Lab 6

Security and Ethical aspects of data

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6.1 Fairness metrics for synthetic datasets

In [ ]:

```
#we import all the required libraries
import numpy as np
import matplotlib.pyplot as plt # for plotting stuff
from random import seed, shuffle
from scipy.stats import multivariate_normal # for generating synthetic data
from sklearn import datasets #For real datasets
SEED = 1122334455
seed(SEED) # set the random seed so that the random permutations can be reproduced again
np.random.seed(SEED)
```

In [ ]:

```
from sklearn.svm import SVC
from sklearn import metrics

def plot_svc_decision_boundary(svm_clf, xmin, xmax):
    w = svm_clf.coef_[0]
    b = svm_clf.intercept_[0]

    # At the decision boundary, w0*x0 + w1*x1 + b = 0
    # => x1 = -w0/w1 * x0 - b/w1
    x0 = np.linspace(xmin, xmax, 200)
    decision_boundary = -w[0]/w[1] * x0 - b/w[1]

    margin = 1/w[1]
    gutter_up = decision_boundary + margin
    gutter_down = decision_boundary - margin
```

```
    svs = svm_clf.support_vectors_
    plt.scatter(svs[:, 0], svs[:, 1], s=180, facecolors='#FFAAAA')
    plt.plot(x0, decision_boundary, "k-", linewidth=2)
    plt.plot(x0, gutter_up, "k--", linewidth=2)
    plt.plot(x0, gutter_down, "k--", linewidth=2)
```

In [ ]:

```
def generate_synthetic_data_bias():

    """
        Code for generating the synthetic data.
        We will have two features and a binary class.

    """


    n_samples = 20 # generate these many data points per class
    #For biased data
    p_sen=0.2 #this parameter sets the probability of being protected (sensitive feature=1)
    delta1=[3,-2] # This is the increment of the mean for the positive class
    delta2=[3,-2] # This is the increment of the mean for the negative class


    def gen_gaussian_sensitive(size, mean_in, cov_in, class_label, sensitive):
        nv = multivariate_normal(mean = mean_in, cov = cov_in)
        X = nv.rvs(size)
        y = np.ones(size, dtype=int) * class_label
        x_sen = np.ones(size, dtype=float) * sensitive
        return nv,X,y,x_sen

    """ Generate the features randomly """
    #For the NON-protected group (sensitive feature=0, for ex. men)
    # We will generate one gaussian cluster for each class
    mu1, sigma1 = [2, 2], [[5, 1], [1, 5]]
    mu2, sigma2 = [-2,-2], [[10, 1], [1, 3]]
    nv1, X1, y1, x_sen1= gen_gaussian_sensitive(int((1-p_sen)*n_samples), mu1, sigma1, 1,0) # positive class
    nv2, X2, y2, x_sen2= gen_gaussian_sensitive(int((1-p_sen)*n_samples),mu2, sigma2, 0,0) # negative class


    #For the Protected group (sensitive feature=1, for ex. women)
    # We will generate one gaussian cluster for each class
    mu3, sigma3 = np.add(mu1,delta1), [[5, 1], [1, 5]]
    mu4, sigma4 = np.add(mu2,delta2), [[10, 1], [1, 3]]
    nv3, X3, y3, x_sen3 = gen_gaussian_sensitive(int(p_sen*n_samples), mu3, sigma3, 1,1.) # positive class
```

```
    nv4, X4, y4, x_sen4 = gen_gaussian_sensitive(int(p_sen*n_samples),mu4, sigma4, 0,1.) # negative class




    # join the positive and negative class clusters
    X = np.vstack((X1, X2, X3, X4))
    y = np.hstack((y1, y2, y3, y4))
    x_prot= np.hstack((x_sen1, x_sen2, x_sen3, x_sen4))


    # shuffle the data
    perm = list(range(0,n_samples*2))
    shuffle(perm)
    X = X[perm]
    y = y[perm]
    x_prot=x_prot[perm]



    return X,y,x_prot
```

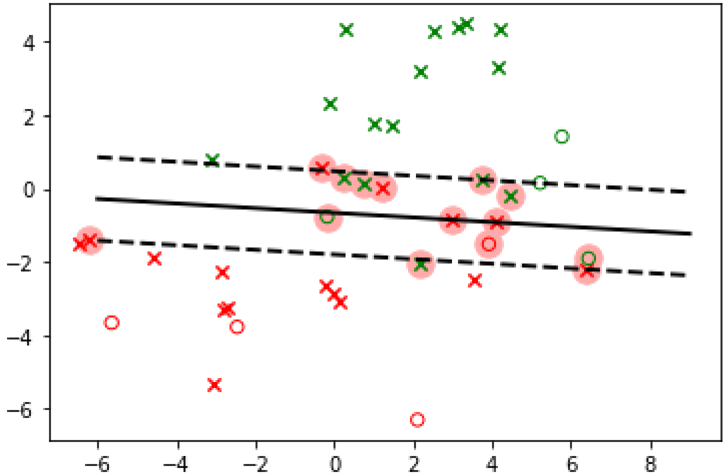
In [ ]:

```
X_syn, y_syn, x_bias = generate_synthetic_data_bias()
```

In [ ]:

```
#plt.scatter(X_syn[y_syn==1][:, 0], X_syn[y_syn==1][:, 1], color='#378661', marker='x', s=40, linewidth=1.5, label= "Cl
#plt.scatter(X_syn[y_syn==0][:, 0], X_syn[y_syn==0][:, 1], color='#A73730', marker='x', s=40, linewidth=1.5, label = "C

X_s_0 = X_syn[x_bias == 0.0]
X_s_1 = X_syn[x_bias == 1.0]
y_s_0 = y_syn[x_bias == 0.0]
y_s_1 = y_syn[x_bias == 1.0]

# SVM Classifier model
#the hyperparameter C control the margin violations
#smaller C leads to more margin violations but wider margin

svm_clf = SVC(kernel="linear", C=float(4))
svm_clf.fit(X_syn, y_syn)

plot_svc_decision_boundary(svm_clf, -6, 9)
plt.scatter(X_s_0[y_s_0==1][:, 0], X_s_0[y_s_0==1][:, 1], color='green', marker='x', s=40, linewidth=1.5, label= "Non-p
```

```
plt.scatter(X_s_0[y_s_0==0][:, 0], X_s_0[y_s_0==0][:, 1], color='red', marker='x', s=40, linewidth=1.5, label = "Non-pr
plt.scatter(X_s_1[y_s_1==1][:, 0], X_s_1[y_s_1==1][:, 1], color='green', marker='o', facecolors='none', s=40, label = "
plt.scatter(X_s_1[y_s_1==0][:, 0], X_s_1[y_s_1==0][:, 1], color='red', marker='o', facecolors='none', s=40, label = "Pr

#plt.savefig('aggre.png')
plt.show()
```



First we calculate the accuracy of the SVM classifier in our dataset:

In [ ]:

```
#Accuracy
y_pred=svm_clf.predict(X_syn)

print("Accuracy: %.1f" % (metrics.accuracy_score(y_syn, y_pred)*100), "%")
```

```
Accuracy: 82.5 %
```

We first implement the equal opportunity metric:

In [ ]:

```
#Let us now implement the equal opportunity metric:
def equal_opportunity(y,y_pred, x_prot):
    Pos_pro=0.0
    Pos_nonpro=0.0
    PPos_pro=0.0
    PPos_nonpro=0.0

    n=y_pred.size
```

```
    for i in range(0,n):
        if (y[i]==1 and x_prot[i]==0):
            Pos_nonpro=Pos_nonpro+1
            if (y_pred[i]==1):
                PPos_nonpro=PPos_nonpro+1
        if (y[i]==1 and x_prot[i]==1):
            Pos_pro=Pos_pro+1
            if (y_pred[i]==1):
                PPos_pro=PPos_pro+1
    #print(Pos_nonpro)
    #print(Pos_pro)
    #print(PPos_pro)
    #print(PPos_nonpro)
    UNF_EOpp=abs((PPos_nonpro/Pos_nonpro)-(PPos_pro/Pos_pro))

    return UNF_EOpp
```

In [ ]:

```
UNF_EOpp=equal_opportunity(y_syn,y_pred, x_bias)
print('UNF_EOpp = %.2f' % (UNF_EOpp*100),"%")
```

```
UNF_EOpp = 43.75 %
```

Questions:

1- Calculate the predictive equality metric for the given dataset and classifier.

2- Calculate the equalized odds metric for the given dataset and classifier.

3- Calculate the predictive parity metric for the given dataset and classifier.

4- Calculate the statistical parity metric for the given dataset and classifier.

5- a)Calculate the disparate impact metric for the given dataset and classifier.

b)Does this classifier satisfy the 80%-rule?

6.2 Fairness metrics for the German dataset

In [ ]:
```
German_data=np.loadtxt('German.txt')
i_prot=40 #the protected features corresponds with column 40 from the txt file
n_sample=500 # we define our training sample size
C_param=5

X_German=np.delete(German_data,[0,i_prot],1) #We eliminate the first column that correspond to labels and the protectec

y_German=German_data[:,0] #labels
x_bias_german=German_data[:,i_prot] #protected feature

#Now let us consider a training set
X_G=X_German[1:n_sample,:]
y_G=y_German[1:n_sample]
x_bias_G=x_bias_german[1:n_sample]


# SVM Classifier model
#the hyperparameter C control the margin violations
#smaller C leads to more margin violations but wider margin

svm_clf = SVC(kernel="linear", C=float(C_param))
svm_clf.fit(X_G, y_G)

y_pred_G=svm_clf.predict(X_G)
```

Questions:

In the code before, we set i_prot=40, which means we consider the protected feature being "female divorced/separated/married". Under this choice:

6- Provide a table with the accuracy and the 6 fairness metrics.

7- Does this classifier satisfy the 80%-rule?

Now choose as protected feature being "male divorced/separated", i.e., i_prot=39. Under this choice:

8- Provide a table with the 6 fairness metrics.

9- Does this classifier satisfy the 80%-rule?

10- Which conclusion do you obtain comparing the tables from 6 and 8?

6.3 The COMPAS dataset. What happens if we change the choice of variables?

Let's take our own decisions:

In [ ]:
```
# filter dplyr warnings
%load_ext rpy2.ipython
import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```
%%R
library(dplyr)
#You can choose your favorite option:
#a)Download the dataset and access it locally
raw_data <- read.csv("./compas-scores-two-years.csv")
#b)Access the dataset directly from the repository
raw_data <- read.csv("https://raw.githubusercontent.com/propublica/compas-analysis/master/compas-scores-two-years.csv")
nrow(raw_data)
colnames(raw_data)
```

```
R[write to console]:
Attaching package: ‘dplyr’


R[write to console]: The following objects are masked from ‘package:stats’:

    filter, lag


R[write to console]: The following objects are masked from ‘package:base’:

    intersect, setdiff, setequal, union


 [1] "id"                      "name"
 [3] "first"                   "last"
 [5] "compas_screening_date"   "sex"
 [7] "dob"                     "age"
 [9] "age_cat"                 "race"
[11] "juv_fel_count"           "decile_score"
[13] "juv_misd_count"          "juv_other_count"
[15] "priors_count"            "days_b_screening_arrest"
[17] "c_jail_in"               "c_jail_out"
```

```
[19] "c_case_number"           "c_offense_date"
[21] "c_arrest_date"           "c_days_from_compas"
[23] "c_charge_degree"         "c_charge_desc"
[25] "is_recid"                "r_case_number"
[27] "r_charge_degree"         "r_days_from_arrest"
[29] "r_offense_date"          "r_charge_desc"
[31] "r_jail_in"               "r_jail_out"
[33] "violent_recid"           "is_violent_recid"
[35] "vr_case_number"          "vr_charge_degree"
[37] "vr_offense_date"         "vr_charge_desc"
[39] "type_of_assessment"      "decile_score.1"
[41] "score_text"              "screening_date"
[43] "v_type_of_assessment"    "v_decile_score"
[45] "v_score_text"            "v_screening_date"
[47] "in_custody"              "out_custody"
[49] "priors_count.1"          "start"
[51] "end"                     "event"
[53] "two_year_recid"
```

Note: if you obtain the following error: "UsageError: Cell magic `%%R` not found." Try this solution: pip install rpy2

Filtering of data

In a 2009 study examining the predictive power of its COMPAS score, Northpointe defined recidivism as “a finger-printable arrest involving a charge and a filing for any uniform crime reporting (UCR) code.” We interpreted that to mean a criminal offense that resulted in a jail booking and took place after the crime for which the person was COMPAS scored.

It was not always clear, however, which criminal case was associated with an individual’s COMPAS score. To match COMPAS scores with accompanying cases, we considered cases with arrest dates or charge dates within 30 days of a COMPAS assessment being conducted. In some instances, we could not find any corresponding charges to COMPAS scores. We removed those cases from our analysis.

Next, we sought to determine if a person had been charged with a new crime subsequent to crime for which they were COMPAS screened. We did not count traffic tickets and some municipal ordinance violations as recidivism. We did not count as recidivists people who were arrested for failing to appear at their court hearings, or people who were later charged with a crime that occurred prior to their COMPAS screening.

*We do the same filtering that in the Propublica Study **BUT** we select different variables.*

Finally we save the filtered csv file.

In [ ]:

```
%%R
df <- dplyr::select(raw_data, age, c_charge_degree, race, age_cat, score_text, sex, priors_count,
                    days_b_screening_arrest, decile_score, is_recid, two_year_recid, c_jail_in, c_jail_out,
                    juv_fel_count,juv_misd_count,juv_other_count,is_violent_recid) %>%
        filter(days_b_screening_arrest <= 30) %>%
        filter(days_b_screening_arrest >= -30) %>%
        filter(is_recid != -1) %>%
        filter(is_violent_recid != -1) %>%
        filter(c_charge_degree != "O") %>%
        filter(score_text != 'N/A')
write.csv(df,"propublica_ext.csv")

nrow(df)
```

```
[1] 6172
```

Now we import the same libraries as in the previous labs.

In [ ]:

```python
#we import all the required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt # for plotting stuff
from random import seed, shuffle
from scipy.stats import multivariate_normal # for generating synthetic data
import seaborn as sns
from sklearn import metrics
from sklearn.metrics import confusion_matrix
SEED = 1122334455
seed(SEED) # set the random seed so that the random permutations can be reproduced again
np.random.seed(SEED)
```

We first read the filtered data.

In [ ]:

```python
df = pd.read_csv("propublica_ext.csv")

print("Size of the dataset: %d" % len(df.index)) #We calculate the number of objects in the dataset
```

```
Size of the dataset: 6172
```

In [ ]:

```python
for col in df:
    print(df[col].unique())
```

```
[   1    2    3 ... 6170 6171 6172]
[69 34 24 44 41 43 39 27 23 37 47 31 25 64 21 32 26 33 30 55 49 29 51 35
 28 53 38 22 62 56 45 40 50 20 36 54 19 42 52 59 61 63 48 46 58 78 57 66
 70 60 65 68 71 83 67 75 72 74 96 73 80 77 76 79 18]
['F' 'M']
['Other' 'African-American' 'Caucasian' 'Hispanic' 'Asian'
 'Native American']
['Greater than 45' '25 - 45' 'Less than 25']
['Low' 'Medium' 'High']
['Male' 'Female']
[ 0  4 14  3  1  7  6  5 13  8  9 21  2 15 10 28 19 11 23 25 36 12 20 33
 16 18 17 22 30 24 27 26 37 29 31 38]
[ -1   0 -20  22  -2 -24 -13 -15 -10 -30  -4 -16 -26  -7  29  -3  23 -11
 -22 -21 -12  -8  -5 -23 -14  -9  -6 -27 -19 -18  26 -29  28   7 -17 -28
   9 -25  13  20  17  30   6   2  16   8   1  18  15  21  27  11   3  14
   5  24]
[ 1  3  4  6 10  5  9  2  7  8]
[0 1]
[0 1]
['2013-08-13 06:03:42' '2013-01-26 03:45:27' '2013-04-13 04:58:34' ...
 '2014-01-13 05:48:01' '2014-03-08 08:06:02' '2014-06-28 12:16:41']
['2013-08-14 05:41:20' '2013-02-05 05:36:53' '2013-04-14 07:02:04' ...
 '2014-01-14 07:49:46' '2014-03-09 12:18:04' '2014-06-30 11:19:23']
[ 0  2  1  8  3  4 20  6  5 10]
[ 0  1  6 12  2  4  3  8  5 13]
[0 1 3 4 2 9 5 6 7]
[0 1]
```

We need to binarize all the categorical features we considered in the dataset:

In [ ]:

```
df = (
    pd.read_csv("propublica_ext.csv")
    #We first binarize the categorical feature c_charge_degree
    .assign(c_charge=lambda x:x['c_charge_degree'].replace({'F': 1, 'M':0}))
    #race
    .assign(african_american=lambda x:x['race'].replace({'Other': 0, 'African-American': 1, 'Caucasian': 0, 'Hispanic':
    .assign(caucasian=lambda x:x['race'].replace({'Other': 0, 'African-American': 0, 'Caucasian': 1, 'Hispanic': 0, 'As
    .assign(native_american=lambda x:x['race'].replace({'Other': 0, 'African-American': 0, 'Caucasian': 0, 'Hispanic':
    .assign(hispanic=lambda x:x['race'].replace({'Other': 0, 'African-American': 0, 'Caucasian': 0, 'Hispanic': 1, 'Asi
    .assign(asian=lambda x:x['race'].replace({'Other': 0, 'African-American': 0, 'Caucasian': 0, 'Hispanic': 0, 'Asian
    .assign(other=lambda x:x['race'].replace({'Other': 1, 'African-American': 0, 'Caucasian': 0, 'Hispanic': 0, 'Asian
    #age_cat
    .assign(less_than_25=lambda x:x['age_cat'].replace({'Greater than 45':0, '25 - 45':0, 'Less than 25':1}))
    .assign(between_25_45=lambda x:x['age_cat'].replace({'Greater than 45':0, '25 - 45':1, 'Less than 25':0}))
    .assign(greater_than_25=lambda x:x['age_cat'].replace({'Greater than 45':1, '25 - 45':0, 'Less than 25':0}))
```

```
    #score_text
    .assign(score_low=lambda x:x['score_text'].replace({'Low':1, 'Medium':0, 'High':0}))
    .assign(score_medium=lambda x:x['score_text'].replace({'Low':0, 'Medium':1, 'High':0}))
    .assign(score_high=lambda x:x['score_text'].replace({'Low':0, 'Medium':0, 'High':1}))
    #sex
    .assign(Male=lambda x:x['sex'].replace({'Male': 1, 'Female':0}))

)
DeleteList=['c_charge_degree','race','age_cat','score_text','sex','c_jail_in','c_jail_out']
df=df.drop(DeleteList, axis=1)
print("Dataset with %d" % df.shape[0],"objects and %d" % df.shape[1], "variables") #We calculate the number of objects

df.head()
```

```
Dataset with 6172 objects and 25 variables
```

Out[ ]:

	Unnamed: 0	age	priors_count	days_b_screening_arrest	decile_score	is_recid	two_year_recid	juv_fel_count	juv_misd_count	juv_other_count	...
0	1	69	0	-1	1	0	0	0	0	0	...
1	2	34	0	-1	3	1	1	0	0	0	...
2	3	24	4	-1	4	1	1	0	0	1	...
3	4	44	0	0	1	0	0	0	0	0	...
4	5	41	14	-1	6	1	1	0	0	0	...

5 rows × 25 columns

Actually, our dataset is only composed of 23 variables, since we do not include the first column as variable, and the variable "two_year_recid" is the binary label to predict.

We then define our data and our label:

In [ ]:

```
display(df.columns)
```

```
Index(['Unnamed: 0', 'age', 'priors_count', 'days_b_screening_arrest',
       'decile_score', 'is_recid', 'two_year_recid', 'juv_fel_count',
       'juv_misd_count', 'juv_other_count', 'is_violent_recid', 'c_charge',
       'african_american', 'caucasian', 'native_american', 'hispanic', 'asian',
       'other', 'less_than_25', 'between_25_45', 'greater_than_25',
```

```
       'score_low', 'score_medium', 'score_high', 'Male'],
      dtype='object')
```

We now select from this list only the variables we want to consider in our classification problem and the corresponding labels:

In [ ]:

```python
# Here is a way to select these columns using the column names

#feature_columns = ['Number_of_Priors', 'score_factor','Age_Above_FourtyFive', 'Age_Below_TwentyFive', 'African_America

feature_columns = ['age', 'priors_count', 'days_b_screening_arrest',
         'juv_fel_count',
       'juv_misd_count', 'juv_other_count', 'is_violent_recid', 'c_charge',
        'less_than_25', 'between_25_45', 'greater_than_25',
        'Male']


data = df[feature_columns].values
y = df['two_year_recid'].values
df=df.assign(COMPAS_Decision=lambda x:x['score_low'].replace({0: 1, 1:0}))
y_compas = df['COMPAS_Decision'].values
```

In [ ]:

```python
#We load the libraries for the SVM

from sklearn.svm import SVC
from sklearn.model_selection import train_test_split

# shuffle the data
#n_samples=data.shape[0]
#perm = list(range(0,n_samples))
#shuffle(perm)
#data = data[perm]
#y = y[perm]
#y_compas=y_compas[perm]


#Create train and validation set
#train_x, test_x, train_y, test_y = train_test_split(data, y, test_size=0.1, shuffle=True, stratify=y, random_state=42,

svm_clf = SVC(kernel="linear", C=1.0)
svm_clf.fit(data, y)

y_pred=svm_clf.predict(data)
```

```
#svm_clf = SVC(kernel="linear", C=1.0)
#svm_clf.fit(train_x, train_y)

#ytrain_pred=svm_clf.predict(train_x)
#ytest_pred=svm_clf.predict(test_x)
```

In [ ]:

```
b_recid = df[df['african_american'] == 1]
w_recid = df[df['caucasian'] == 1]
print(
    ' Accuracy SVM (All):  \t %.2f' % (metrics.accuracy_score(y, y_pred)*100), "%\n",
    'Accuracy SVM (Black):\t %.2f' % (metrics.accuracy_score(y_pred[df['african_american'] == 1], b_recid['two_year_rec
    'Accuracy SVM (White):\t %.2f' % (metrics.accuracy_score(y_pred[df['caucasian'] == 1], w_recid['two_year_recid'])*1

)

pd.crosstab(y_pred, df['two_year_recid'], rownames=['Predicted recividism'],colnames=['Actual recividism'],normalize='c

FPR_s=pd.crosstab(y_pred, df['two_year_recid'], rownames=['Predicted recividism'],colnames=['Actual recividism'],normal
FNR_s=pd.crosstab(y_pred, df['two_year_recid'], rownames=['Predicted recividism'],colnames=['Actual recividism'],normal

print("FPR SVM %.2f" % (FPR_s*100),"%")
print("FNR SVM %.2f" % (FNR_s*100),"%")
```

```
 Accuracy SVM (All):     70.01 %
 Accuracy SVM (Black):   68.57 %
 Accuracy SVM (White):   71.18 %

FPR SVM 9.60 %
FNR SVM 54.40 %
```

Questions:

11- *Provide the accuracy for the COMPAS dataset.*

12- *Provide the accuracy for black defendants for the COMPAS dataset.*

13- *Provide the accuracy for white defendants for the COMPAS dataset.*

14- *Provide the FPR for the COMPAS dataset.*

15- *Provide the FNR for the COMPAS dataset.*

In [ ]:
```
#For the COMPAS:
FPR_b=pd.crosstab(b_recid['COMPAS_Decision'], b_recid['two_year_recid'], rownames=['Predicted recividism'],colnames=['A
FNR_b=pd.crosstab(b_recid['COMPAS_Decision'], b_recid['two_year_recid'], rownames=['Predicted recividism'],colnames=['A

print("FPR of Black %.2f" % (FPR_b*100),"%")
print("FNR of Black %.2f" % (FNR_b*100),"%")
```

```
FPR of Black 42.34 %
FNR of Black 28.48 %
```

Questions:

For the COMPAS classifier:

16- *Calculate the FPR for white defendants.*

17- *Calculate the FNR for white defendants.*

18- *Replace **x** by the right number in the two following statement:*

*"FPR of Black is **x** times greater than for White"*

19- *Replace **x** by the right number in the two following statement:*

*"FNR of Black is **x** times smaller than for White"*

In [ ]:
```
#For the SVM:
FPR_b=pd.crosstab(y_pred[df['african_american'] == 1], b_recid['two_year_recid'], rownames=['Predicted recividism'],col
FNR_b=pd.crosstab(y_pred[df['african_american'] == 1], b_recid['two_year_recid'], rownames=['Predicted recividism'],col

print("FPR of Black %.2f" % (FPR_b*100),"%")
print("FNR of Black %.2f" % (FNR_b*100),"%")
```

```
FPR of Black 13.74 %
FNR of Black 47.56 %
```

Questions:

For the SVM classifier:

20- *Calculate the FPR for white defendants.*

21- *Calculate the FNR for white defendants.*

22- *Replace **x** by the right number in the two following statement:*

*"FPR of Black is **x** times greater than for White"*

23- *Replace **x** by the right number in the two following statement:*

*"FNR of Black is **x** times smaller than for White"*

Questions:

24- *Fill in the following table:*

25- *Which is the best solution in terms of accuracy? Is it fair (in terms of accuracy)?*

26- *Which is the best solution in terms of FPR? Based on answers 18 and 22, which solution is more fair (in terms of FPR)?*

27- *Which is the best solution in terms of FNR? Based on answers 19 and 23, which solution is more fair (in terms of FNR)?*

28- *Calculate the 6 fairness metrics for the COMPAS classifier.*

29- *Calculate the 6 fairness metrics for the SVM classifier.*

30- *As a future (or actual) data scientist, which solution would you choose for **this** specific problem? Justify your answer.*

SVM

	All	Black	White
Accuracy			
FPR			
FNR			

COMPAS

	All	Black	White
Accuracy			
FPR			
FNR			