optimize it

Here are the steps I will take in this project:

```
1. Data Collection
2. Data Exploration: This will be done to identify the most important features and combine them in new ways.
3. Data Preprocessing: Lay out a pipeline of tasks for transforming data for use in my machine learning model.
4. Model Assessment: Determine the type of descrimination.
6. How to improve the fairness
7. Conclusion & recommendations
```

2. Data Collection

In this step I do two things:

- Identify data sources
- Split the data into training and test sets

Before starting, as a first step, I will call some libraries I need in order to build my model.

In [ ]:
```
# Libraries
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from IPython.display import set_matplotlib_formats
%matplotlib inline
import os
import warnings
from sklearn.model_selection import StratifiedShuffleSplit
```

```python
warnings.filterwarnings("ignore")
from sklearn.datasets import make_regression, make_classification, make_blobs
import sklearn.model_selection
import sklearn.linear_model
```

Source of the data: (kaggle.com, n.d.)

In [3]:
```python
# Load the data from Kaggle Repository
initial_data = pd.read_csv('cox-violent-parsed.csv')

# Examine date structure and return the top 5 rows of the data frame.
initial_data.head(5)
```

Out[3]:

	id	name	first	last	compas_screening_date	sex	dob	age	age_cat	race	...	v_type_of_assessment	v_decile_score	v_score_text	v_screening_date	in_custody	out_custody	priors_count.1	start	end
0	1.0	miguel hernandez	miguel	hernandez	14/08/2013	Male	18/04/1947	69	Greater than 45	Other	...	Risk of Violence	1	Low	14/08/2013	07/07/2014	14/07/2014	0	0	327
1	2.0	miguel hernandez	miguel	hernandez	14/08/2013	Male	18/04/1947	69	Greater than 45	Other	...	Risk of Violence	1	Low	14/08/2013	07/07/2014	14/07/2014	0	334	961
2	3.0	michael ryan	michael	ryan	31/12/2014	Male	06/02/1985	31	25 - 45	Caucasian	...	Risk of Violence	2	Low	31/12/2014	30/12/2014	03/01/2015	0	3	457
3	4.0	kevon dixon	kevon	dixon	27/01/2013	Male	22/01/1982	34	25 - 45	African-American	...	Risk of Violence	1	Low	27/01/2013	26/01/2013	05/02/2013	0	9	159
4	5.0	ed philo	ed	philo	14/04/2013	Male	14/05/1991	24	Less than 25	African-American	...	Risk of Violence	3	Low	14/04/2013	16/06/2013	16/06/2013	4	0	63

5 rows × 52 columns

In the table above, the date columns are displayed in object format

In [4]:
```python
# Convert date columns from object format to time format

# attributes is the list of columns to be converted
attributes= ["in_custody","out_custody","v_screening_date","compas_screening_date", "dob","c_jail_in","c_jail_out","c_offense_date",
             "screening_date","vr_offense_date","r_jail_out","r_jail_in","r_offense_date","c_arrest_date"]

initial_data = pd.read_csv('cox-violent-parsed.csv',parse_dates=attributes)

# Create a copy of the original data
my_data = initial_data.copy()

# Examine my data structure and return the top 5 rows of the data frame.
my_data.head(5)
```

Out[4]:

	id	name	first	last	compas_screening_date	sex	dob	age	age_cat	race	...	v_type_of_assessment	v_decile_score	v_score_text	v_screening_date	in_custody	out_custody	priors_count.1	start	end	ever
0	1.0	miguel hernandez	miguel	hernandez	2013-08-14	Male	1947-04-18	69	Greater than 45	Other	...	Risk of Violence	1	Low	2013-08-14	2014-07-07	2014-07-14	0	0	327	
1	2.0	miguel hernandez	miguel	hernandez	2013-08-14	Male	1947-04-18	69	Greater than 45	Other	...	Risk of Violence	1	Low	2013-08-14	2014-07-07	2014-07-14	0	334	961	
2	3.0	michael ryan	michael	ryan	2014-12-31	Male	1985-06-02	31	25 - 45	Caucasian	...	Risk of Violence	2	Low	2014-12-31	2014-12-30	2015-03-01	0	3	457	
3	4.0	kevon dixon	kevon	dixon	2013-01-27	Male	1982-01-22	34	25 - 45	African-American	...	Risk of Violence	1	Low	2013-01-27	2013-01-26	2013-05-02	0	9	159	
4	5.0	ed philo	ed	philo	2013-04-14	Male	1991-05-14	24	Less than 25	African-American	...	Risk of Violence	3	Low	2013-04-14	2013-06-16	2013-06-16	4	0	63	

5 rows × 52 columns

In [5]:

```
#Check the type data of my attributes
my_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18316 entries, 0 to 18315
Data columns (total 52 columns):
 #   Column                   Non-Null Count  Dtype         
---  ------                   --------------  -----         
 0   id                       11001 non-null  float64       
 1   name                     18316 non-null  object        
 2   first                    18316 non-null  object        
 3   last                     18316 non-null  object        
 4   compas_screening_date    18316 non-null  datetime64[ns]
 5   sex                      18316 non-null  object        
 6   dob                      18316 non-null  datetime64[ns]
 7   age                      18316 non-null  int64         
 8   age_cat                  18316 non-null  object        
 9   race                     18316 non-null  object        
 10  juv_fel_count            18316 non-null  int64         
 11  decile_score             18316 non-null  int64         
 12  juv_misd_count           18316 non-null  int64         
 13  juv_other_count          18316 non-null  int64         
 14  priors_count             18316 non-null  int64         
 15  days_b_screening_arrest  17019 non-null  float64       
 16  c_jail_in                17019 non-null  datetime64[ns]
 17  c_jail_out               17019 non-null  datetime64[ns]
 18  c_case_number            17449 non-null  object        
 19  c_offense_date           14364 non-null  datetime64[ns]
 20  c_arrest_date            3085 non-null   datetime64[ns]
 21  c_days_from_compas       17449 non-null  float64       
 22  c_charge_degree          17449 non-null  object        
 23  c_charge_desc            17435 non-null  object        
 24  is_recid                 18316 non-null  int64         
 25  r_case_number            8417 non-null   object        
 26  r_charge_degree          8417 non-null   object        
 27  r_days_from_arrest       6359 non-null   float64       
 28  r_offense_date           8417 non-null   datetime64[ns]
 29  r_charge_desc            8277 non-null   object        
 30  r_jail_in                6359 non-null   datetime64[ns]
 31  r_jail_out               6359 non-null   datetime64[ns]
 32  violent_recid            0 non-null      float64       
 33  is_violent_recid         18316 non-null  int64         
 34  vr_case_number           1339 non-null   object        
 35  vr_charge_degree         1339 non-null   object        
 36  vr_offense_date          1339 non-null   datetime64[ns]
 37  vr_charge_desc           1339 non-null   object        
 38  type_of_assessment       18316 non-null  object        
 39  decile_score.1           18316 non-null  int64         
 40  score_text               18293 non-null  object        
 41  screening_date           18316 non-null  datetime64[ns]
 42  v_type_of_assessment     18316 non-null  object        
 43  v_decile_score           18316 non-null  int64         
 44  v_score_text             18310 non-null  object        
 45  v_screening_date         18316 non-null  datetime64[ns]
 46  in_custody               17722 non-null  datetime64[ns]
 47  out_custody              17722 non-null  datetime64[ns]
 48  priors_count.1           18316 non-null  int64         
 49  start                    18316 non-null  int64         
 50  end                      18316 non-null  int64         
 51  event                    18316 non-null  int64         
dtypes: datetime64[ns](14), float64(5), int64(14), object(19)
memory usage: 7.3+ MB
```

In [6]:

```
#Check if there are null values in my dataset
my_data_not_nut = my_data.isnull().sum()
```

```
#display non null data
my_data_not_nut[my_data_not_nut>0]
```

Out[6]:

```
id                         7315
days_b_screening_arrest    1297
c_jail_in                  1297
c_jail_out                 1297
c_case_number               867
c_offense_date             3952
c_arrest_date             15231
c_days_from_compas          867
c_charge_degree             867
c_charge_desc               881
r_case_number              9899
r_charge_degree            9899
r_days_from_arrest        11957
r_offense_date             9899
r_charge_desc             10039
r_jail_in                 11957
r_jail_out                11957
violent_recid             18316
vr_case_number            16977
vr_charge_degree          16977
vr_offense_date           16977
vr_charge_desc            16977
score_text                   23
v_score_text                  6
in_custody                  594
out_custody                 594
dtype: int64
```

48% (25 from 51) of the attributes has null values!

The dataset I have has 52 attributes, to make my analysis more efficient I will drop the unecessary ones to my study

In [7]:

```
#List of the attributes I am keeping
needed_attributes = ["id","name","dob","compas_screening_date","c_offense_date","sex","age","age_cat","race","c_charge_degree","c_charge_desc",
"days_b_screening_arrest", "decile_score", "is_recid","r_offense_date", "c_case_number","v_decile_score",
"is_violent_recid","vr_offense_date","score_text"]

#Copy my data in a new variable, to keep the original one untouched
analysis = my_data.loc[:,needed_attributes].copy()
analysis
```

Out[7]:

	id	name	dob	compas_screening_date	c_offense_date	sex	age	age_cat	race	c_charge_degree	c_charge_desc	days_b_screening_arrest	decile_score	is_recid	r_offense_date	c_case_number	v_decile_scc
0	1.0	miguel hernandez	1947-04-18	2013-08-14	2013-08-13	Male	69	Greater than 45	Other	(F3)	Aggravated Assault w/Firearm	-1.0	1	0	NaT	13011352CF10A	
1	2.0	miguel hernandez	1947-04-18	2013-08-14	2013-08-13	Male	69	Greater than 45	Other	(F3)	Aggravated Assault w/Firearm	-1.0	1	0	NaT	13011352CF10A	
2	3.0	michael ryan	1985-06-02	2014-12-31	NaT	Male	31	25 - 45	Caucasian	NaN	NaN	NaN	5	-1	NaT	NaN	
3	4.0	kevon dixon	1982-01-22	2013-01-27	2013-01-26	Male	34	25 - 45	African-American	(F3)	Felony Battery w/Prior Convict	-1.0	3	1	2013-05-07	13001275CF10A	
4	5.0	ed philo	1991-05-14	2013-04-14	2013-04-13	Male	24	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	4	1	2013-06-16	13005330CF10A	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
18311	NaN	alexsandra beauchamps	1984-12-21	2014-12-29	2014-12-28	Female	31	25 - 45	African-American	(M1)	Battery	-1.0	6	0	NaT	14018106MM10A	
18312	NaN	winston gregory	1958-01-10	2014-01-14	2014-01-13	Male	57	Greater than 45	Other	(F2)	Aggravated Battery / Pregnant	-1.0	1	0	NaT	14000581CF10A	
18313	NaN	farrah jean	1982-11-17	2014-09-03	2014-08-03	Female	33	25 - 45	African-American	(M1)	Battery on Law Enforc Officer	-1.0	2	0	NaT	14003308CF10A	
18314	NaN	florencia sanmartin	1992-12-18	2014-06-30	2014-06-28	Female	23	Less than 25	Hispanic	(F3)	Possession of Ethylone	-2.0	4	1	2015-03-15	14008895CF10A	
18315	NaN	florencia sanmartin	1992-12-18	2014-06-30	2014-06-28	Female	23	Less than 25	Hispanic	(F3)	Possession of Ethylone	-2.0	4	1	2015-03-15	14008895CF10A	

18316 rows × 20 columns

In [8]:

```
# Check if my dataset has any duplicates for the same name

analysis.duplicated().sum()
analysis[analysis.duplicated(["name","age","sex","race","dob"],keep=False)]
```

Out[8]:

	id	name	dob	compas_screening_date	c_offense_date	sex	age	age_cat	race	c_charge_degree	c_charge_desc	days_b_screening_arrest	decile_score	is_recid	r_offense_date	c_case_number	v_decile_score
0	1.0	miguel hernandez	1947-04-18	2013-08-14	2013-08-13	Male	69	Greater than 45	Other	(F3)	Aggravated Assault w/Firearm	-1.0	1	0	NaT	13011352CF10A	1
1	2.0	miguel hernandez	1947-04-18	2013-08-14	2013-08-13	Male	69	Greater than 45	Other	(F3)	Aggravated Assault w/Firearm	-1.0	1	0	NaT	13011352CF10A	1
4	5.0	ed philo	1991-05-14	2013-04-14	2013-04-13	Male	24	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	4	1	2013-06-16	13005330CF10A	3
5	6.0	ed philo	1991-05-14	2013-04-14	2013-04-13	Male	24	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	4	1	2013-06-16	13005330CF10A	3
6	7.0	ed philo	1991-05-14	2013-04-14	2013-04-13	Male	24	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	4	1	2013-06-16	13005330CF10A	3
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
18306	NaN	raheem smith	1995-06-28	2013-10-20	2013-10-19	Male	20	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	9	0	NaT	13014650CF10A	9
18307	NaN	raheem smith	1995-06-28	2013-10-20	2013-10-19	Male	20	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	9	0	NaT	13014650CF10A	9
18308	NaN	raheem smith	1995-06-28	2013-10-20	2013-10-19	Male	20	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	9	0	NaT	13014650CF10A	9
18314	NaN	florencia sanmartin	1992-12-18	2014-06-30	2014-06-28	Female	23	Less than 25	Hispanic	(F3)	Possession of Ethylone	-2.0	4	1	2015-03-15	14008895CF10A	4
18315	NaN	florencia sanmartin	1992-12-18	2014-06-30	2014-06-28	Female	23	Less than 25	Hispanic	(F3)	Possession of Ethylone	-2.0	4	1	2015-03-15	14008895CF10A	4

11423 rows × 20 columns

The data has many multiple duplicates.

In [9]:

```
# remove duplication of the same case, every case should be represented one time
analysis_ND=analysis.drop_duplicates(subset='c_case_number',keep='last')
analysis_ND
```

Out[9]:

	id	name	dob	compas_screening_date	c_offense_date	sex	age	age_cat	race	c_charge_degree	c_charge_desc	days_b_screening_arrest	decile_score	is_recid	r_offense_date	c_case_number	v_decile_sco
1	2.0	miguel hernandez	1947-04-18	2013-08-14	2013-08-13	Male	69	Greater than 45	Other	(F3)	Aggravated Assault w/Firearm	-1.0	1	0	NaT	13011352CF10A	
3	4.0	kevon dixon	1982-01-22	2013-01-27	2013-01-26	Male	34	25 - 45	African-American	(F3)	Felony Battery w/Prior Convict	-1.0	3	1	2013-05-07	13001275CF10A	
8	9.0	ed philo	1991-05-14	2013-04-14	2013-04-13	Male	24	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	4	1	2013-06-16	13005330CF10A	
9	10.0	marcu brown	1993-01-21	2013-01-13	2013-12-01	Male	23	Less than 25	African-American	(F3)	Possession of Cannabis	NaN	8	0	NaT	13000570CF10A	
10	11.0	bouthy pierrelouis	1973-01-22	2013-03-26	NaT	Male	43	25 - 45	Other	(F7)	arrest case no charge	NaN	1	0	NaT	12014130CF10A	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
18310	NaN	malcolm simmons	1993-03-25	2014-01-02	2014-01-31	Male	23	Less than 25	African-American	(F3)	Leaving the Scene of Accident	-1.0	3	0	NaT	14001422CF10A	
18311	NaN	alexsandra beauchamps	1984-12-21	2014-12-29	2014-12-28	Female	31	25 - 45	African-American	(M1)	Battery	-1.0	6	0	NaT	14018106MM10A	
18312	NaN	winston gregory	1958-01-10	2014-01-14	2014-01-13	Male	57	Greater than 45	Other	(F2)	Aggravated Battery / Pregnant	-1.0	1	0	NaT	14000581CF10A	
18313	NaN	farrah jean	1982-11-17	2014-09-03	2014-08-03	Female	33	25 - 45	African-American	(M1)	Battery on Law Enforc Officer	-1.0	2	0	NaT	14003308CF10A	
18315	NaN	florencia sanmartin	1992-12-18	2014-06-30	2014-06-28	Female	23	Less than 25	Hispanic	(F3)	Possession of Ethylone	-2.0	4	1	2015-03-15	14008895CF10A	

10310 rows × 20 columns

after applying drop duplicate, 1123 Rows deleted from the dataset, now I have only 10310 case remaining

My next step would be prepare my data for analysis

2. Preparing dataset for analysis

Before starting to prepare my data, I remove both the attributes name and dob

In [10]:
```
# Drop the attributes name and dob because they will not impact my study
analysis_ND = analysis_ND.drop("dob", axis=1)
analysis_ND = analysis_ND.drop("name", axis=1)
analysis_ND
```

Out[10]:

	id	compas_screening_date	c_offense_date	sex	age	age_cat	race	c_charge_degree	c_charge_desc	days_b_screening_arrest	decile_score	is_recid	r_offense_date	c_case_number	v_decile_score	is_violent_recid
1	2.0	2013-08-14	2013-08-13	Male	69	Greater than 45	Other	(F3)	Aggravated Assault w/Firearm	-1.0	1	0	NaT	13011352CF10A	1	0
3	4.0	2013-01-27	2013-01-26	Male	34	25 - 45	African-American	(F3)	Felony Battery w/Prior Convict	-1.0	3	1	2013-05-07	13001275CF10A	1	1
8	9.0	2013-04-14	2013-04-13	Male	24	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	4	1	2013-06-16	13005330CF10A	3	0
9	10.0	2013-01-13	2013-12-01	Male	23	Less than 25	African-American	(F3)	Possession of Cannabis	NaN	8	0	NaT	13000570CF10A	6	0
10	11.0	2013-03-26	NaT	Male	43	25 - 45	Other	(F7)	arrest case no charge	NaN	1	0	NaT	12014130CF10A	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
18310	NaN	2014-01-02	2014-01-31	Male	23	Less than 25	African-American	(F3)	Leaving the Scene of Accident	-1.0	3	0	NaT	14001422CF10A	5	0
18311	NaN	2014-12-29	2014-12-28	Female	31	25 - 45	African-American	(M1)	Battery	-1.0	6	0	NaT	14018106MM10A	4	0
18312	NaN	2014-01-14	2014-01-13	Male	57	Greater than 45	Other	(F2)	Aggravated Battery / Pregnant	-1.0	1	0	NaT	14000581CF10A	1	0
18313	NaN	2014-09-03	2014-08-03	Female	33	25 - 45	African-American	(M1)	Battery on Law Enforc Officer	-1.0	2	0	NaT	14003308CF10A	2	0
18315	NaN	2014-06-30	2014-06-28	Female	23	Less than 25	Hispanic	(F3)	Possession of Ethylone	-2.0	4	1	2015-03-15	14008895CF10A	4	0

10310 rows × 18 columns

1. Keep only rows that has a case number and has an id

In [11]:

```
# keep only rows with a case number
analysis_ND = analysis_ND[analysis_ND["c_case_number"] != "NaN"]
```

In [12]:

```
# remove all rows with any NaN and NaT values
#analysis_ND =  analysis_ND.dropna()
analysis_ND = analysis_ND.dropna( how='any', subset=['id'])
analysis_ND
```

Out[12]:

	id	compas_screening_date	c_offense_date	sex	age	age_cat	race	c_charge_degree	c_charge_desc	days_b_screening_arrest	decile_score	is_recid	r_offense_date	c_case_number	v_decile_score	is_viol
1	2.0	2013-08-14	2013-08-13	Male	69	Greater than 45	Other	(F3)	Aggravated Assault w/Firearm	-1.0	1	0	NaT	13011352CF10A	1	
3	4.0	2013-01-27	2013-01-26	Male	34	25 - 45	African-American	(F3)	Felony Battery w/Prior Convict	-1.0	3	1	2013-05-07	13001275CF10A	1	
8	9.0	2013-04-14	2013-04-13	Male	24	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	4	1	2013-06-16	13005330CF10A	3	
9	10.0	2013-01-13	2013-12-01	Male	23	Less than 25	African-American	(F3)	Possession of Cannabis	NaN	8	0	NaT	13000570CF10A	6	
10	11.0	2013-03-26	NaT	Male	43	25 - 45	Other	(F7)	arrest case no charge	NaN	1	0	NaT	12014130CF10A	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
10989	10990.0	2013-03-18	2013-03-17	Male	34	25 - 45	African-American	(F3)	Possession Of Alprazolam	-1.0	9	1	2013-05-20	13003878CF10A	4	
10992	10993.0	2013-03-22	2013-03-22	Male	23	Less than 25	African-American	(F3)	Poss3,4 Methylenedioxymethcath	0.0	9	0	NaT	13004155CF10A	9	
10994	10995.0	2014-04-28	NaT	Female	31	25 - 45	African-American	(F1)	arrest case no charge	-3.0	4	0	NaT	14005707CF10A	5	
10996	10997.0	2013-08-02	2013-07-02	Male	30	25 - 45	Hispanic	(F3)	Poss Unlaw Issue Driver Licenc	0.0	2	1	2014-07-06	13001942CF10A	2	
10997	10998.0	2014-02-24	2014-02-23	Male	52	Greater than 45	African-American	(F3)	Tampering With Physical Evidence	-1.0	1	0	NaT	14002552CF10A	1	

6204 rows × 18 columns

1. I want explore how long people take to be charge for a crime and see if I can filter my selection for cases

In [13]:
```
#Check how long arrested people take to be charged for a crime
analysis_ND["days_b_screening_arrest"].describe()
```

Out[13]:
```
count    5942.000000
mean       -0.120498
std        74.925514
min      -578.000000
25%        -1.000000
50%        -1.000000
75%        -1.000000
max      1040.000000
Name: days_b_screening_arrest, dtype: float64
```

More than 75% have less than -1 and with -597 as minimum to keep only quality data, we will limit my analysis on crimes charger within 30 days of arrest

In [14]:
```
# Keep only crimes charged within 30 days of arrest.
analysis_ND = analysis_ND.loc[(analysis_ND["days_b_screening_arrest"] > -30) & (analysis_ND["days_b_screening_arrest"] <30)]
```

1. Since my purpose is evalute Compass, I will remove all the cases that has the crime after the compass screening

In [15]:
```
# Remove cases where the date of crime is after copmas screening
analysis_ND = analysis_ND[analysis_ND["c_offense_date"] < analysis_ND["compas_screening_date"]]
```

1. Now, I will create 3 groups: Age, Race and Score using CategoricalDtype

In [16]:
```
# Group 1: Age
grp_age = pd.CategoricalDtype(categories=["Less than 25","25 - 45","Greater than 45"],ordered=True)
analysis_ND["age_cat"] = analysis_ND["age_cat"].astype(grp_age)

# Group 2: Race
grp_race = pd.CategoricalDtype(categories=['African-American','Caucasian','Hispanic',"Other",'Asian',
'Native American'],ordered=True)
analysis_ND["race"] = analysis_ND["race"].astype(grp_race)

# Group 3: Score
grp_score = pd.CategoricalDtype(categories=["Low","Medium","High"],ordered=True)
analysis_ND["score_text"] = analysis_ND["score_text"].astype(grp_score)
```

In [17]:
```
#convert the attributes between "Sex" and "c_charge_degree" to categories with the function astype

for att in ["sex","c_charge_degree"]:
    analysis_ND[att] = analysis_ND[att].astype("category")
```

1. Remove all the rows that has empty value for the attribute score_text

In [18]:
```
#remove rows with score text equals NaN
analysis_ND = analysis_ND[analysis_ND["score_text"] != "NaN"]
```

In [19]:
```
#I will not consider traffic tickets & munipal violations as repeated offense (charge degree equals O)
#analysis_ND = analysis_ND[analysis_ND["c_charge_degree"] != "O"]
```

1. I want to know since when the Compass screening happened for both ordinary and violent offenses (I call both variables 2y_r and 2y_v), to do that I first substract the columns of time, then I assign 3 different values for every case:
   - 0: the offender didnot commit any crime since 1st arrest
   - 1: the offender committed a new crime in less than 2 years
   - 2: the offender committed a new crime after 2 years

In [20]:
```
# I will call my function nbr_offenses
def nbr_offenses(att,recid):

    # Subtract the columns of time
    analysis_ND["days"] = analysis_ND[att] - analysis_ND["compas_screening_date"]

    # Convert the output to an integer by using the .days parameter
    analysis_ND["days"] = analysis_ND["days"].apply(lambda x:x.days)

    # Assign the values 0, 1 and 2
    analysis_ND["offence"] = np.where(analysis_ND[recid]==0,0,
                np.where((analysis_ND[recid]==1) & (analysis_ND["days"] < 730),1,2))

    return analysis_ND["offence"]
```

In [21]:
```
# calcualte both 2y_r and 2y_v
analysis_ND["2y_r"] = nbr_offenses("r_offense_date","is_recid")
analysis_ND["2y_v"] = nbr_offenses("vr_offense_date","is_violent_recid")
```

1. I want to foucs only on offenders who didnot or did repeat crime in less then 2 years, so I will remove Offenders who has 2y_r and 2y_v equals 2

In [22]:
```
# remove offenders who committed new ordinary crimes after 2 years
analysis_nd_r = analysis_ND[analysis_ND["2y_r"] !=2].copy()

# remove offenders who committed new violent crimes after 2 years
analysis_nd_v = analysis_ND[analysis_ND["2y_v"] != 2].copy()
```

In [23]:
```
# reset the index to  make it easier for me to work with the dataset
analysis_nd_r.reset_index(drop=True,inplace=True)
analysis_nd_v.reset_index(drop=True,inplace=True)
```

1. In order to make data extraction easier, I add another 2 new attributes:
   - **Attribute 1 :** devide cases in 2 categories based on the score using binary values, so if the score >5, the case category will be 1, if the score is lower than 5 the case category will be 0
   - **Attribute 2 :** This attribute will help me know if the prediction of Compass was correct or wrong, so if it is "True", the prediction of Compass was correct, if "False" the prediction was wrong

In [24]:
```
#Attribute 1: grouping cases in 2 categories (high score (>=5 and low score <5))
analysis_nd_r["binary_score"] = np.where(analysis_nd_r["decile_score"] >=5,1,0)
analysis_nd_v["binary_v_score"] = np.where(analysis_nd_v["v_decile_score"] >=5,1,0)
```

In [25]:
```
# Attribute 2: if the prediction is correct return True,else return false

# For ordinary offense
analysis_nd_r["prediction_recid"] = analysis_nd_r['is_recid'] == analysis_nd_r["binary_score"]

# For violent offense
analysis_nd_v["prediction_vrecid"] = analysis_nd_v['is_violent_recid'] == analysis_nd_v["binary_v_score"]
```

In [26]:
```
# Index reset
analysis_nd_r.reset_index(drop=True,inplace=True)
analysis_nd_v.reset_index(drop=True,inplace=True)
```

In [27]:
```
#Checking the new values
analysis_nd_r.head(3)
```

Out[27]:

	id	compas_screening_date	c_offense_date	sex	age	age_cat	race	c_charge_degree	c_charge_desc	days_b_screening_arrest	...	v_decile_score	is_violent_recid	vr_offense_date	score_text	days	offence	2y_r	2y_v	bina
0	2.0	2013-08-14	2013-08-13	Male	69	Greater than 45	Other	(F3)	Aggravated Assault w/Firearm	-1.0	...	1	0	NaT	Low	NaN	0	0	0	
1	4.0	2013-01-27	2013-01-26	Male	34	25 - 45	African-American	(F3)	Felony Battery w/Prior Convict	-1.0	...	1	1	2013-05-07	Low	100.0	1	1	1	
2	9.0	2013-04-14	2013-04-13	Male	24	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	...	3	0	NaT	Low	NaN	0	1	0	

3 rows × 24 columns

In [28]:
```
analysis_nd_v.head(3)
```

Out[28]:

	id	compas_screening_date	c_offense_date	sex	age	age_cat	race	c_charge_degree	c_charge_desc	days_b_screening_arrest	...	v_decile_score	is_violent_recid	vr_offense_date	score_text	days	offence	2y_r	2y_v	bina
0	2.0	2013-08-14	2013-08-13	Male	69	Greater than 45	Other	(F3)	Aggravated Assault w/Firearm	-1.0	...	1	0	NaT	Low	NaN	0	0	0	
1	4.0	2013-01-27	2013-01-26	Male	34	25 - 45	African-American	(F3)	Felony Battery w/Prior Convict	-1.0	...	1	1	2013-05-07	Low	100.0	1	1	1	
2	9.0	2013-04-14	2013-04-13	Male	24	Less than 25	African-American	(F3)	Possession of Cocaine	-1.0	...	3	0	NaT	Low	NaN	0	1	0	

3 rows × 24 columns

Now my data is ready for the exporatory analysis

3. Data Exploration

In this step, I will be exploring my data to understand more about: the relationship between the crime, race, gender, age and the frequent commited crimes

In [29]:
```
# check data
analysis_nd_r.describe().T
```

Out[29]:

	count	mean	std	min	25%	50%	75%	max
id	3527.0	5511.070031	3171.661078	2.0	2703.0	5531.0	8284.0	10998.0
age	3527.0	34.908704	12.090702	18.0	25.0	32.0	42.0	96.0
days_b_screening_arrest	3527.0	-1.666005	4.413039	-29.0	-1.0	-1.0	-1.0	29.0
decile_score	3527.0	4.199036	2.843142	-1.0	2.0	4.0	6.0	10.0
is_recid	3527.0	0.322937	0.467665	0.0	0.0	0.0	1.0	1.0
v_decile_score	3527.0	3.442586	2.444397	-1.0	1.0	3.0	5.0	10.0
is_violent_recid	3527.0	0.074568	0.262730	0.0	0.0	0.0	0.0	1.0
days	263.0	314.019011	250.267909	-218.0	123.5	295.0	489.0	1046.0
offence	3527.0	0.078537	0.283426	0.0	0.0	0.0	0.0	2.0
2y_r	3527.0	0.322937	0.467665	0.0	0.0	0.0	1.0	1.0
2y_v	3527.0	0.078537	0.283426	0.0	0.0	0.0	0.0	2.0
binary_score	3527.0	0.410547	0.492003	0.0	0.0	0.0	1.0	1.0

As shown in the table above, from the ordinary 3527 cases:

- 75% of the cases assessed by compass got score 6
- 75% of the offenders are above 42 years old where 32% are recidivists and 7 % are violent recidivist

In [30]:
```
analysis_nd_r.describe(include=["object","category"]).T
```

Out[30]:

	count	unique	top	freq
sex	3527	2	Male	2791
age_cat	3527	3	25 - 45	1978
race	3527	6	African-American	1725
c_charge_degree	3527	12	(F3)	1907
c_charge_desc	3526	321	Battery	737
c_case_number	3527	3527	13011352CF10A	1
score_text	3523	3	Low	2075

From the table above, we notice:

- One of the most common cases is Battery with charge degree F3 with the main race African Americans
- TMost reported cases are from males aging between 25 and 45

After cleaning data, and preparing it, now I will apply SVM to classify it

3.1 Explore Race

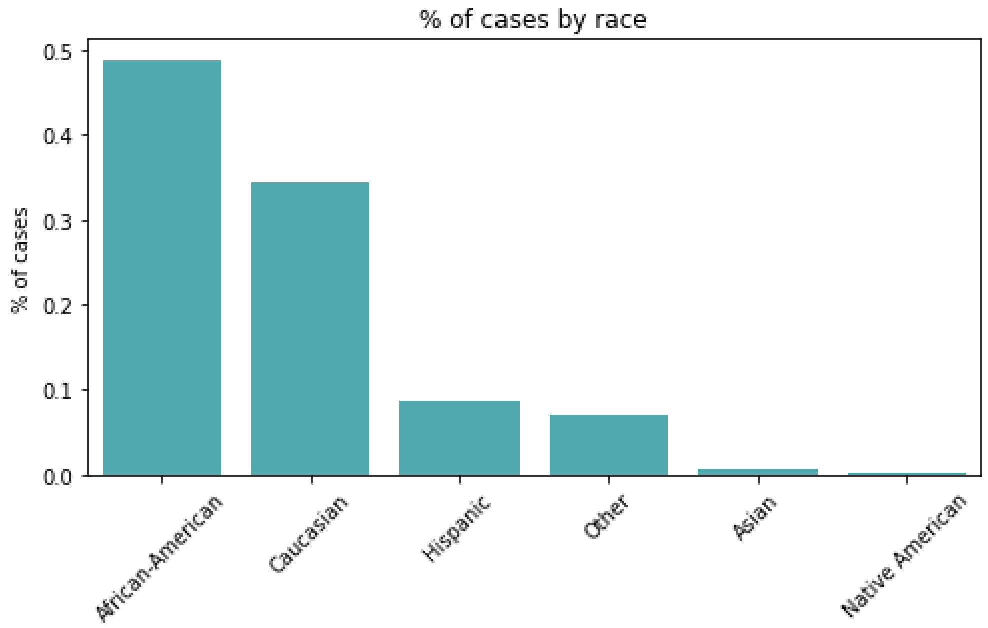
{change me}

- **th race, when looking at the statistics, we must always keep in mind that there is very little data on Asians and Native Americans (a good idea would be to group them together with Other in a single category to make it more representative).**
    - **In general, we realize that almost 50% of the cases belong to African Americans and they are also the ones with the highest percentage of recidivism (almost 40% of the cases are African American).**
    - **This is important because the dataset is not balanced and can be very biased due to the predominance of this ethnic group.**

In [31]:

```
race_g = analysis_nd_r["race"].value_counts(normalize=True,ascending=False).reset_index()

plt.figure(figsize=(8,4))
sns.barplot(x=race_g["index"],y=race_g["race"],color='#42b7bd')
plt.xticks(rotation=45)
plt.xlabel("")
plt.ylabel("% of cases")
plt.title("% of cases by race")
plt.show(block=False)
```



- **50% of the cases belong to African-Americans, 35% to Caucasian, and the rest is below 1%**

In [32]:
```
analysis_nd_r.groupby("race",as_index=False)["2y_r"].mean().style.background_gradient(cmap='Reds',axis=0)
```

Out[32]:

	race	2y_r
0	African-American	0.385507
1	Caucasian	0.279376
2	Hispanic	0.231270
3	Other	0.240816
4	Asian	0.173913
5	Native American	0.000000

- **For Recidivism rate, 39 % of African Americans are recidivist and for Caucasian 28%**

In [33]:
```
##Obtain percentages by rows with normalize
pd.crosstab(analysis_nd_r["race"],analysis_nd_r["age_cat"],normalize=0).style.background_gradient(cmap='Oranges',axis=1)
```

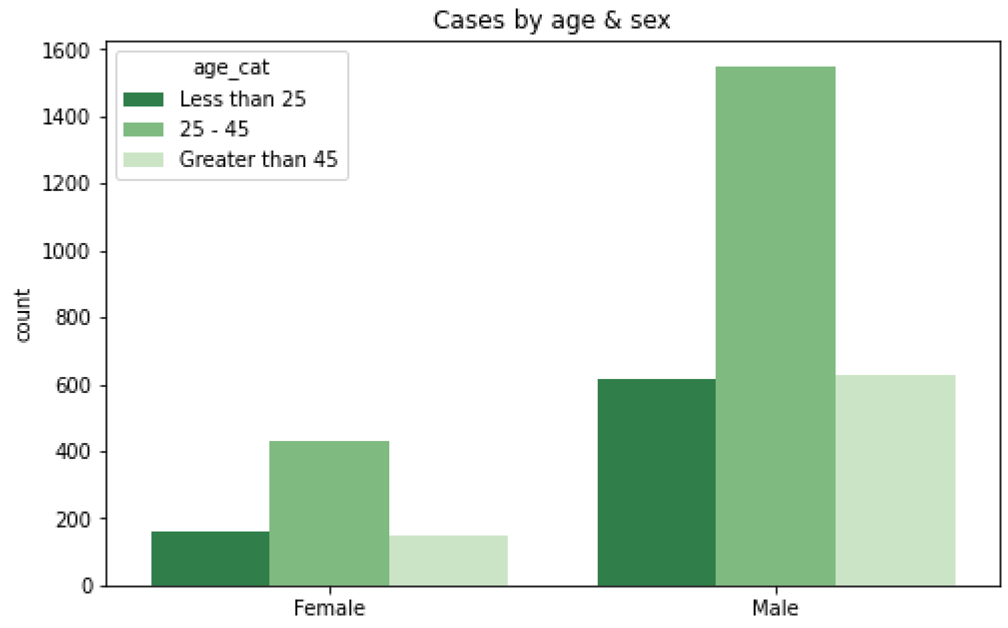
Out[33]:

age_cat	Less than 25	25 - 45	Greater than 45
race			
African-American	0.267826	0.572174	0.160000
Caucasian	0.156943	0.548069	0.294988
Hispanic	0.198697	0.540717	0.260586
Other	0.220408	0.567347	0.212245
Asian	0.217391	0.565217	0.217391
Native American	0.100000	0.600000	0.300000

- **From the table above, we notice that the predominant age for the different races is between 25 and 45**

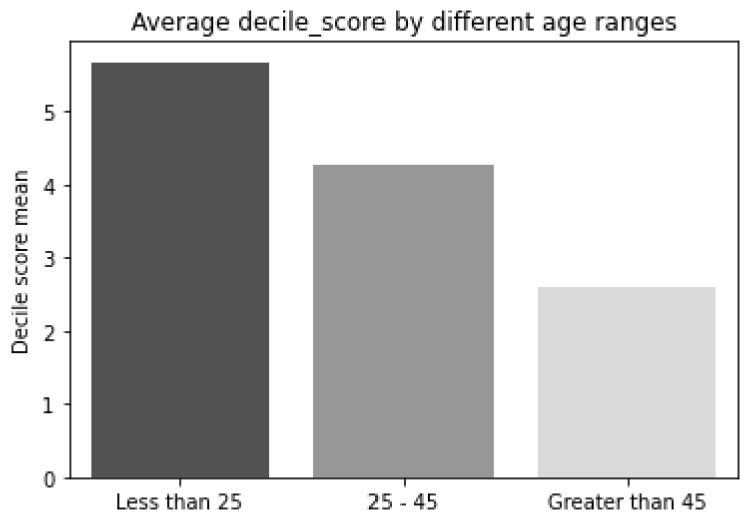
3.2 Explore link between sex and age

In [34]:
```
plt.figure(figsize=(8,5))
sns.countplot(data=analysis_nd_r,x="sex",hue="age_cat",palette="Greens_r")
plt.title("Cases by age & sex")
plt.xlabel("")
plt.show(block=False)
```



Females are secondary compared to males

In [35]:
```
decile_mean_age = analysis_nd_r.groupby("age_cat")["decile_score"].mean().reset_index()
sns.barplot(data=decile_mean_age,x="age_cat",y="decile_score",palette="Greys_r")
plt.ylabel("Decile score mean")
plt.xlabel("")
plt.title("Average decile_score by different age ranges")
plt.show(block=False)
```

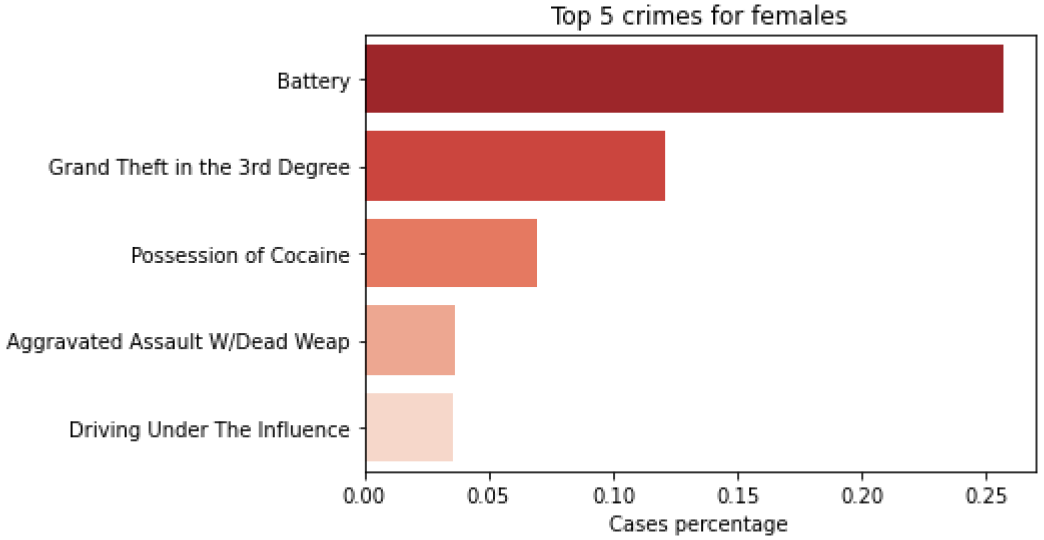


- **There is a correlation between age and decile score, the younger the person, the more penalized is.**

3.3 Type of crime per sex (gender)

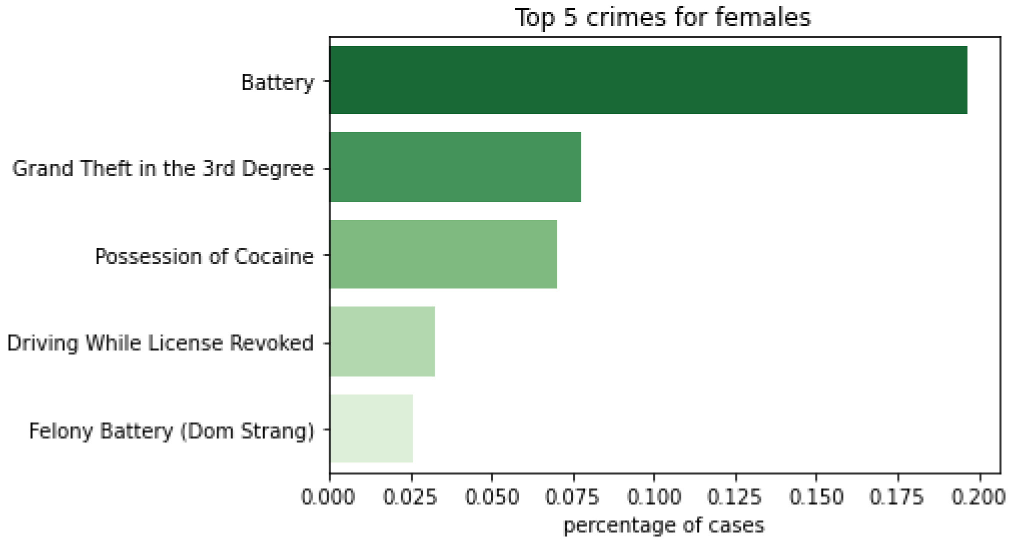
I focus, because of their great variety, only on the 10 most typical. Many could be grouped by type of crime (drugs, vehicle, robbery and assault...) to facilitate the study of the data.

In [36]:
```
#Top 5 crimes for women
female_crime = analysis_nd_r[analysis_nd_r["sex"]=="Female"]["c_charge_desc"].value_counts(normalize=True,ascending=False)[:5].reset_index()
sns.barplot(data=female_crime,x="c_charge_desc",y="index",palette="Reds_r")
plt.title("Top 5 crimes for females")
plt.ylabel("")
plt.xlabel("Cases percentage")
plt.show(block=False)
```



In [37]:
```
#Top 5 crimes for men
male_crime= analysis_nd_r[analysis_nd_r["sex"]=="Male"]["c_charge_desc"].value_counts(normalize=True,ascending=False)[:5].reset_index()

sns.barplot(data=male_crime,x="c_charge_desc",y="index",palette="Greens_r")
plt.title("Top 5 crimes for females")
plt.ylabel("")
plt.xlabel("percentage of cases")
# so only the graphic appears without any text referring to the object type.
plt.show(block=False)
```



Men and women commit the same top 3 offenses

3.4 Top offenses by both race and sex

In [38]:
```python
# Here I only consider the top 5 cases by counting their valuses then filtering with the function isin
top_5_cases = analysis_nd_r["c_charge_desc"].value_counts()[:5].index.tolist()
top_cases = analysis_nd_r[analysis_nd_r["c_charge_desc"].isin(top_5_cases)]
```

Lets explore in more depth top crimes by race

In [39]:
```python
pd.crosstab(index=top_cases["c_charge_desc"],columns=top_cases["race"],normalize=1)\
    .style.background_gradient(cmap='Reds',axis=0)
```

Out[39]:

race c_charge_desc	African-American	Caucasian	Hispanic	Other	Asian	Native American
Battery	0.422006	0.562500	0.538462	0.658537	0.750000	0.666667
Driving While License Revoked	0.094708	0.040323	0.059829	0.040650	0.083333	0.000000
Felony Battery (Dom Strang)	0.050139	0.044355	0.094017	0.065041	0.000000	0.333333
Grand Theft in the 3rd Degree	0.245125	0.165323	0.213675	0.186992	0.000000	0.000000
Possession of Cocaine	0.188022	0.187500	0.094017	0.048780	0.166667	0.000000

- **We already saw from the previous sections, Battery is top committed crime, but what we know more now is that its is taking the highest % for the different races.**
- **For the top cases, we still have the sames result.**
- **The exception we see that both Asian and Native American don't have any crimes on the category Driving while Licesne revoked and also no Grand Theft.**

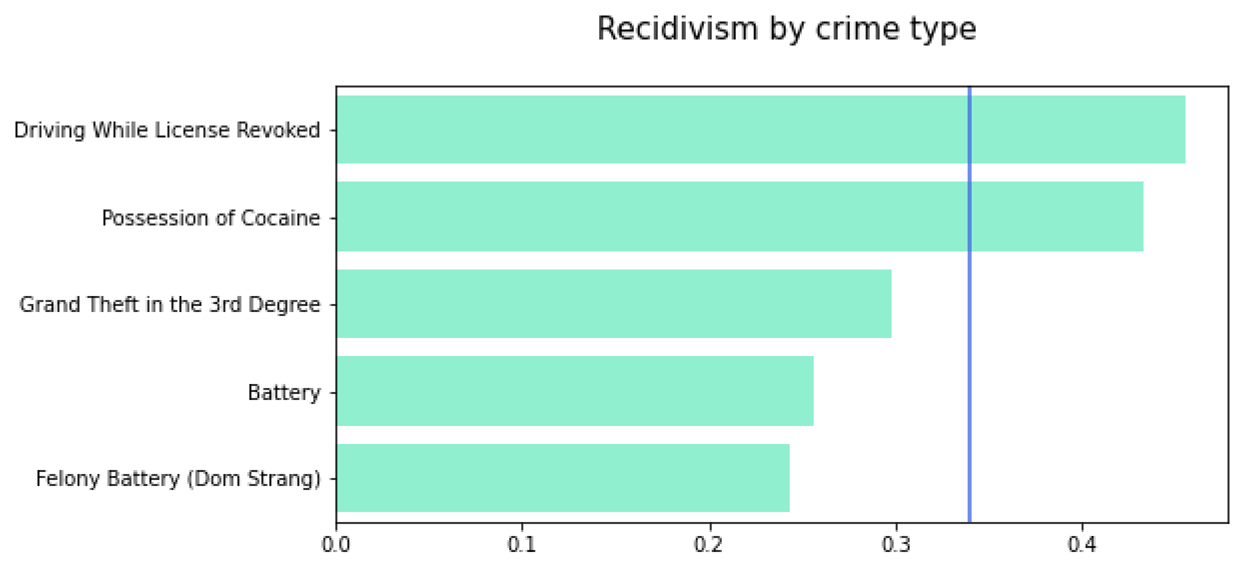
In [40]:
```python
# Recidivism % between race and the type of the case
pd.pivot_table(data=top_cases,values="2y_r",index="c_charge_desc",columns="race",fill_value=0)\
    .style.background_gradient(cmap='Oranges',axis=1)
```

Out[40]:

race c_charge_desc	African-American	Caucasian	Hispanic	Other	Asian	Native American
Battery	0.316832	0.243728	0.174603	0.160494	0.111111	0
Driving While License Revoked	0.485294	0.500000	0.285714	0.200000	0.000000	0
Felony Battery (Dom Strang)	0.222222	0.272727	0.363636	0.125000	0.000000	0
Grand Theft in the 3rd Degree	0.306818	0.329268	0.200000	0.217391	0.000000	0
Possession of Cocaine	0.488889	0.376344	0.181818	0.500000	0.500000	0

In [41]:
```python
# % of recidivism by crime type
percentage_recid_cases= top_cases.groupby("c_charge_desc")["2y_r"].mean().reset_index().sort_values(by="2y_r",ascending=False)

plt.figure(figsize=(8,4))
sns.barplot(data=percentage_recid_cases,y="c_charge_desc",x="2y_r", color="#7FFFD4")
plt.title(" Recidivism by crime type\n",fontsize=15)
plt.xlabel("")
plt.ylabel("")
plt.axvline(x=0.34,color="#4169E1")
plt.show(block=False)
```



4. Check the fairness of the model & how to improve it

- **I will compare both ordinary & violent offences and see wich one has better accuracy using logisitc linear**
- **I will also see the result by both race and sex**

In [42]:
```
# first I will calcualte TPR, FPR, FNR, TNR for normal offences
from sklearn.metrics import classification_report
print(classification_report(analysis_nd_r['2y_r'],analysis_nd_r["binary_score"]))
```

```
              precision    recall  f1-score   support

           0       0.78      0.68      0.73      2388
           1       0.48      0.61      0.53      1139

    accuracy                           0.66      3527
   macro avg       0.63      0.65      0.63      3527
weighted avg       0.69      0.66      0.67      3527
```

In [43]:
```
# calcualte TPR, FPR, FNR, TNR for normal offences
cross_tab = pd.crosstab(analysis_nd_r["binary_score"],analysis_nd_r['2y_r'],normalize="columns").style.background_gradient(cmap='Reds',axis=1)
cross_tab
```

Out[43]:

2y_r	0	1
binary_score		
0	0.683417	0.392450
1	0.316583	0.607550

- **This model has an accuray of 66%**
- **Of the actual positive cases it predicted 61% where it is correct in 48% of the cases => False Positive Rate : 1-0.68 = 0.32**
- **Of the actual negative cases, the model predicted 68% of the cases where it was correct for the 78% cases => False Negative Rate 1-0.61=0.39**

Now I check the prediction for violent crimes

In [44]:
```
# analysis_nd_v only cases with violent crimes
pd.crosstab(analysis_nd_v["binary_v_score"],analysis_nd_v['2y_v'],normalize="columns").style.background_gradient(cmap='Greens',axis=1)
```

Out[44]:

2y_v	0	1
binary_v_score		
0	0.717326	0.469880
1	0.282674	0.530120

In [45]:
```
print(classification_report(analysis_nd_v['2y_v'],analysis_nd_v["binary_v_score"]))
```

```
              precision    recall  f1-score   support

           0       0.95      0.72      0.82      3336
           1       0.12      0.53      0.20       249

    accuracy                           0.70      3585
   macro avg       0.54      0.62      0.51      3585
weighted avg       0.90      0.70      0.78      3585
```

The prediction here is worse than the previous one even though the accuracy shows a higher score, as we see, the prediction for positive cases is higher compared to the previous one (18% more)

In [46]:
```
analysis_nd_v['2y_v'].value_counts(normalize=True)
```

Out[46]:
```
0    0.930544
1    0.069456
Name: 2y_v, dtype: float64
```

In [47]:
```
analysis_nd_r["2y_r"].value_counts(normalize=True)
```

Out[47]:
```
0    0.677063
1    0.322937
Name: 2y_r, dtype: float64
```

- **Despite the accuracy being higher (0.70 > 0.66)**
- **In case of violent crimes, the model is less accurate for positive cases (diffirence 18% higher)**
- **False Positive Rate : 0.46**
- **False Negative Rate: 0.28**

Conclusion, it shows more accuracy with less accurate predicition for positive cases

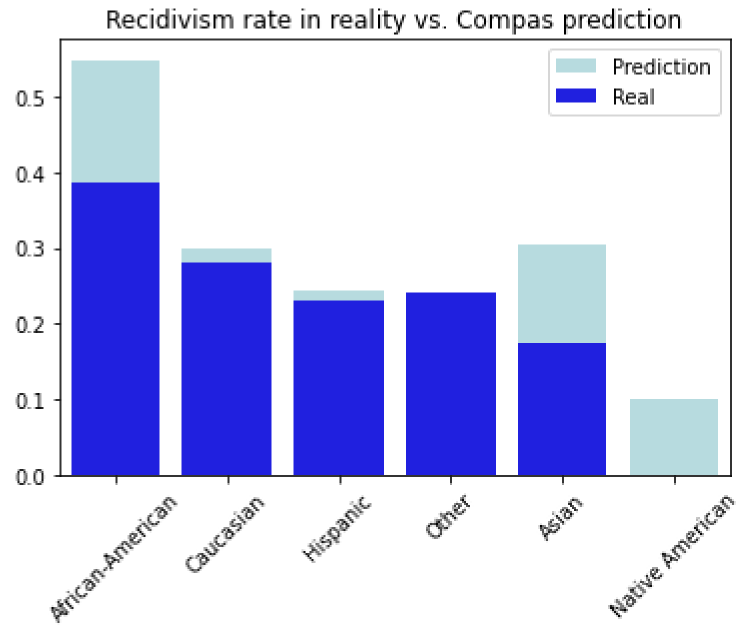
4.1 Check Descrimination of COMPASS for both the race and sex

In [48]:
```
# Comparaison between Revidivism &  Compas forcast
reality = analysis_nd_r.groupby("race",as_index=False)["2y_r"].mean()
compas_prediction = analysis_nd_r.groupby("race")["binary_score"].mean().reset_index()

sns.barplot(data=compas_prediction,x="race",y="binary_score",color="powderblue",label="Prediction")

ax= sns.barplot(data=reality,x="race",y="2y_r",color="blue",label="Real")

plt.title("Recidivism rate in reality vs. Compas prediction")
plt.xticks(rotation=45)
plt.xlabel("")
plt.ylabel("")
plt.legend()
plt.show(block=False)
```



Comparing the reality with the system COMPASS, shows hi less accuray for false positive prediction where the highest % goes for Afriacan american followed by Asians and Native Americans

In [49]:

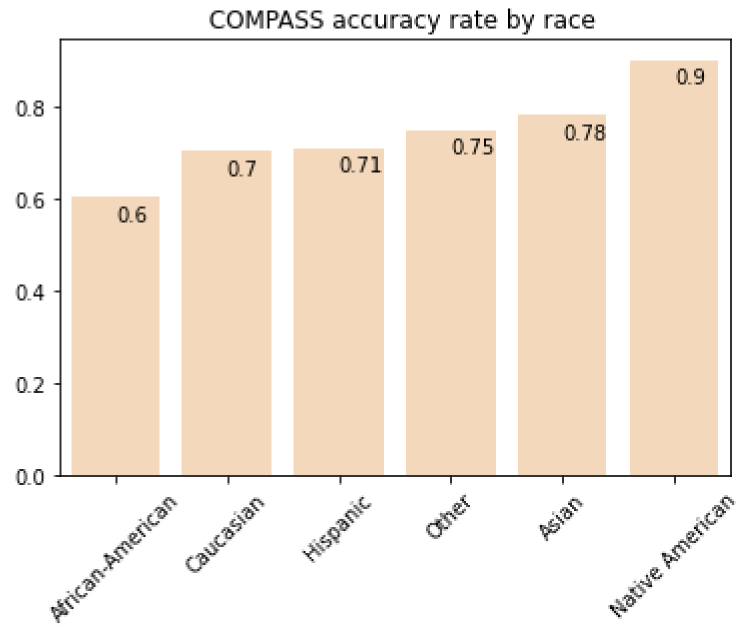
```
analysis_nd_r.groupby("race").agg({"2y_r":"mean",
                                    "binary_score":"mean"}).style.background_gradient(cmap='Greens',axis=1)
```

Out[49]:

race	2y_r	binary_score
African-American	0.385507	0.548986
Caucasian	0.279376	0.299918
Hispanic	0.231270	0.244300
Other	0.240816	0.216327
Asian	0.173913	0.304348
Native American	0.000000	0.100000

In [50]:

```
race_acc = analysis_nd_r.groupby("race")["prediction_recid"].mean().reset_index()
ax= sns.barplot(data=race_acc,x="race",y="prediction_recid",color="#FED8B1")
plt.title("  COMPASS accuracy rate by race")
plt.xticks(rotation=45)
plt.xlabel("")
plt.ylabel("")
for num,text in zip(range(6),round(race_acc["prediction_recid"],2)):
    ax.text(num,text-0.05,text)
```



In [51]:
```
# Recidivism by gender
prediction_sex = analysis_nd_r.groupby("sex")["binary_score"].mean()
recidivism_sex = analysis_nd_r.groupby("sex")["2y_r"].mean()
comparacion_sex = analysis_nd_r.groupby("sex")["prediction_recid"].mean()

dt_comp_sex_recidivism = pd.concat([prediction_sex,recidivism_sex,comparacion_sex],axis=1).reset_index()
dt_comp_sex_recidivism.columns = ["sex","decile_score","2y_r","accuracy"]
dt_comp_sex_recidivism.round(2).style.background_gradient(cmap='Greens',axis=1)
```

Out[51]:

	sex	decile_score	2y_r	accuracy
0	Female	0.360000	0.210000	0.660000
1	Male	0.420000	0.350000	0.660000

If we look into sex, in real world males are more recidivists than females and we see same in compass.

4.2 Percentage of false positives and negative positives

In [52]:
```
# Create 2 attributes one for the name and one for the result
def wrong_prediction(att):
    # Build 2 lists one for the FPR and one for FNR
    list_att = []
    FPR = []
    FNR = []
    for x in analysis_nd_r[att].unique().tolist():
        #Filter by race or gender
        data = analysis_nd_r[analysis_nd_r[att]==x]
        # create sorting report (with output_dict we return a dictionary)
        classif_race = classification_report(data['2y_r'],data["binary_score"],output_dict=True)
        list_att.append(x)
        # False Positive Rate is 1-exahusivity(recall)
        false_positive = 1 - classif_race.get("0")["recall"]
        FPR.append(false_positive)
        # False Negative Rate 1-TPR
        false_negative = 1 - classif_race.get("1")["recall"]
        FNR.append(false_negative)
    # creamos dataframe
```

```
    df_fpr = pd.DataFrame({x:list_att,"FPR":FPR,"FNR":FNR})
    return df_fpr
```

In [53]:
```
wrong_prediction("race").style.background_gradient(cmap='Oranges',axis=1)
```

Out[53]:

	Native American	FPR	FNR
0	Other	0.150538	0.576271
1	African-American	0.455660	0.302256
2	Caucasian	0.220068	0.494118
3	Hispanic	0.199153	0.605634
4	Asian	0.210526	0.250000
5	Native American	0.100000	1.000000

We can see clearly in the table above, that the African- American has the highest % of False positive rate compared to the rest of races. => This shows clearly the mistreat discrimination

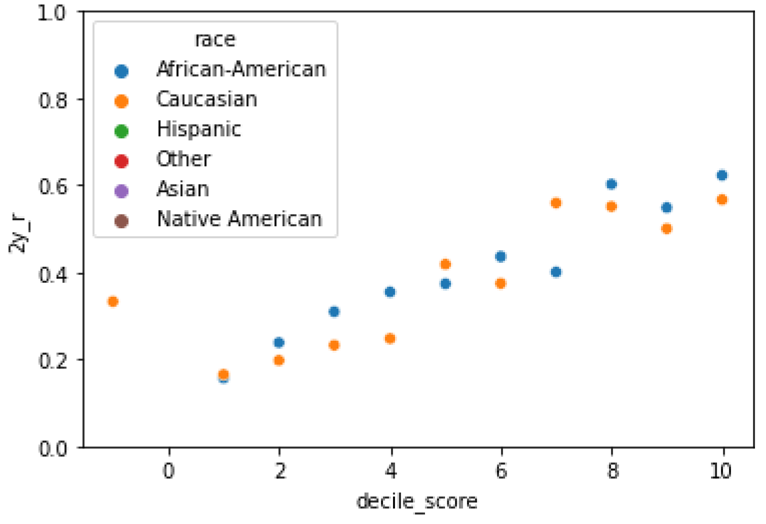
In [55]:
```
wrong_prediction("sex").style.background_gradient(cmap='Blues',axis=1)
```

Out[55]:

	Female	FPR	FNR
0	Male	0.317829	0.383756
1	Female	0.312715	0.448052

For Gender, Recidivism is same for both gender.

In [56]:
```
d = analysis_nd_r.groupby(["decile_score","race"]).agg({"2y_r":"mean"}).reset_index()
d = d[d["race"].isin(["African-American","Caucasian"])]
im = sns.scatterplot(data=d,x="decile_score",y="2y_r",hue="race")
im.set(ylim=(0,1))
plt.show(block=False)
```



4.SUMMARY

1. **Compas evaluates by race and gender; there are some differences in results, but we must not forget that one of the races has the highest prevalence (nearly 50%) and they are also the most likely to recidivate (nearly 40%).**
2. **Adding the two_year_r feature based on compas report was for the purpose to see if adding this feature will help to narrow the prediction coming from COMPASS**

3. **We saw that is_violent_racid got better compard to is_recid but no improvement on Positive cases prediction it became worse. My suggestion, is to remove the race from the full data and train the model in a way that it will be always independant from the race. In that way the discrimination will be avoided, maybe not fully but at least it would be better.**

9.References

kaggle.com. (n.d.). Compas: thoroughly investigating the controversial. [online] Available at: https://www.kaggle.com/code/gonzalogarciafuste/compas-thoroughly-investigating-the-controversial/data [Accessed 25 OCt. 2022].