Context

Every day, the introduction of data science into the field of law and justice is becoming more common. A well-known example of this is the COMPAS system (Correctional Offender Management Profiling for Alternative Sanctions), which is used in several states in the United States to assess the risk of recidivism for detained individuals. A brief description of the system can be found on the page https://en.wikipedia.org/wiki/COMPAS_(software).

In this case, it provides a set of raw data with information from assessments (compas-scores.csv file) and the legal history of around 11,000 cases in the years 2013 and 2014 (one of the original files used in an independent analysis of the COMPAS system conducted by ProPublica, available on the internet). Although the dataset contains additional information, the following fields are necessary to address the issues raised in this case (aside from some self-explanatory fields):

- "compas_screening_date": refers to the date on which the evaluation was conducted.
- "decile_score": is a number from 1 to 10 indicating the overall risk of recidivism (higher risk corresponds to a higher number).
- "v_decile_score": is a number from 1 to 10, potentially different from the previous one, indicating the risk of recidivism in violent offenses. When evaluating a case in COMPAS, two scores are generated, among other things.
- "is_recid": indication of whether the person is a recidivist (at the time data is collected: there is no information on whether the person is a recidivist beyond certain dates, and it is important to consider this for ensuring homogeneous comparisons).
- "r_offense_date": date on which the offense for which the person is considered a recidivist was committed.
- "is_violent_recid": indication of whether the person is a recidivist in a violent offense (the same considerations about dates as for "is_recid" apply here).
- "vr_offense_date": date on which the violent offense that leads to the consideration of recidivism occurred.

We import the libraries needed to perform an exploratory analysis and assess the quality of the data. Specifically, we will evaluate the integrity, validity, and timeliness of the data and propose strategies to mitigate any potential issues encountered.

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

compas_score_raw = pd.read_csv('./compas-scores.csv')
compas_score_raw.head()
```

Out[ ]:

	id	name	first	last	compas_screening_date	sex	dob	age	age_cat	
0	1	miguel hernandez	miguel	hernandez	2013-08-14	Male	1947-04-18	69	Greater than 45	
1	2	michael ryan	michael	ryan	2014-12-31	Male	1985-02-06	31	25 - 45	C
2	3	kevon dixon	kevon	dixon	2013-01-27	Male	1982-01-22	34	25 - 45	/
3	4	ed philo	ed	philo	2013-04-14	Male	1991-05-14	24	Less than 25	/
4	5	marcu brown	marcu	brown	2013-01-13	Male	1993-01-21	23	Less than 25	/

5 rows × 47 columns

In [ ]:

```
compas_score_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11757 entries, 0 to 11756
Data columns (total 47 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   id                       11757 non-null  int64  
 1   name                     11757 non-null  object 
 2   first                    11757 non-null  object 
 3   last                     11757 non-null  object 
 4   compas_screening_date    11757 non-null  object 
 5   sex                      11757 non-null  object 
 6   dob                      11757 non-null  object 
 7   age                      11757 non-null  int64  
 8   age_cat                  11757 non-null  object 
 9   race                     11757 non-null  object 
 10  juv_fel_count            11757 non-null  int64  
 11  decile_score             11757 non-null  int64  
 12  juv_misd_count           11757 non-null  int64  
 13  juv_other_count          11757 non-null  int64  
 14  priors_count             11757 non-null  int64  
 15  days_b_screening_arrest  10577 non-null  float64
 16  c_jail_in                10577 non-null  object 
 17  c_jail_out               10577 non-null  object 
 18  c_case_number            11015 non-null  object 
 19  c_offense_date           9157 non-null   object 
 20  c_arrest_date            1858 non-null   object 
 21  c_days_from_compas       11015 non-null  float64
 22  c_charge_degree          11757 non-null  object 
 23  c_charge_desc            11008 non-null  object 
 24  is_recid                 11757 non-null  int64  
 25  num_r_cases              0 non-null      float64
 26  r_case_number            3703 non-null   object 
 27  r_charge_degree          11757 non-null  object 
 28  r_days_from_arrest       2460 non-null   float64
 29  r_offense_date           3703 non-null   object 
 30  r_charge_desc            3643 non-null   object 
 31  r_jail_in                2460 non-null   object 
 32  r_jail_out               2460 non-null   object 
 33  is_violent_recid         11757 non-null  int64  
 34  num_vr_cases             0 non-null      float64
 35  vr_case_number           882 non-null    object 
 36  vr_charge_degree         882 non-null    object 
 37  vr_offense_date          882 non-null    object 
 38  vr_charge_desc           882 non-null    object 
 39  v_type_of_assessment     11757 non-null  object 
 40  v_decile_score           11757 non-null  int64  
 41  v_score_text             11752 non-null  object 
 42  v_screening_date         11757 non-null  object 
 43  type_of_assessment       11757 non-null  object 
 44  decile_score.1           11757 non-null  int64  
 45  score_text               11742 non-null  object 
 46  screening_date           11757 non-null  object 
dtypes: float64(5), int64(11), object(31)
memory usage: 4.2+ MB
```

In [ ]:
```
compas_score_raw.columns
```

Out[ ]:
```
Index(['id', 'name', 'first', 'last', 'compas_screening_date', 'sex', 'do
b',
       'age', 'age_cat', 'race', 'juv_fel_count', 'decile_score',
       'juv_misd_count', 'juv_other_count', 'priors_count',
       'days_b_screening_arrest', 'c_jail_in', 'c_jail_out', 'c_case_numbe
r',
       'c_offense_date', 'c_arrest_date', 'c_days_from_compas',
       'c_charge_degree', 'c_charge_desc', 'is_recid', 'num_r_cases',
       'r_case_number', 'r_charge_degree', 'r_days_from_arrest',
       'r_offense_date', 'r_charge_desc', 'r_jail_in', 'r_jail_out',
       'is_violent_recid', 'num_vr_cases', 'vr_case_number',
       'vr_charge_degree', 'vr_offense_date', 'vr_charge_desc',
       'v_type_of_assessment', 'v_decile_score', 'v_score_text',
       'v_screening_date', 'type_of_assessment', 'decile_score.1',
       'score_text', 'screening_date'],
      dtype='object')
```

We will create a function that gives us the relevant information to facilitate data cleaning. Also, we will create a dataframe in which we will be adding the variables involved in our analysis, with the data already cleaned and prepared to be used.

In [ ]:
```
def cleaning(df, col):
    print(f'Column: {col} - Data type: {df[col].dtype}')
    print(f'Number of nulls: {df[col].isnull().sum()} - Number of distincts
    print('Frequent values:')
    for i, v in df[col].value_counts().iloc[:10].items() :
        print(i, '\t', v)

compas_score = pd.DataFrame()
```

In [ ]:
```
cleaning(compas_score_raw, 'id')
```

```
Column: id - Data type: int64
Number of nulls: 0 - Number of distincts values: 11757
Frequent values:
1        1
7832     1
7834     1
7835     1
7836     1
7837     1
7838     1
7839     1
7840     1
7841     1
```

There is nothing to change, we will directly add the variable to our new dataframe.

In [ ]:
```
compas_score['id'] = compas_score_raw['id']
```

In [ ]:
```
cleaning(compas_score_raw, 'name')
```

```
Column: name - Data type: object
Number of nulls: 0 - Number of distincts values: 11584
Frequent values:
robert taylor    4
carlos vasquez   4
john brown       4
michael cunningham       4
james williams   3
james smith      3
anthony smith    3
michael williams         3
gregory williams         3
anthony jackson          3
```

We can observe that there are some names that repeat.

In [ ]:
```
compas_score['name'] = compas_score_raw['name'].astype('string')
```

We check that our variables are being added to the dataframe correctly.

In [ ]:
```
compas_score.head()
```

Out[ ]:

	id	name
0	1	miguel hernandez
1	2	michael ryan
2	3	kevon dixon
3	4	ed philo
4	5	marcu brown

In [ ]:
```
cleaning(compas_score_raw, 'sex')
```

```
Column: sex - Data type: object
Number of nulls: 0 - Number of distincts values: 2
Frequent values:
Male      9336
Female    2421
```

In [ ]:
```
compas_score['sex'] = compas_score_raw['sex'].astype('category')
```

In [ ]:
```
cleaning(compas_score_raw, 'age')
```

```
Column: age - Data type: int64
Number of nulls: 0 - Number of distincts values: 66
Frequent values:
26       540
24       539
25       521
23       507
27       506
22       503
21       500
29       456
30       441
28       430
```

In [ ]:
```
compas_score['age'] = compas_score_raw['age']
```

In [ ]:
```
cleaning(compas_score_raw, 'dob')
```

```
Column: dob - Data type: object
Number of nulls: 0 - Number of distincts values: 7800
Frequent values:
1991-08-12      6
1988-07-25      6
1994-01-24      6
1992-10-15      6
1989-04-27      6
1988-04-15      6
1989-10-14      6
1989-09-27      6
1990-05-02      6
1986-01-03      6
```

In [ ]:
```
compas_score['dob'] = pd.to_datetime(compas_score_raw['dob'])
```

In [ ]:
```
cleaning(compas_score_raw, 'race')
```

```
Column: race - Data type: object
Number of nulls: 0 - Number of distincts values: 6
Frequent values:
African-American        5813
Caucasian       4085
Hispanic        1100
Other   661
Asian   58
Native American         40
```

In [ ]:
```
compas_score['race'] = compas_score_raw['race'].astype('category')
```

In [ ]:
```
cleaning(compas_score_raw, 'compas_screening_date')
```

```
Column: compas_screening_date - Data type: object
Number of nulls: 0 - Number of distincts values: 704
Frequent values:
2013-03-20      39
2013-04-20      38
2013-09-23      35
2013-02-20      34
2013-02-22      33
2013-09-26      33
2013-02-07      32
2014-11-12      32
2013-08-27      32
2013-08-07      31
```

In [ ]:
```
compas_score['compas_screening_date'] = pd.to_datetime(compas_score_raw['cor
```

In [ ]:
```
cleaning(compas_score_raw, 'decile_score')
```

```
Column: decile_score - Data type: int64
Number of nulls: 0 - Number of distincts values: 11
Frequent values:
1       2577
2       1572
3       1259
4       1199
5       1034
6       993
7       900
9       802
8       796
10      610
```

In [ ]:
```
cleaning(compas_score_raw, 'v_decile_score')
```

```
Column: v_decile_score - Data type: int64
Number of nulls: 0 - Number of distincts values: 11
Frequent values:
1        3359
2        1789
3        1581
4        1239
5        1083
6        919
7        666
8        476
9        440
10       200
```

In [ ]:
```
compas_score['decile_score'] = compas_score_raw['decile_score']
compas_score['v_decile_score'] = compas_score_raw['v_decile_score']
```

In [ ]:
```
cleaning(compas_score_raw, 'is_recid')
```

```
Column: is_recid - Data type: int64
Number of nulls: 0 - Number of distincts values: 3
Frequent values:
0        7335
1        3703
-1       719
```

In [ ]:
```
compas_score['is_recid'] = compas_score_raw['is_recid'].astype('category')

# We define the categorical type
r_types = pd.CategoricalDtype(
    [
        'Yes', 'No', 'Incomplete'
    ],
    ordered=True
)

# We define a dictionary to map the values:
dict_r = {
    0: 'No',
    1: 'Yes',
    -1: 'Incomplete'
}

compas_score['is_recid'] = compas_score['is_recid'].apply(
    lambda x: dict_r.get(x)
).astype(r_types)
```

In [ ]:
```
compas_score.head()
```

Out[ ]:

	id	name	sex	age	dob	race	compas_screening_date	decile_score	v_deci
0	1	miguel hernandez	Male	69	1947-04-18	Other	2013-08-14	1	
1	2	michael ryan	Male	31	1985-02-06	Caucasian	2014-12-31	5	
2	3	kevon dixon	Male	34	1982-01-22	African-American	2013-01-27	3	
3	4	ed philo	Male	24	1991-05-14	African-American	2013-04-14	4	
4	5	marcu brown	Male	23	1993-01-21	African-American	2013-01-13	8	

Vemos en la página de publicación que '-1' significa que los datos están incompletos, por tanto, podemos excluirlos de nuestro análisis:

In [ ]:
```
(compas_score['is_recid'] == 'Incomplete').value_counts()
```

Out[ ]:
```
is_recid
False    11038
True       719
Name: count, dtype: int64
```

In [ ]:
```
# We remove the 719 cases that have unreliable information:
compas_score.drop(compas_score[compas_score['is_recid'] == 'Incomplete'].in
compas_score.nunique()
```

Out[ ]:
```
id                       11038
name                     10902
sex                          2
age                         66
dob                       7466
race                         6
compas_screening_date      704
decile_score                11
v_decile_score              11
is_recid                     2
r_offense_date            1090
is_violent_recid             2
vr_offense_date            599
dtype: int64
```

In [ ]:
```
cleaning(compas_score_raw, 'r_offense_date')
```

```
Columna: r_offense_date - Tipos de datos: object
Número de valores nulos: 8054 - Número de valores distintos: 1090
Valores más frecuentes:
2014-12-08       12
2015-02-10       11
2015-01-28       11
2014-06-05       10
2014-06-07       10
2015-03-11       10
2014-04-03       10
2014-09-15       10
2014-10-17       10
2015-02-18       9
```

In [ ]:
```
compas_score['r_offense_date'] = pd.to_datetime(compas_score_raw['r_offense_
```

In [ ]:
```
cleaning(compas_score_raw, 'is_violent_recid')
```

```
Column: is_violent_recid - Data type: int64
Number of nulls: 0 - Number of distincts values: 2
Frequent values:
0        10875
1        882
```

In [ ]:
```
compas_score['is_violent_recid'] = compas_score_raw['is_violent_recid'].asty

vr_types = pd.CategoricalDtype(
    [
        'Yes', 'No'
    ],
    ordered=True
)

dict_vr = {
    0: 'No',
    1: 'Yes'
}

compas_score['is_violent_recid'] = compas_score['is_violent_recid'].apply(
    lambda x: dict_vr.get(x)
).astype(vr_types)
```

In [ ]:
```
cleaning(compas_score_raw, 'vr_offense_date')
```

```
Column: vr_offense_date - Data type: object
Number of nulls: 10875 - Number of distincts values: 599
Frequent values:
2015-08-15       6
2015-09-04       5
2015-10-14       4
2014-10-29       4
2014-07-28       4
2014-09-28       4
2015-06-13       4
2015-09-07       4
2015-03-29       4
2015-04-27       4
```

In [ ]:
```
compas_score['vr_offense_date'] = pd.to_datetime(compas_score_raw['vr_offens
```

In [ ]:
```
compas_score.head()
```

Out[ ]:

	id	name	sex	age	dob	race	compas_screening_date	decile_score	v_decil
0	1	miguel hernandez	Male	69	1947-04-18	Other	2013-08-14	1	
2	3	kevon dixon	Male	34	1982-01-22	African-American	2013-01-27	3	
3	4	ed philo	Male	24	1991-05-14	African-American	2013-04-14	4	
4	5	marcu brown	Male	23	1993-01-21	African-American	2013-01-13	8	
5	6	bouthy pierrelouis	Male	43	1973-01-22	Other	2013-03-26	1	

'R-Offense Date' y 'VR-Offense Date' deberían coincidir con el campo 'No' de su categoría correspondiente, comprobamos si lo hacen:

In [ ]:
```
compas_score['is_recid'][compas_score['r_offense_date'].isnull()].unique()
```

Out[ ]:
```
['No']
Categories (3, object): ['Yes' < 'No' < 'Incomplete']
```

In [ ]:
```
compas_score['is_violent_recid'][compas_score['vr_offense_date'].isnull()].u
```

Out[ ]:
```
['No']
Categories (2, object): ['Yes' < 'No']
```

In [ ]:
```
compas_score.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 11038 entries, 0 to 11756
Data columns (total 13 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     11038 non-null  int64
 1   name                   11038 non-null  string
 2   sex                    11038 non-null  category
 3   age                    11038 non-null  int64
 4   dob                    11038 non-null  datetime64[ns]
 5   race                   11038 non-null  category
 6   compas_screening_date  11038 non-null  datetime64[ns]
 7   decile_score           11038 non-null  int64
 8   v_decile_score         11038 non-null  int64
 9   is_recid               11038 non-null  category
 10  r_offense_date         3703 non-null   datetime64[ns]
 11  is_violent_recid       11038 non-null  category
 12  vr_offense_date        882 non-null    datetime64[ns]
dtypes: category(4), datetime64[ns](4), int64(4), string(1)
memory usage: 906.0 KB
```

In [ ]:
```
compas_score.nunique()
```

Out[ ]:
```
id                      11038
name                    10902
sex                         2
age                        66
dob                      7466
race                        6
compas_screening_date     704
decile_score               11
v_decile_score             11
is_recid                    2
r_offense_date           1090
is_violent_recid            2
vr_offense_date           599
dtype: int64
```

We see that there are repeated names. We can also check, although it may seem commonplace, for any type of error and, in some cases, if it refers to the same person.

In [ ]:
```
compas_score[compas_score.duplicated(['name', 'age'], keep=False)].sort_valu
```

Out[ ]:

	id	name	sex	age	dob	race	compas_screening_date	decile_score
7707	7708	jeffrey williams	Male	28	1987-06-27	African-American	2013-04-16	6
10164	10165	jeffrey williams	Male	28	1987-10-08	African-American	2014-06-25	2
1004	1005	john brown	Male	65	1950-09-02	African-American	2014-04-11	2
11713	11714	john brown	Male	65	1950-12-01	African-American	2013-09-23	1
949	950	michael williams	Male	23	1993-02-10	African-American	2013-05-24	10
10537	10538	michael williams	Male	23	1993-01-15	African-American	2013-01-26	6
3491	3492	roderick thomas	Male	23	1993-01-07	African-American	2014-03-10	7
7476	7477	roderick thomas	Male	23	1992-05-28	African-American	2013-02-12	8
112	113	troy smith	Male	22	1993-09-21	African-American	2013-08-25	3
2022	2023	troy smith	Male	22	1993-09-08	African-American	2013-03-22	7

The birthdates do not match; therefore, they are not the same individuals. There are no apparent errors.

Our aim is to see if "is_recid" and "is_violent_recid" are suitable to evaluate the accuracy of risk estimates generated by the COMPAS system. The risk estimates are evaluated by "decile_score" and "v_decile_score", respectively. The higher the risk, the higher its value will be. Given that the threshold for implementing preventive measures for recidivism is 7 or higher, we will consider the risk to be high when it is >= 7. We create a contingency table to see if there is a match between is_recid = "Yes" and decile_score >= 7:

In [ ]:
```
precision_crosstab = pd.crosstab(compas_score['is_recid'] == 'No', compas_s
precision_crosstab
```

Out[ ]:

Risk	False	True
Prediction		
False	2200	1503
True	5877	1458

We have 2198 + 5868 = 8066 individuals with a decile_score less than 7, indicating low risk. Additionally, 1503 + 1458 = 2961 individuals have a high risk. Among those with low risk, only 5868 individuals have is_recid = 'No'. The remaining 2198 are recidivists. Similarly, there are 1458 high-risk individuals with is_recid 'No'. This indicates that relying solely on "is_recid" is not reliable. We calculate a more reliable feature. We use a regression model to try to predict "decile_score".

In [ ]:
```
from statsmodels.formula.api import ols

fitted_decile_score = ols('decile_score ~ age + C(sex) + C(race) + C(is_rec
print(fitted_decile_score.summary())
```

```
                            OLS Regression Results
==============================================================================
===
Dep. Variable:           decile_score   R-squared:                       0.
255
Model:                            OLS   Adj. R-squared:                  0.
254
Method:                 Least Squares   F-statistic:                     41
8.8
Date:                Sat, 02 Mar 2024   Prob (F-statistic):
0.00
Time:                        18:15:24   Log-Likelihood:                -257
05.
No. Observations:               11038   AIC:                         5.143e
+04
Df Residuals:                   11028   BIC:                         5.150e
+04
Df Model:                           9
Covariance Type:            nonrobust
==============================================================================
===================
                                 coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
-------------------
Intercept                      8.5416      0.116     73.369      0.000
8.313       8.770
C(sex)[T.Male]                 0.2248      0.059      3.813      0.000
0.109       0.340
C(race)[T.Asian]              -2.0587      0.343     -5.997      0.000
-2.732      -1.386
C(race)[T.Caucasian]          -1.1807      0.053    -22.079      0.000
-1.285      -1.076
C(race)[T.Hispanic]           -1.6600      0.086    -19.411      0.000
-1.828      -1.492
C(race)[T.Native American]    -0.4522      0.416     -1.088      0.277
-1.267       0.362
C(race)[T.Other]              -2.1345      0.106    -20.220      0.000
-2.341      -1.928
C(is_recid)[T.No]             -1.1354      0.056    -20.291      0.000
-1.245      -1.026
C(is_recid)[T.Incomplete]  -4.864e-15   9.03e-16     -5.387      0.000   -
6.63e-15   -3.09e-15
C(is_violent_recid)[T.No]     -0.3293      0.096     -3.432      0.001
-0.517      -0.141
age                           -0.0731      0.002    -35.981      0.000
-0.077      -0.069
==============================================================================
===
Omnibus:                      571.225   Durbin-Watson:                   1.
967
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              471.
965
Skew:                           0.429   Prob(JB):                    3.27e-
103
Kurtosis:                       2.462   Cond. No.                     3.28e
+19
==============================================================================
===

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corr
ectly specified.
```

```
[2] The smallest eigenvalue is 1.41e-32. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Here are several things to comment on:

- The closer 'R-squared' is to 1, the more reliable our regression model will be. In this case, it is 0.254, so it is not very reliable.
- P > |t|: This is a measure of the model's emphasis on the associated variable. The higher it is, the worse. In this case, we see that 'Native American' is not very relevant. This is likely because there are few people of that race.

In [ ]:
```
(compas_score.race=='Native American').sum()
```

Out[ ]:
```
36
```

We verify that there are only 36 individuals in the model corresponding to this race, so it is not very significant.

In [ ]:
```
predicted = fitted_decile_score.predict(compas_score)
```

We generate a contingency table for the prediction with a value greater than or equal to 7, along with those values that are actually greater than or equal to 7:

In [ ]:
```
predicted_crosstab = pd.crosstab(predicted >= 7, compas_score['decile_score
predicted_crosstab
```

Out[ ]:

Real Prediction	False	True
False	8020	2858
True	57	103

We observe that in 8009 cases, we were able to predict that decile_score is less than 7. In 2858 cases, the prediction was less than 7, but in reality, they were not (Type II Error). On the other hand, 103 individuals have a decile_score greater than 7, and the prediction is correct. With the last 57 cases, we thought they would be greater than 7 according to the prediction, but they were not (Type I Error).

In [ ]:
```
from sklearn.metrics import classification_report
print(classification_report(compas_score.decile_score>=7, predicted>=7))
```

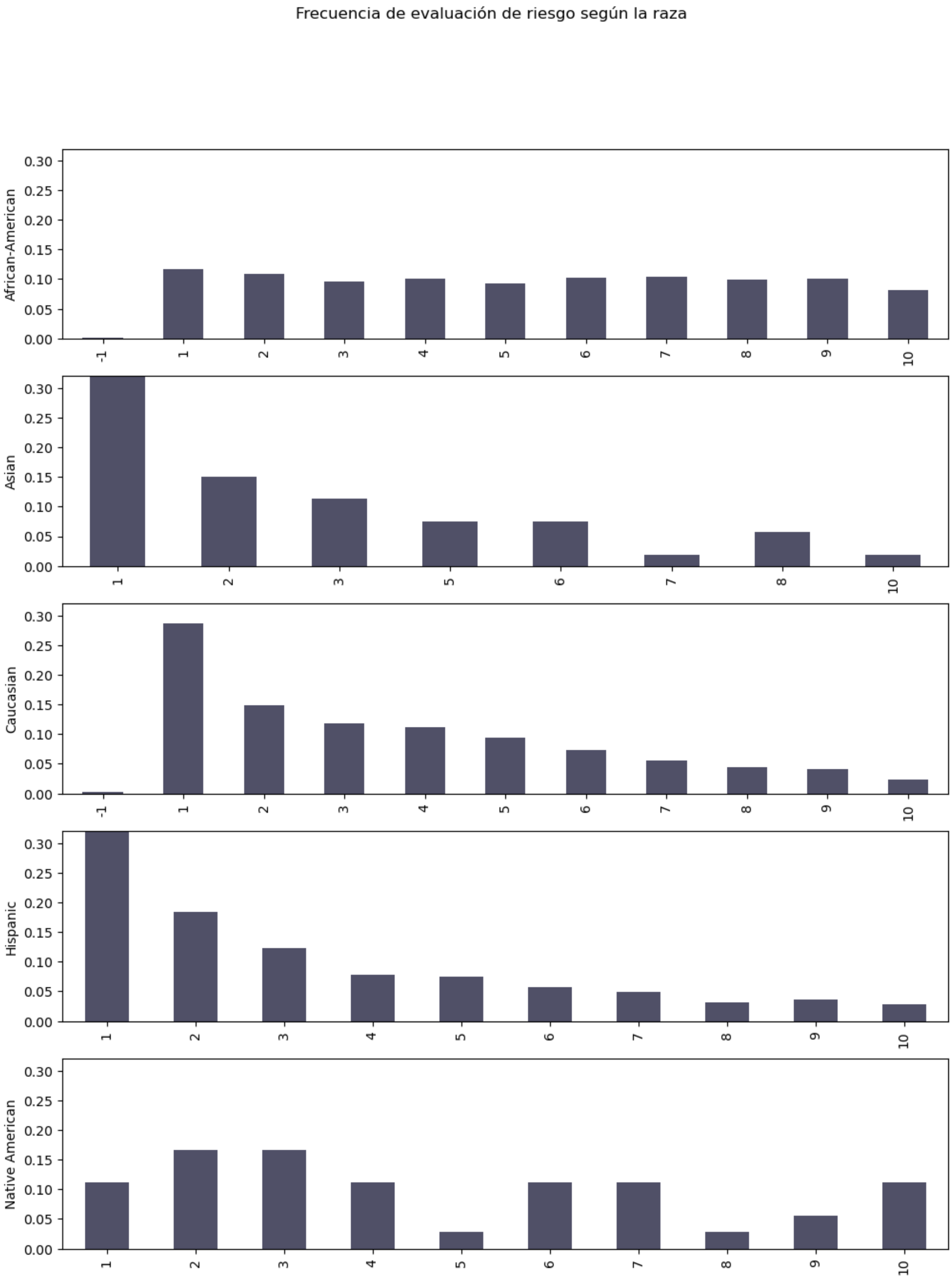
```
              precision    recall  f1-score   support

       False       0.74      0.99      0.85      8077
        True       0.64      0.03      0.07      2961

    accuracy                           0.74     11038
   macro avg       0.69      0.51      0.46     11038
weighted avg       0.71      0.74      0.64     11038
```

The system, on average, assigns higher risk assessments to men than to women and to individuals of African American race than to those of Caucasian race. However, the recidivism rates are also higher for these groups, although it is not clear whether the risk assignment is "fair" or not. Display these differences through graphical representations and use them to analyze whether the risk assessments are fair or not. First, let's examine the risk assessments based on race.

In [ ]:
```
compas_score.race
```

Out[ ]:
```
0                     Other
2          African-American
3          African-American
4          African-American
5                     Other
                ...
11752                 Other
11753             Caucasian
11754                 Other
11755             Caucasian
11756                 Asian
Name: race, Length: 11038, dtype: category
Categories (6, object): ['African-American', 'Asian', 'Caucasian', 'Hispani
c', 'Native American', 'Other']
```

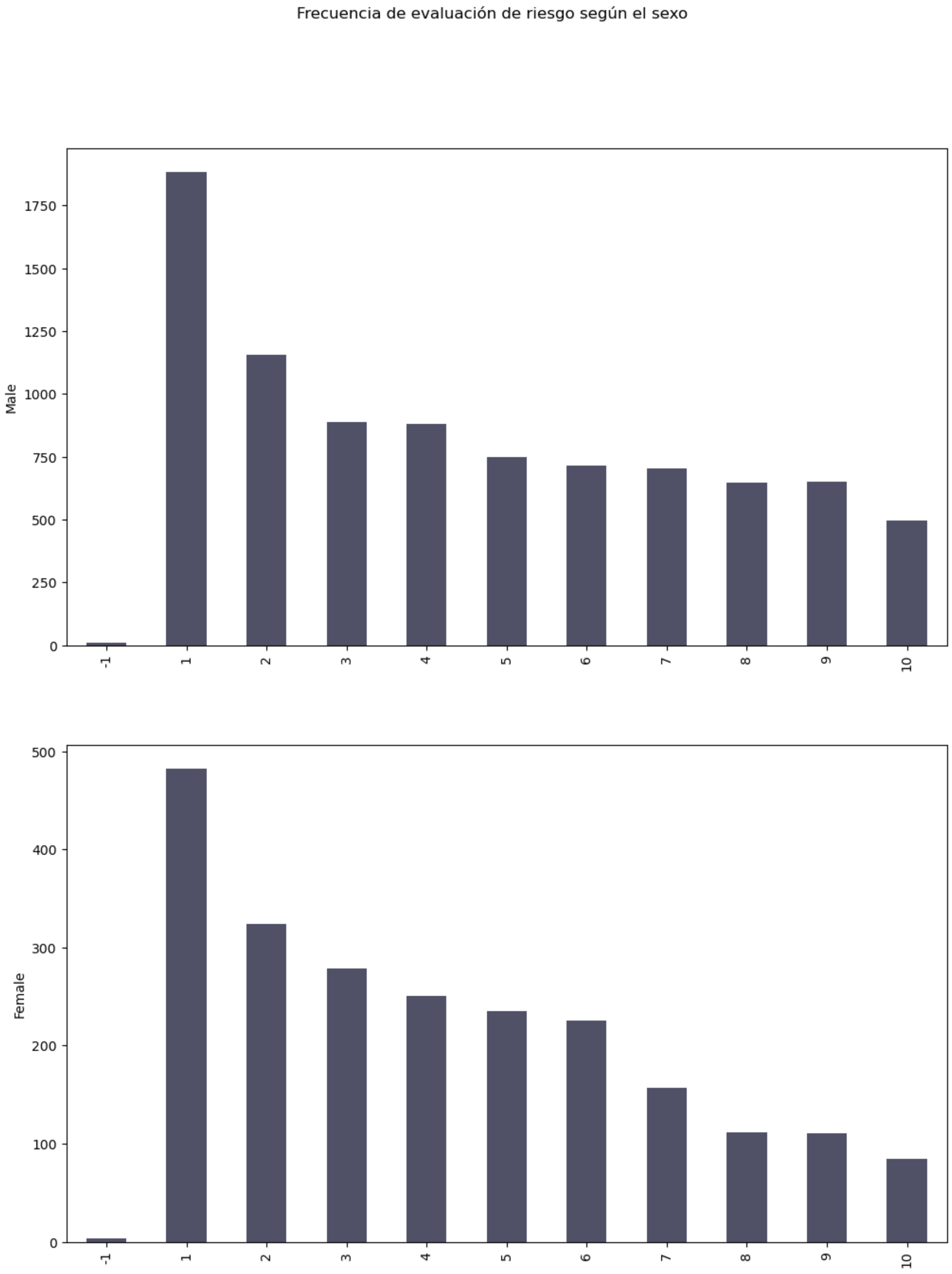
In [ ]:
```
race_group = compas_score.groupby("race")
race_count = compas_score.groupby("race")["name"].count()

fig, ax = plt.subplots(5, figsize=(12, 15))

for (i, race) in enumerate(["African-American", "Asian", "Caucasian", "Hispa
    (
        (race_group
            .get_group(race)
            .groupby("decile_score")["name"].count() / race_count[race]
        )
        .plot(kind="bar", ax=ax[i], color="#505067")
    )
    ax[i].set_ylabel(race)
    ax[i].set_xlabel("")

    ax[i].set_ylim(0, 0.32)

fig.suptitle("Frequency of risk assessment by race")
plt.show()
```



Note that the African American race has a uniformly distributed risk assessment. In contrast, for the other races, the majority of individuals are at the lower levels of risk.

In [ ]:
```
sex_group = compas_score.groupby("sex")
race_count = compas_score.groupby("sex")["name"].count()

fig, ax = plt.subplots(2, figsize=(12, 15))

for (i, sex) in enumerate(["Male", "Female"]):
    (
        (sex_group
            .get_group(sex)
            .groupby("decile_score")["name"].count()
```

```
            #/ race_count[race]
            )
            .plot(kind="bar", ax=ax[i], color="#505067")
        )
        ax[i].set_ylabel(sex)
        ax[i].set_xlabel("")

 #   ax[i].set_ylim(0, 0.)

fig.suptitle("Frequency of risk assessment by gender")
plt.show()
```



In this case, we observe a tendency for fewer women to be in the high-risk levels.

We repeat the same process for the risk assessment in violent offenses.

In [ ]:
```
fitted_v_decile_score = ols('v_decile_score ~ age + C(sex) + C(race) + C(is_
print(fitted_v_decile_score.summary())
```

```
                            OLS Regression Results
==============================================================================
===
Dep. Variable:         v_decile_score   R-squared:                       0.
394
Model:                            OLS   Adj. R-squared:                  0.
393
Method:                 Least Squares   F-statistic:                     79
5.4
Date:                Sat, 02 Mar 2024   Prob (F-statistic):
0.00
Time:                        18:24:15   Log-Likelihood:                -230
35.
No. Observations:               11038   AIC:                         4.609e
+04
Df Residuals:                   11028   BIC:                         4.616e
+04
Df Model:                           9
Covariance Type:            nonrobust
==============================================================================
===================
                                  coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
-------------------
Intercept                       8.0738      0.091     88.335      0.000
7.895       8.253
C(sex)[T.Male]                  0.7012      0.046     15.148      0.000
0.610       0.792
C(race)[T.Asian]               -1.5070      0.270     -5.592      0.000
-2.035      -0.979
C(race)[T.Caucasian]           -0.8414      0.042    -20.041      0.000
-0.924      -0.759
C(race)[T.Hispanic]            -1.0077      0.067    -15.009      0.000
-1.139      -0.876
C(race)[T.Native American]     -0.3745      0.326     -1.148      0.251
-1.014       0.265
C(race)[T.Other]               -1.2659      0.083    -15.275      0.000
-1.428      -1.103
C(is_recid)[T.No]              -0.6124      0.044    -13.939      0.000
-0.698      -0.526
C(is_recid)[T.Incomplete]  -3.585e-15   7.09e-16     -5.056      0.000   -
4.97e-15    -2.2e-15
C(is_violent_recid)[T.No]      -0.4418      0.075     -5.865      0.000
-0.589      -0.294
age                            -0.1072      0.002    -67.166      0.000
-0.110      -0.104
==============================================================================
===
Omnibus:                      924.375   Durbin-Watson:                   2.
005
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              1170.
232
Skew:                           0.775   Prob(JB):                     7.71e-
255
Kurtosis:                       3.380   Cond. No.                     3.28e
+19
==============================================================================
===

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corr
ectly specified.
```

```
[2] The smallest eigenvalue is 1.41e-32. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

We make a prediction of the v_decile_score value based on the previously mentioned data. We generate the contingency table, comparing the cases where a value greater than or equal to 7 is predicted with those where the actual value is greater than or equal to 7.

In [ ]:

```
v_predicted = fitted_v_decile_score.predict(compas_score)
tabla = pd.crosstab(v_predicted >= 7, compas_score['v_decile_score'] >= 7, r
tabla
```

Out[ ]:

Real	False	True
Prediction		
False	9330	1708

In [ ]:

```
from sklearn.metrics import classification_report
print(classification_report(compas_score['v_decile_score'] >= 7, v_predicted
```

```
              precision    recall  f1-score   support

       False       0.85      1.00      0.92      9330
        True       0.00      0.00      0.00      1708

    accuracy                           0.85     11038
   macro avg       0.42      0.50      0.46     11038
weighted avg       0.71      0.85      0.77     11038
```

```
/Users/danielperez/anaconda3/lib/python3.11/site-packages/sklearn/metrics/_
classification.py:1469: UndefinedMetricWarning: Precision and F-score are i
ll-defined and being set to 0.0 in labels with no predicted samples. Use `z
ero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/danielperez/anaconda3/lib/python3.11/site-packages/sklearn/metrics/_
classification.py:1469: UndefinedMetricWarning: Precision and F-score are i
ll-defined and being set to 0.0 in labels with no predicted samples. Use `z
ero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/danielperez/anaconda3/lib/python3.11/site-packages/sklearn/metrics/_
classification.py:1469: UndefinedMetricWarning: Precision and F-score are i
ll-defined and being set to 0.0 in labels with no predicted samples. Use `z
ero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

We see that the accuracy is 85%, indicating that the system has a higher predictive capability for risk assessments in violent offenses.