PREPARED BY

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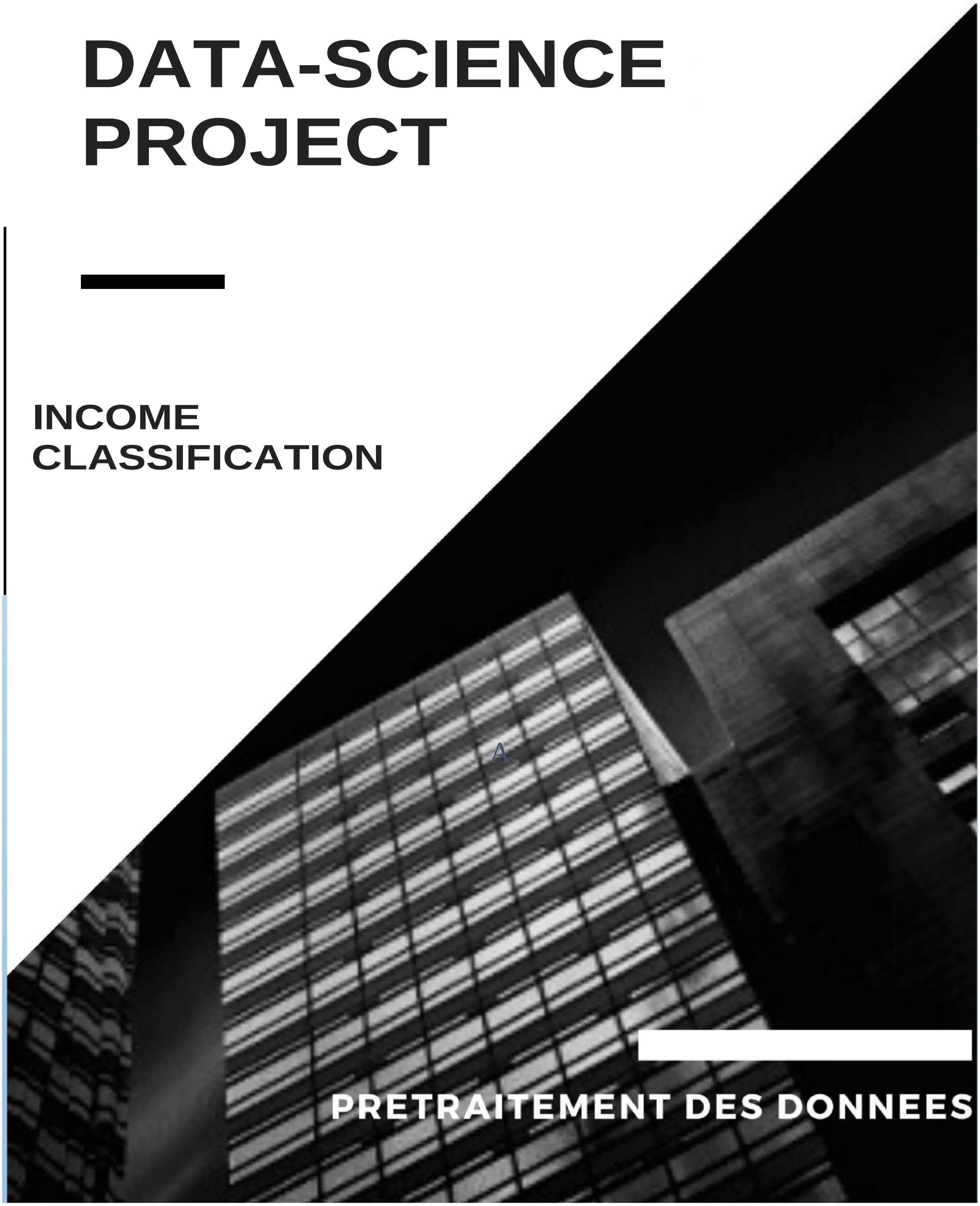
DATA-SCIENCE PROJECT

INCOME CLASSIFICATION



Contents

A. Description and purpose of the database

1. Database search

Before pre-processing the data, we had to choose a suitable database on which to carry out cleaning operations.
Among the criteria we took into consideration:

1- Must have categorical and numerical data.

2- Presence of missing data in our chosen database.

3- A minimum number of instances to build a good model.

2. THE DATA BUSINESS AND ITS CONTENT

The dataset selected provided predictive features such as education, employment status, marital status to predict whether the salary is above $50,000.

It can be used to practice machine learning problems like classification, we can use it to predict whether a person has a job or not.

The selected data contains Number of instances: 43957.

Number of attributes: 15, the last of which is Target [Income >50k].

In the following table you'll find all the attributes and their types, as well as the contents of the categorical attributes.

ATTRIBUTES	DESCRIPTION
Age	Type: Numerical Age of the person
workclass	Type: Categorical Categorical variable indicating the type of work workclass ['Private' 'State-gov' 'Self-emp-not-inc' 'Federal-gov' 'Local-gov' 'Self-emp-inc' 'Without-pay']
Fnlwgt	Type: Numerous Final weight
education	Type: Categorical education ['Doctorate' '12th' 'Bachelors' '7th-8th' 'Some-college' 'HS-grad' '9th' '10th' '11th' 'Masters' 'Preschool' '5th-6th' 'Prof-school' 'Assoc-voc' 'Assoc-acdm' '1st-4th']
educational-num	Type: Numerous Education as Integer
marital-status	Type: Categorical marital-status ['Divorced' 'Never-married' 'Married-civ-spouse' 'Widowed' 'Separated' 'Married-spouse-absent' 'Married-AF-spouse']
occupation	Type: Categorical occupation ['Exec-managerial' 'Other-service' 'Transport-moving' 'Adm-clerical' 'Machine-op-inspct' 'Sales' 'Handlers-cleaners' 'Farming-fishing' 'Protective-serv' 'Prof-specialty' 'Craft-repair' 'Tech-support' 'Priv-house-serv' 'Armed-Forces']
relationship	Type: Categorical relationship ['Not-in-family' 'Own-child' 'Husband' 'Wife' 'Unmarried' 'Other-relative']
race	Type: Categorical race ['White' 'Black' 'Asian-Pac-Islander' 'Other' 'Amer-Indian-Eskimo']
gender	Type: Categorical gender ['Male' 'Female']
capital-gain	Type: Numerous
capital-loss	Type: Numerous
hours-per-week	Type: Numerous
native-country	Type: Categorical native-country ['United-States' 'Japan' 'South' 'Portugal' 'Italy' 'Mexico' 'Ecuador' 'England' 'Philippines' 'China' 'Germany' 'Dominican-Republic' 'Jamaica' 'Vietnam' 'Thailand' 'Puerto-Rico' 'Cuba' 'India' 'Cambodia' 'Yugoslavia' 'Iran' 'El-Salvador' 'Poland' 'Greece' 'Ireland' 'Canada' 'Guatemala' 'Scotland' 'Columbia' 'Outlying-US(Guam-USVI-etc)' 'Haiti' 'Peru' 'Nicaragua' 'Trinadad&Tobago' 'Laos' 'Taiwan' 'France' 'Hungary' 'Honduras' 'Hong' 'Holland-Netherlands']
Income >50k	Type: Numerous Target column

B. Data preprocessing

1. Importing and viewing data:

We imported the NUMPY, PANDAS, MATPLOTLIB and SEABORN python libraries. We read the database using pandas.read_csv.

Then display data with

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns

In [2]: df = pd.read_csv("Downloads/archive (10)/train.csv")

In [3]: df
Out[3]:
```

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gender	capital-gain	capital-loss	hours-per-week	native-country	income_>50K
0	67	Private	366425	Doctorate	16	Divorced	Exec-managerial	Not-in-family	White	Male	99999	0	60	United-States	1
1	17	Private	244602	12th	8	Never-married	Other-service	Own-child	White	Male	0	0	15	United-States	0
2	31	Private	174201	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	40	United-States	1
3	58	State-gov	110199	7th-8th	4	Married-civ-spouse	Transport-moving	Husband	White	Male	0	0	40	United-States	0
4	25	State-gov	149248	Some-college	10	Never-married	Other-service	Not-in-family	Black	Male	0	0	40	United-States	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
43952	52	Private	68982	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	50	United-States	1
43953	19	Private	116562	HS-grad	9	Never-married	Other-service	Own-child	White	Female	0	0	40	United-States	0
43954	30	Private	197947	Some-college	10	Divorced	Sales	Not-in-family	White	Male	0	0	58	United-States	0
43955	46	Private	97883	Bachelors	13	Never-married	Sales	Not-in-family	White	Female	0	0	35	United-States	0
43956	30	Private	375827	HS-grad	9	Never-married	Handlers-cleaners	Other-relative	White	Male	0	0	40	United-States	0

43957 rows × 15 columns

2. Visualization of attribute type distribution

```
In [78]: data.dtypes

Out[78]: age                  int64
         workclass           object
         fnlwgt               int64
         education           object
         educational-num      int64
         marital-status      object
         occupation          object
         relationship        object
         race                object
         gender              object
         capital-gain         int64
         capital-loss         int64
         hours-per-week       int64
         native-country      object
         income_>50K          int64
         dtype: object
```

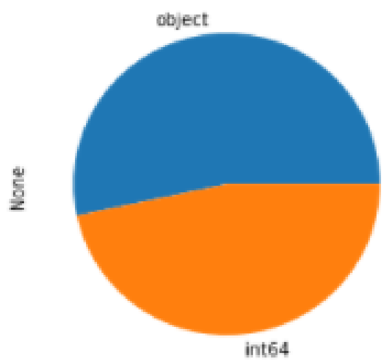
Nos attributs sont de types soit integer(numérique) et catégorique

```
In [79]: data.dtypes.value_counts()

Out[79]: object    8
         int64     7
         dtype: int64
```

```
data.dtypes.value_counts().plot.pie()

<AxesSubplot:ylabel='None'>
```



We have visualized the attribute types of our data.

3. Detection and deletion of rows where missing values are detected.

In this part we try to eliminate the rows with missing values. We began by searching for missing values by attributes.

```
In [82]: data.isnull().mean(axis=0).sort_values()*len(data)

Out[82]: age                   0.0
         fnlwgt                0.0
         education             0.0
         educational-num       0.0
         marital-status        0.0
         relationship          0.0
         race                  0.0
         gender                0.0
         capital-gain          0.0
         capital-loss          0.0
         hours-per-week        0.0
         income_>50K           0.0
         native-country      763.0
         workclass          2498.0
         occupation         2506.0
         dtype: float64
```

L'attribut 'native-contry' contient 763 valeur manquantes

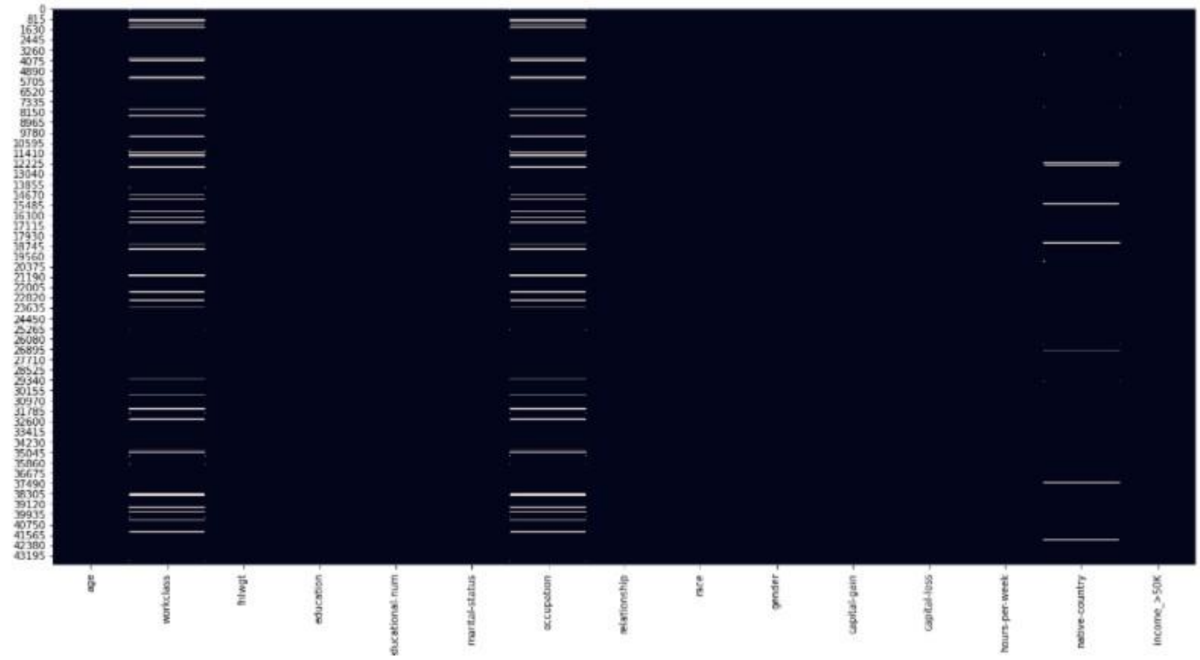
L'attribut 'workclass' contient 2498 valeur manquantes

L'attribut 'occupation' contient 2506 valeur manquantes

We notice that the attributes *native country* and *workclass* as well as*occupation* have missing values, so we're going to eliminate these rows.

```
plt.figure(figsize=(20,10))
sns.heatmap(data.isna(), cbar=False)
```

```
<AxesSubplot:>
```



HEAT MAP: Viewing missing values.

```
data = data.dropna(subset=['native-country'])
```

On élimine les données manquantes de l'attribut 'native-country'

```
data = data.dropna(subset=['occupation'])
```

On élimine les données manquantes de l'attribut 'occupation'

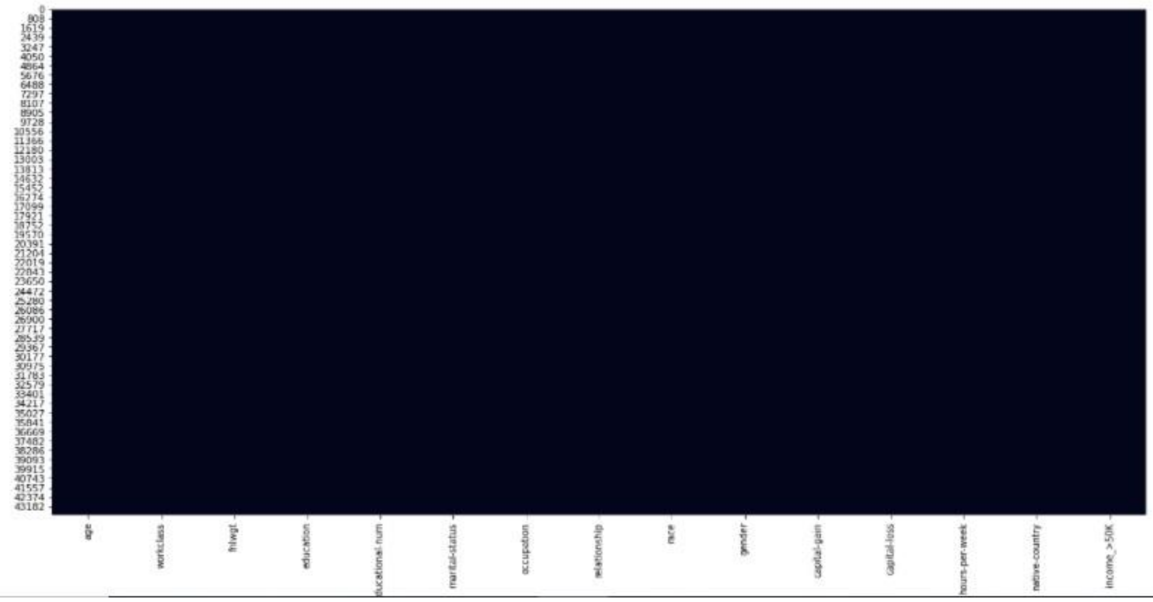
```
data = data.dropna(subset=['workclass'])
```

On élimine les données manquantes de l'attribut 'workclass'

We will display the values after deleting the rows with missing values.

Notre base de données a maintenant 40727 lignes(instances) et 15 colonnes(attributs)

```
In [89]: plt.figure(figsize=(20,10))
         sns.heatmap(data.isna(), cbar=False)
Out[89]: <AxesSubplot:>
```

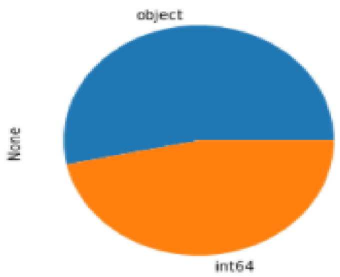


Our database now has 40727 rows (instances) and 15 columns (attributes)

4. Background analysis: Target attribute analysis

```
In [91]: data['income_>50K'].value_counts()
Out[91]: 0    30635
         1    10092
         Name: income_>50K, dtype: int64
```

```
data.dtypes.value_counts().plot.pie()
<AxesSubplot:ylabel='None'>
```



We found that:

30635 people with an income of less than 50K 75.22%.

10092 people with income over 50K 24,77%.

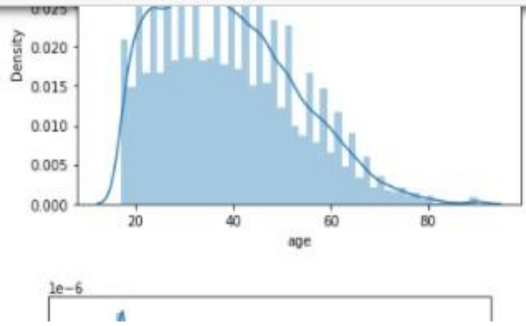
5. Background analysis: Histogram of numerical values

```
In [94]: for col in data.select_dtypes('int64'):
             print(col)
```

```
age
fnlwgt
educational-num
capital-gain
capital-loss
hours-per-week
income_>50K
```

L'ensemble des attributs ayant des données numérique

```
In [95]: for col in data.select_dtypes('int64'):
             plt.figure()
             sns.distplot(df[col])
```



We used: for col in data. Select_dtypes('int64') because the set of all numeric values is of type "int 64".

We visualized the histograms, but we couldn't find a way to eliminate any attribute.

6. Background analysis for categorical variables

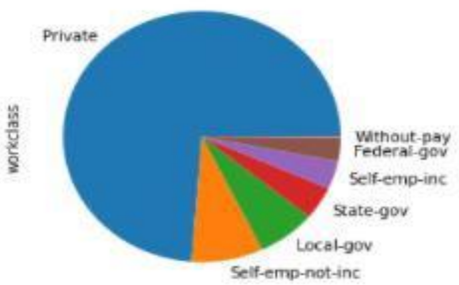
```
for col in data.select_dtypes('object'):
    print(col,data[col].unique())
```

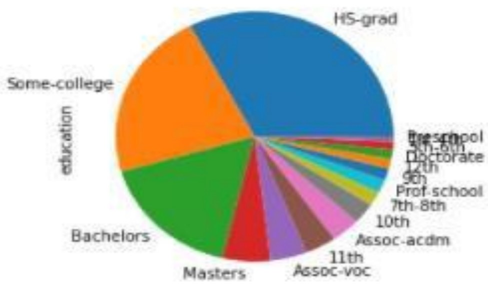
```
workclass ['Private' 'State-gov' 'Self-emp-not-inc' 'Federal-gov' 'Local-gov'
 'Self-emp-inc' 'Without-pay']
education ['Doctorate' '12th' 'Bachelors' '7th-8th' 'Some-college' 'HS-grad' '9th'
 '10th' '11th' 'Masters' 'Preschool' '5th-6th' 'Prof-school' 'Assoc-voc'
 'Assoc-acdm' '1st-4th']
marital-status ['Divorced' 'Never-married' 'Married-civ-spouse' 'Widowed' 'Separated'
 'Married-spouse-absent' 'Married-AF-spouse']
occupation ['Exec-managerial' 'Other-service' 'Transport-moving' 'Adm-clerical'
 'Machine-op-inspct' 'Sales' 'Handlers-cleaners' 'Farming-fishing'
 'Protective-serv' 'Prof-specialty' 'Craft-repair' 'Tech-support'
 'Priv-house-serv' 'Armed-Forces']
relationship ['Not-in-family' 'Own-child' 'Husband' 'Wife' 'Unmarried' 'Other-relative']
race ['White' 'Black' 'Asian-Pac-Islander' 'Other' 'Amer-Indian-Eskimo']
gender ['Male' 'Female']
native-country ['United-States' 'Japan' 'South' 'Portugal' 'Italy' 'Mexico' 'Ecuador'
 'England' 'Philippines' 'China' 'Germany' 'Dominican-Republic' 'Jamaica'
 'Vietnam' 'Thailand' 'Puerto-Rico' 'Cuba' 'India' 'Cambodia' 'Yugoslavia'
 'Iran' 'El-Salvador' 'Poland' 'Greece' 'Ireland' 'Canada' 'Guatemala'
 'Scotland' 'Columbia' 'Outlying-US(Guam-USVI-etc)' 'Haiti' 'Peru'
 'Nicaragua' 'Trinadad&Tobago' 'Laos' 'Taiwan' 'France' 'Hungary'
 'Honduras' 'Hong' 'Holand-Netherlands']
```

We have visualized the attributes using the pie chart

```
plt.figure(figsize=(30,15))
for col in data.select_dtypes('object'):
    plt.figure()
    data[col].value_counts().plot.pie()
```

```
<Figure size 2160x1080 with 0 Axes>
```





We found something interesting:

For the 'native country' attribute

```
In [98]: ((data['native-country'].value_counts())/len(data))*100

Out[98]: United-States              91.261325
         Mexico                      2.057603
         Philippines                 0.640853
         Germany                     0.432146
         Puerto-Rico                 0.390404
         Canada                      0.341297
         El-Salvador                 0.336386
         India                       0.319199
         Cuba                        0.294645
         China                       0.260270
         England                     0.250448
         Jamaica                     0.230805
         South                       0.223439
         Dominican-Republic          0.223439
         Italy                       0.218528
         Japan                       0.198885
         Guatemala                   0.189064
         Vietnam                     0.184153
         Columbia                    0.176787
         Poland                      0.162055
         Haiti                       0.159599
         Portugal                    0.135046
         Iran                        0.122769
         Taiwan                      0.120313
         Nicaragua                   0.110492
         Greece                      0.108036
         Ecuador                     0.098215
         Peru                        0.095760
         Ireland                     0.076117
         France                      0.073661
         Thailand                    0.068750
         Hong                        0.066295
         Cambodia                    0.054018
         Trinadad&Tobago             0.051563
         Honduras                    0.046652
         Yugoslavia                  0.046652
         Scotland                    0.044197
```

We've noticed that there's a large percentage of the American population.

And we're interested in doing a study that can be generalized worldwide.

So, we decided to eliminate the native country attribute since we're not interested in people's origins to predict their income.

```
In [99]: data = data.drop('native-country',axis=1,inplace=False)
```

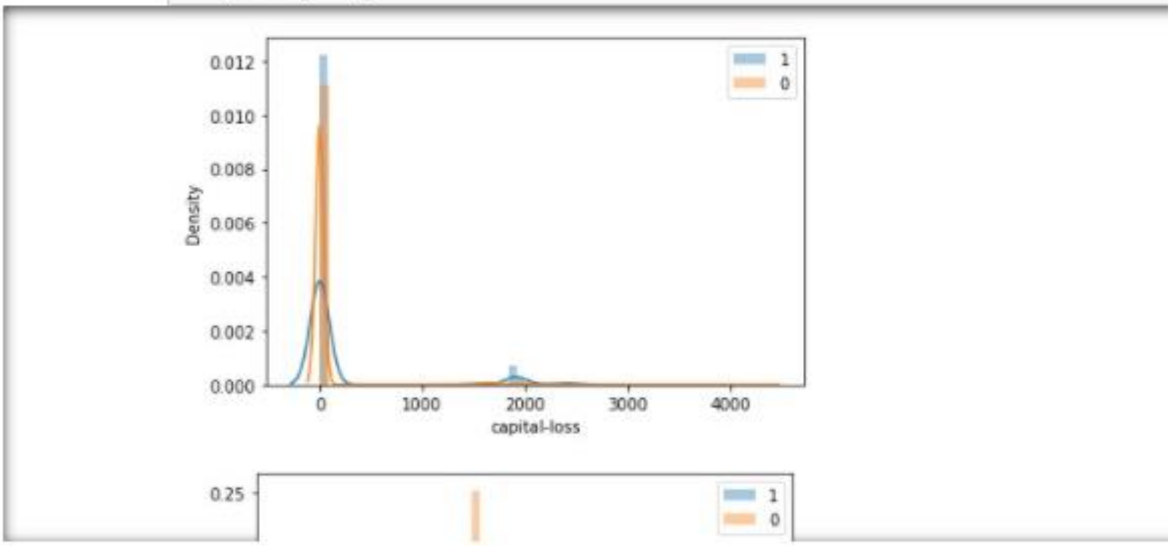
7. Separation of variables according to classification result:

```
data1 = data[data['income_>50K'] == 1]
data1
```

```
In [102]: data0 = data[data['income_>50K'] == 0]
          data0
```

Then we did a visualization

```
In [103]: for col in data.select_dtypes('int64'):
              plt.figure()
              sns.distplot(data1[col], label='1')
              sns.distplot(data0[col], label='0')
              plt.legend()
```



We've deduced that the capital loss and capital gain attributes are insignificant, so we're going to eliminate them from our dataset.

since most of their contents are zeros. For capital gain 91.632087% are zeros. For capital loss 91.632087% are zeros.

```
In [104]: ((data['capital-gain'].value_counts())/len(data))*100
Out[104]: 0        91.632087
          15024     1.075454
          7688      0.866747
          7298      0.775898
          99999     0.527905
                      ...
          2993      0.004911
          1639      0.002455
          7262      0.002455
          1731      0.002455
          22040     0.002455
          Name: capital-gain, Length: 120, dtype: float64
```

Cette colonne n'est signifiante vue que plus que 90% des valeurs ont une valeur égale à 0.

```
In [105]: data = data.drop('capital-gain',axis=1,inplace=False)
```

The same was done for capital loss.

8. DIVIDE DATA INTO CATEGORICAL AND NUMERICAL CATEGORIES:

```
In [114]: cat_data=[]
          num_data=[]
          for i, c in enumerate(data.dtypes):
              if c==object:
                  cat_data.append(data.iloc[:,i])
              else:
                  num_data.append(data.iloc[:,i])
          cat_data=pd.DataFrame(cat_data).transpose()
          num_data=pd.DataFrame(num_data).transpose()
```

```
In [115]: cat_data
```

Out[115]:

	workclass	education	marital-status	occupation	relationship	race	gender
0	Private	Doctorate	Divorced	Exec-managerial	Not-in-family	White	Male
1	Private	12th	Never-married	Other-service	Own-child	White	Male
2	Private	Bachelors	Married-civ-spouse	Exec-managerial	Husband	White	Male
3	State-gov	7th-8th	Married-civ-spouse	Transport-moving	Husband	White	Male
4	State-gov	Some-college	Never-married	Other-service	Not-in-family	Black	Male
...	...	...	...	...	...	...	...
43952	Private	Bachelors	Married-civ-spouse	Exec-managerial	Husband	White	Male
43953	Private	HS-grad	Never-married	Other-service	Own-child	White	Female
43954	Private	Some-college	Divorced	Sales	Not-in-family	White	Male
43955	Private	Bachelors	Never-married	Sales	Not-in-family	White	Female
43956	Private	HS-grad	Never-married	Handlers-cleaners	Other-relative	White	Male

40727 rows × 7 columns

9. Transforming categorical values into numerical ones and concatenating the two sub-data

In [116]:
```
for i in cat_data:
    cat_data[i]=le.fit_transform(cat_data[i])
cat_data
```

Out[116]:

	workclass	education	marital-status	occupation	relationship	race	gender
0	2	10	0	3	1	4	1
1	2	2	4	7	3	4	1
2	2	9	2	3	0	4	1
3	5	5	2	13	0	4	1
4	5	15	4	7	1	2	1
...	...	...	...	...	...	...	...
43952	2	9	2	3	0	4	1
43953	2	11	4	7	3	4	0
43954	2	15	0	11	1	4	1
43955	2	9	4	11	1	4	0
43956	2	11	4	5	2	4	1

40727 rows × 7 columns

After transforming categorical data into numerical data, we will concatenate them.

In [117]:
```
X=pd.concat([cat_data,num_data],axis=1)
```

In [118]:
```
X
```

Out[118]:

	workclass	education	marital-status	occupation	relationship	race	gender	age	fnlwgt	educational-num	hours-per-week	income_>50K
0	2	10	0	3	1	4	1	67	366425	16	60	1
1	2	2	4	7	3	4	1	17	244602	8	15	0
2	2	9	2	3	0	4	1	31	174201	13	40	1
3	5	5	2	13	0	4	1	58	110199	4	40	0
4	5	15	4	7	1	2	1	25	149248	10	40	0
...	...	...	...	...	...	...	...	...	...	...	...	...
43952	2	9	2	3	0	4	1	52	68982	13	50	1
43953	2	11	4	7	3	4	0	19	116562	9	40	0
43954	2	15	0	11	1	4	1	30	197947	10	58	0
43955	2	9	4	11	1	4	0	46	97883	13	35	0
43956	2	11	4	5	2	4	1	30	375827	9	40	0

40727 rows × 12 columns

Now we have data ready for use in training and model creation.

C. Data analysis: Training & prediction

1. Data import and separation in train and test:

Model

```
In [54]: from sklearn.model_selection import train_test_split
```

```
In [55]: X_train, X_test, y_train, y_test = train_test_split(I, Y, test_size=0.3, random_state=40)
```

```
In [56]: from sklearn.linear_model import SGDClassifier
         from sklearn.preprocessing import StandardScaler
         from sklearn.pipeline import make_pipeline
         from sklearn.model_selection import GridSearchCV
```

```
In [57]: scaler = StandardScaler()
```

```
In [58]: X_train = scaler.fit_transform(X_train)
```

```
In [59]: X_test = scaler.fit_transform(X_test)
```

We're going to use the decision tree to classify people, since our data is designed to classify people according to their income.

```
from sklearn.tree import DecisionTreeClassifier
```

```
pgrid={"splitter":["best","random"],
            "max_depth":range(2,20,1),
            "min_samples_leaf":range(1,15,1),
            "min_samples_split":range(2,20,1)
           }
```

```
grid_search = GridSearchCV(DecisionTreeClassifier(), param_grid=pgrid, cv=5)
grid_search.fit(X_train, y_train)
grid_search.best_estimator_.score(X_test, y_test)
```

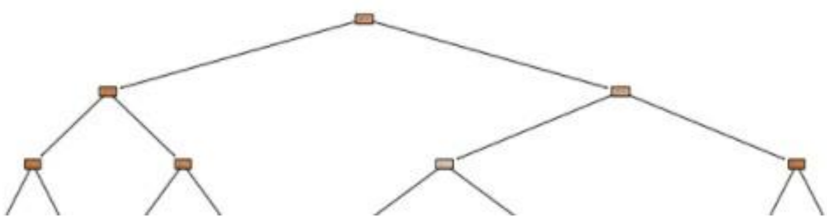
```
0.8194614943939766
```

```
grid_search.best_estimator_
```

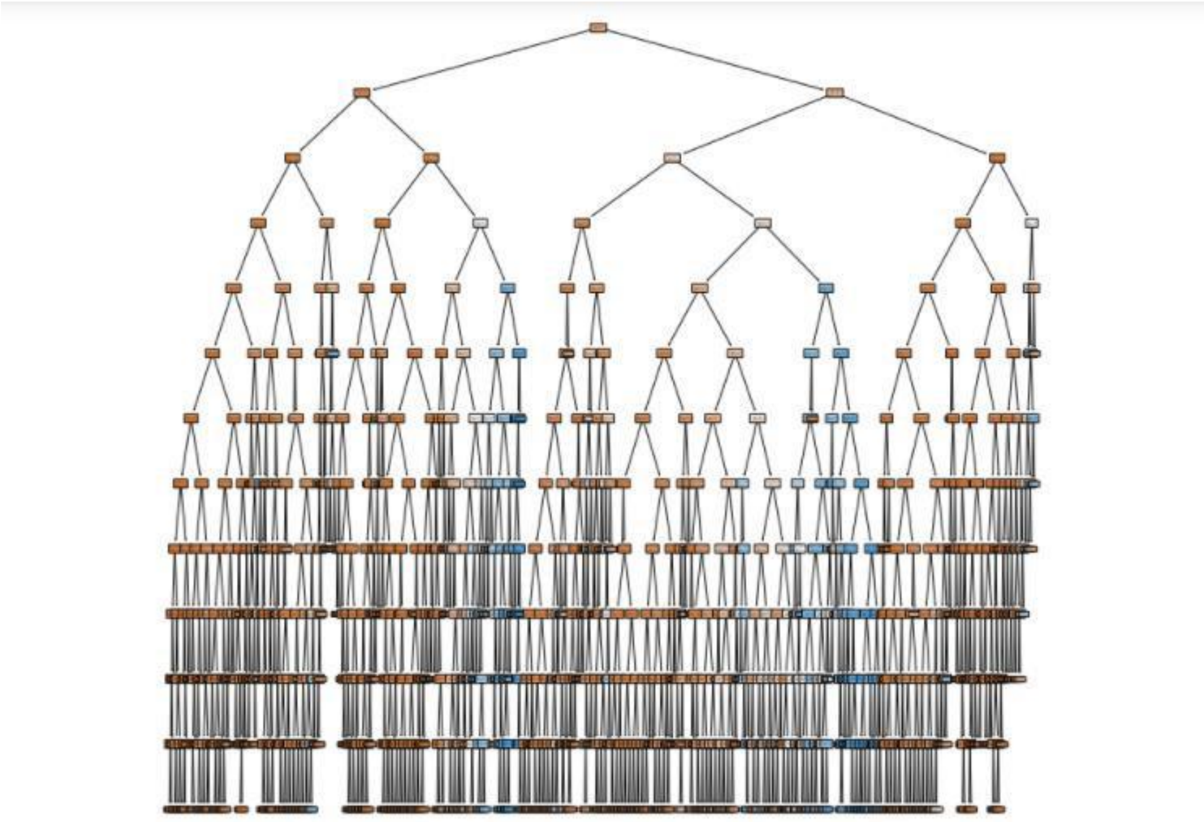
```
DecisionTreeClassifier(max_depth=12, min_samples_leaf=9, min_samples_split=16,
                       splitter='random')
```

```
from sklearn import tree
```

```
plt.figure(figsize=(12,12))
tree.plot_tree(grid_search.best_estimator_,rounded=True,filled=True)
plt.show()
```



Notre model



D. Conclusion

In this data pre-processing project, we worked on a database that classifies people according to whether their income is >50 K or not.

This dataset allows us to predict, based on university level, gender, occupation, and many other attributes, whether a person earns more than 50 K or not.

First, we cleaned the data of outliers and missing values.

Then we applied different visualizations to understand the attributes and find the relationships between them to deduce their meanings.

All this enabled us to create clean data, which we then used to create a classification model using the decision tree model to predict whether a person is in the class of people earning more than 50 K or not.