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In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statistics  as sts
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.neural_network import MLPClassifier
```

1) Resumo geral da base de dados

In [2]:
```
df=pd.read_csv('adult.csv')
df
```

Out[2]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation
0	90	?	77053	HS-grad	9	Widowed	?
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial
2	66	?	186061	Some-college	10	Widowed	?
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct
4	41	Private	264663	Some-college	10	Separated	Prof-specialty
...	...	...	...	...	...	...	...
32556	22	Private	310152	Some-college	10	Never-married	Protective-serv
32557	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support
32558	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct
32559	58	Private	151910	HS-grad	9	Widowed	Adm-clerical
32560	22	Private	201490	HS-grad	9	Never-married	Adm-clerical

32561 rows × 15 columns

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education.num   32561 non-null  int64 
 5   marital.status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital.gain    32561 non-null  int64 
 11  capital.loss    32561 non-null  int64 
 12  hours.per.week  32561 non-null  int64 
 13  native.country  32561 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [4]:
```
df.describe()
```

Out[4]:

	age	fnlwgt	education.num	capital.gain	capital.loss	hours
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	325
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	

In [5]:
```
df['income'].value_counts()
```

Out[5]:
```
<=50K    24720
>50K      7841
Name: income, dtype: int64
```

In [6]:
```
df.shape
```

Out[6]:
```
(32561, 15)
```

2) Pré-processamento

In [7]:
```python
df.columns
```

Out[7]:
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'education.num',
       'marital.status', 'occupation', 'relationship', 'race', 'sex',
       'capital.gain', 'capital.loss', 'hours.per.week', 'native.country',
       'income'],
      dtype='object')
```

In [8]:
```python
df[df == '?'] = np.nan
```

In [9]:
```python
total = df.isnull().sum().sort_values(ascending=False)
percent_1 = df.isnull().sum()/df.isnull().count()*100
percent_2 = (round(percent_1, 1)).sort_values(ascending=False)
missing_data = pd.concat([total, percent_2], axis=1, keys=['Total', '%'])
missing_data.head(5)
```

Out[9]:

	Total	%
occupation	1843	5.7
workclass	1836	5.6
native.country	583	1.8
age	0	0.0
fnlwgt	0	0.0

In [10]:
```python
for col in ['workclass', 'occupation', 'native.country']:
    df[col].fillna(df[col].mode()[0], inplace=True)
```

In [11]:
```python
df.isnull().sum()
```

Out[11]:
```
age               0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
capital.gain      0
capital.loss      0
hours.per.week    0
native.country    0
income            0
dtype: int64
```

Encoding Categorical Features

In [12]:
```
df.nunique()
```

Out[12]:
```
age                  73
workclass             8
fnlwgt            21648
education            16
education.num        16
marital.status        7
occupation           14
relationship          6
race                  5
sex                   2
capital.gain        119
capital.loss         92
hours.per.week       94
native.country       41
income                2
dtype: int64
```

In [13]:
```
from sklearn.preprocessing import LabelEncoder
```

In [14]:
```
df['income'].value_counts()
```

Out[14]:
```
<=50K    24720
>50K      7841
Name: income, dtype: int64
```

In [15]:
```
df['sex'].value_counts()
```

Out[15]:
```
Male      21790
Female    10771
Name: sex, dtype: int64
```

In [16]:
```
labelencoder = LabelEncoder()
df[["income","sex", "education"]] = \
df[["income","sex", "education"]].apply(labelencoder.fit_transform)
```

In [17]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  int64 
 4   education.num   32561 non-null  int64 
 5   marital.status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  int64 
 10  capital.gain    32561 non-null  int64 
 11  capital.loss    32561 non-null  int64 
 12  hours.per.week  32561 non-null  int64 
 13  native.country  32561 non-null  object
 14  income          32561 non-null  int64 
dtypes: int64(9), object(6)
memory usage: 3.7+ MB
```

In [18]:

```
categorical = ['workclass', 'marital.status', 'occupation', 'relationship',
df = pd.get_dummies(df, columns=categorical)
```

In [19]:

```
df
```

Out[19]:

	age	fnlwgt	education	education.num	sex	capital.gain	capital.loss	hours.p
0	90	77053	11	9	0	0	4356	
1	82	132870	11	9	0	0	4356	
2	66	186061	15	10	0	0	4356	
3	54	140359	5	4	0	0	3900	
4	41	264663	15	10	0	0	3900	
...	...	...	...	...	...	...	...	
32556	22	310152	15	10	1	0	0	
32557	27	257302	7	12	0	0	0	
32558	40	154374	11	9	1	0	0	
32559	58	151910	11	9	0	0	0	
32560	22	201490	11	9	1	0	0	

32561 rows × 90 columns

Normalização dos dados

In [20]:
```
df_copy = df.copy()
```

In [21]:
```
std=StandardScaler()
columns = ['age','fnlwgt','education.num', 'capital.gain', 'capital.loss', '
df[columns] =\
std.fit_transform(df[columns])
```

In [22]:
```
df.describe()
```

Out[22]:

	age	fnlwgt	education	education.num	sex	ca
count	3.256100e+04	3.256100e+04	3.256100e+04	3.256100e+04	32561.000000	3.25
mean	-3.666078e-17	-1.008172e-16	4.102516e-17	1.466431e-16	0.669205	4.18
std	1.000015e+00	1.000015e+00	1.000015e+00	1.000015e+00	0.470506	1.00
min	-1.582206e+00	-1.681631e+00	-2.660895e+00	-3.529656e+00	0.000000	-1
25%	-7.757679e-01	-6.816910e-01	-3.354369e-01	-4.200596e-01	0.000000	-1
50%	-1.159546e-01	-1.082193e-01	1.813316e-01	-3.136003e-02	1.000000	-1
75%	6.904838e-01	4.478765e-01	4.397159e-01	7.460392e-01	1.000000	-1
max	3.769612e+00	1.226856e+01	1.214869e+00	2.300838e+00	1.000000	1.33

8 rows × 90 columns

3) Algoritmos de Classificação

- Árvore de Decisão
- KNN
- Redes Neurais
- K-Means

In [23]:
```
models = []
models.append(['Decision Tree', DecisionTreeClassifier()])
models.append(['KNN', KNeighborsClassifier(n_neighbors=5)])
models.append(['MLP', MLPClassifier(hidden_layer_sizes=(10,5), activation='r
```

In [24]:
```
X = df.drop(['income'], axis=1).values
y = df['income'].values
```

In [25]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

In [26]:
```
lst_1= []

for m in range(len(models)):
    lst_2= []
    model = models[m][1]
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    DT_score = model.score(X_train, y_train)
    DT_test = model.score(X_test, y_test)

    cm = confusion_matrix(y_test,y_pred)
    print(models[m][0],':')
    print('Training Score',DT_score)
    print('Testing Score \n',DT_test)
    print(cm)
    print('-----------------------------------')
    lst_2.append(models[m][0])
    lst_2.append(DT_score)
    lst_2.append(DT_test)
    lst_1.append(lst_2)
```

```
Decision Tree :
Training Score 0.999956124956125
Testing Score
 0.8145153035111066
[[6475  922]
 [ 890 1482]]
-----------------------------------
KNN :
Training Score 0.8791681291681291
Testing Score
 0.8385709898659024
[[6751  646]
 [ 931 1441]]
-----------------------------------
MLP :
Training Score 0.8553001053001053
Testing Score
 0.8578155389497389
[[6905  492]
 [ 897 1475]]
-----------------------------------
```

In [27]:
```
df_compare = pd.DataFrame(lst_1, columns= ['Model', 'Training Score', 'Testi
df_compare
```

Out[27]:

	Model	Training Score	Testing Score
0	Decision Tree	0.999956	0.814515
1	KNN	0.879168	0.838571
2	MLP	0.855300	0.857816

K-Means

Erro Mínimos Quadrados

In [28]:
```
df_K = df.drop('income', axis=1)
```

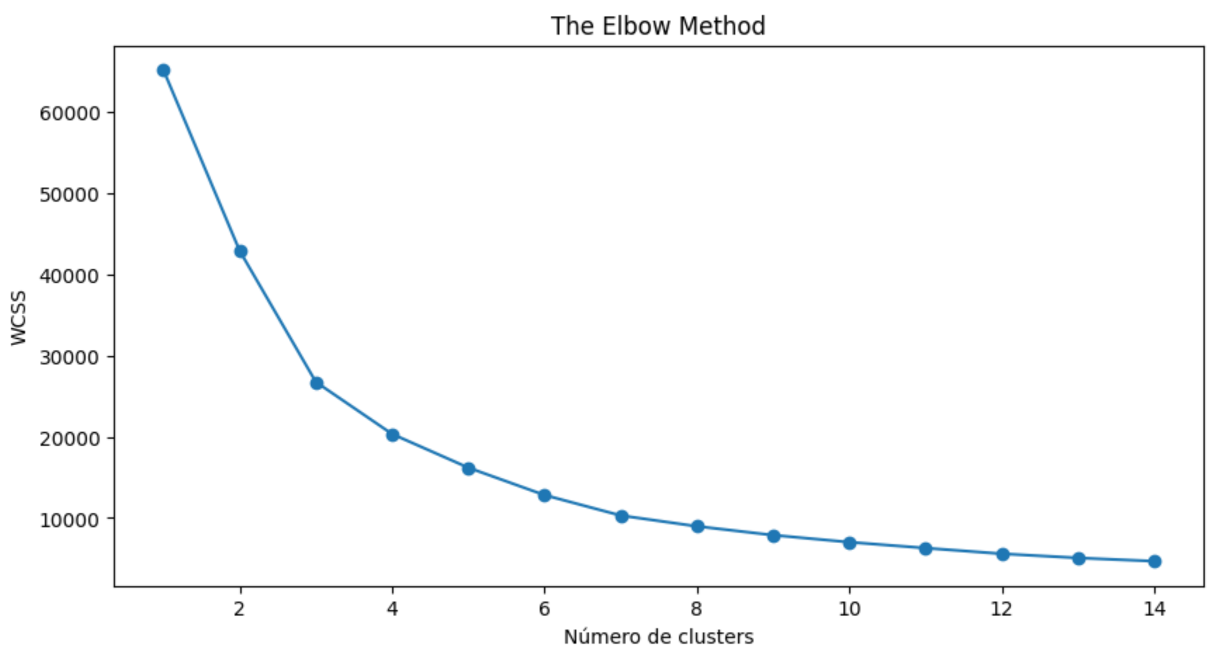
In [29]:
```
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 15):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 5, ma
    kmeans.fit(df_K[['age','education']])
    # inertia: Método para gerar o wcss
    wcss.append(kmeans.inertia_)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

In [30]:
```
wcss
```

Out[30]:
```
[65122.000000000335,
 42886.91863615351,
 26741.452969445756,
 20340.577884400926,
 16197.99200090575,
 12826.012684261126,
 10310.77805418053,
 8981.880640855929,
 7894.745667679277,
 7028.826778422109,
 6302.476566979283,
 5603.4606724818095,
 5090.686261670233,
 4689.003813146657]
```

In [31]:
```
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(10,5))
plt.plot(range(1,15),wcss, marker='o')
plt.title('The Elbow Method')
plt.xlabel('Número de clusters')
plt.ylabel('WCSS')
plt.show()
```



Agrupamento

In [32]:
```
kmeans = KMeans(n_clusters = 4, init = 'k-means++', random_state = 5, max_it
kmeans1 = kmeans.fit(df_K[['age','education']])
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: Futu
reWarning: The default value of `n_init` will change from 10 to 'auto' in 1.
4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

In [33]:

```
import plotly.express as px
centroids = kmeans1.cluster_centers_
classification = kmeans1.labels_
graph = px.scatter(x = df_K['age'], y = df_K['education'], color=classificat
graph.show()
```

In [34]:

```
#SepalLengthCm x PetalLengthCm
import plotly.graph_objects as go

graf1 = px.scatter(x = df_K['age'], y = df_K['education'], color=classificat
graf2 = px.scatter(x = centroids[:,0], y = centroids[:,1], size = [10, 10, 1
graf3 = go.Figure(data = graf1.data + graf2.data)
graf3.update_layout(width=800,height=500,title_text='Agrupamento K-Means')
graf3.update_xaxes(title = 'x')
graf3.update_yaxes(title = 'y')
graf3.show()
```

In [35]:
```
# Adiciona a coluna cluster
df_copy['cluster'] = kmeans1.labels_
df_copy.head()
```

Out[35]:

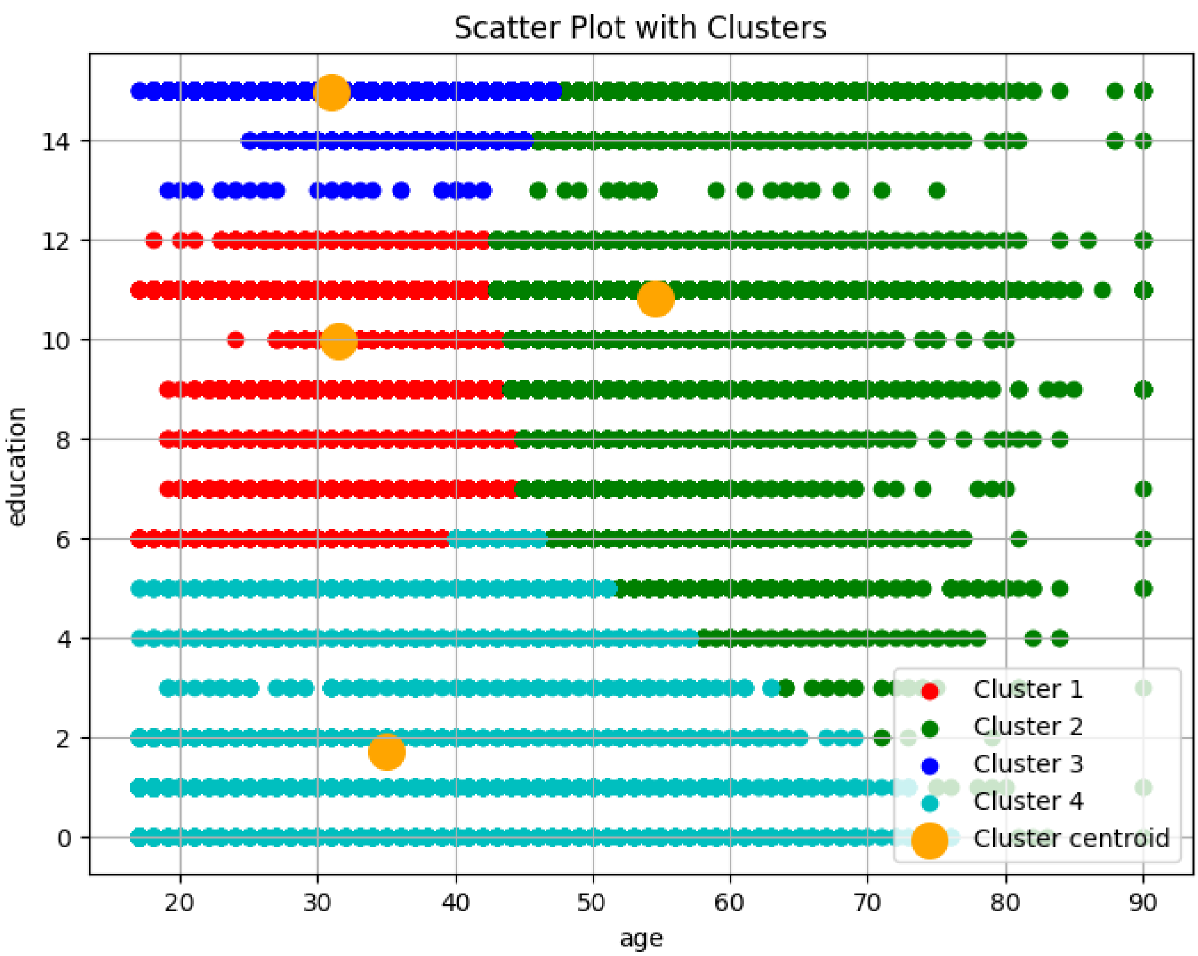
	age	fnlwgt	education	education.num	sex	capital.gain	capital.loss	hours.per.w
0	90	77053	11	9	0	0	4356	
1	82	132870	11	9	0	0	4356	
2	66	186061	15	10	0	0	4356	
3	54	140359	5	4	0	0	3900	
4	41	264663	15	10	0	0	3900	

5 rows × 91 columns

In [36]:
```
colors = ['r', 'g', 'b', 'c']
```

```
# Create the scatter plot with different colors for each cluster
plt.figure(figsize=(8, 6))
for i in range(4):
    cluster_data = df_copy[df_copy['cluster'] == i]
    plt.scatter(cluster_data['age'], cluster_data['education'], c=colors[i],
    if i == 3:  # Add the centroid legend entry only for the first cluster
        plt.scatter(cluster_data['age'].mean(), cluster_data['education'].me
    else:
        plt.scatter(cluster_data['age'].mean(), cluster_data['education'].me

plt.xlabel('age')
plt.ylabel('education')
plt.title('Scatter Plot with Clusters')
plt.legend()
plt.grid(True)
plt.show()
```



4) validação cruzada

In [37]:
```
from sklearn.model_selection import StratifiedKFold
```

In [38]:
```
lst_1= []

for m in range(len(models)):
  lst_2= []
```

```
model = models[m][1]
# Create StratifiedKFold object.
skf = StratifiedKFold(n_splits=10, shuffle=True, random_state=1)
lst_accu_stratified = []

for train_index, test_index in skf.split(X, y):
    x_train_fold, x_test_fold = X[train_index], X[test_index]
    y_train_fold, y_test_fold = y[train_index], y[test_index]
    model.fit(x_train_fold, y_train_fold)
    lst_accu_stratified.append(model.score(x_test_fold, y_test_fold))

# Print the output.
print(models[m][0],':')
print('\nLista de ACC:', lst_accu_stratified)
print('\nMaior ACC:',
      max(lst_accu_stratified)*100, '%')
print('\nMenor ACC:',
      min(lst_accu_stratified)*100, '%')
print('\nMédia ACC:',
      sts.mean(lst_accu_stratified)*100, '%')
print('\nDesvio Padrão:', sts.stdev(lst_accu_stratified))
print('------------------------------------')
lst_2.append(models[m][0])
lst_2.append(max(lst_accu_stratified)*100)
lst_2.append(min(lst_accu_stratified)*100)
lst_2.append(sts.mean(lst_accu_stratified)*100)
lst_2.append(sts.stdev(lst_accu_stratified))
lst_1.append(lst_2)
```

```
Decision Tree :

Lista de ACC: [0.8216149831132944, 0.8194103194103194, 0.8203316953316954, 0.8105036855036855, 0.8218673218673219, 0.8135749385749386, 0.8135749385749386, 0.8203316953316954, 0.8154176904176904, 0.8181818181818182]

Maior ACC: 82.18673218673219 %

Menor ACC: 81.05036855036855 %

Média ACC: 81.74809086307397 %

Desvio Padrão: 0.00394758405450171
-----------------------------------
KNN :

Lista de ACC: [0.8449493398833282, 0.832002457002457, 0.8286240786240786, 0.8289312039312039, 0.8329238329238329, 0.835995085995086, 0.8347665847665847, 0.8230958230958231, 0.8445945945945946, 0.8332309582309583]

Maior ACC: 84.49493398833282 %

Menor ACC: 82.30958230958231 %

Média ACC: 83.39113959047947 %

Desvio Padrão: 0.006797524296142586
-----------------------------------
MLP :

Lista de ACC: [0.8645993245317777, 0.8544226044226044, 0.8581081081081081, 0.8516584766584766, 0.8562653562653563, 0.8547297297297297, 0.8544226044226044, 0.8516584766584766, 0.8624078624078624, 0.855958230958231]

Maior ACC: 86.45993245317777 %

Menor ACC: 85.16584766584766 %

Média ACC: 85.64230774163228 %

Desvio Padrão: 0.004242941936118842
-----------------------------------
```

In [39]:
```
df_compare = pd.DataFrame(lst_1, columns= ['Model', 'Maior ACC', 'Menor ACC'
df_compare
```

Out[39]:

	Model	Maior ACC	Menor ACC	Média ACC	Desvio Padrão
0	Decision Tree	82.186732	81.050369	81.748091	0.003948
1	KNN	84.494934	82.309582	83.391140	0.006798
2	MLP	86.459932	85.165848	85.642308	0.004243

5) Balanceamento das classes

- https://medium.com/analytics-vidhya/undersampling-and-oversampling-an-old-and-a-new-approach-4f984a0e8392

- Abordagem SMOTE

In [40]:
```
df['income'].value_counts()
```

Out[40]:
```
0    24720
1     7841
Name: income, dtype: int64
```

In [41]:
```
from imblearn.over_sampling import SMOTE
```

In [42]:
```
lst_1= []

for m in range(len(models)):
  lst_2= []
  model = models[m][1]
  # Create StratifiedKFold object.
  skf = StratifiedKFold(n_splits=10, shuffle=True, random_state=1)
  lst_accu_stratified = []

  for train_index, test_index in skf.split(X, y):
      x_train_fold, x_test_fold = X[train_index], X[test_index]
      y_train_fold, y_test_fold = y[train_index], y[test_index]
      sm = SMOTE()
      x_train_oversampled, y_train_oversampled = sm.fit_resample(x_train_fol
      model.fit(x_train_oversampled, y_train_oversampled)
      lst_accu_stratified.append(model.score(x_test_fold, y_test_fold))
  # Print the output.
  print(models[m][0],':')
  print('\nLista de ACC:', lst_accu_stratified)
  print('\nMaior ACC:',
        max(lst_accu_stratified)*100, '%')
  print('\nMenor ACC:',
        min(lst_accu_stratified)*100, '%')
  print('\nMédia ACC:',
        sts.mean(lst_accu_stratified)*100, '%')
  print('\nDesvio Padrão:', sts.stdev(lst_accu_stratified))
  print('------------------------------------')
  lst_2.append(models[m][0])
  lst_2.append(max(lst_accu_stratified)*100)
  lst_2.append(min(lst_accu_stratified)*100)
  lst_2.append(sts.mean(lst_accu_stratified)*100)
  lst_2.append(sts.stdev(lst_accu_stratified))
  lst_1.append(lst_2)
```

```
Decision Tree :

Lista de ACC: [0.8136321768498619, 0.8083538083538083, 0.8025184275184275,
0.8019041769041769, 0.8058968058968059, 0.8175675675675675, 0.80620393120393
12, 0.7862407862407862, 0.8071253071253072, 0.8028255528255528]

Maior ACC: 81.75675675675676 %

Menor ACC: 78.62407862407862 %

Média ACC: 80.52268540486224 %

Desvio Padrão: 0.008315587238904425
-----------------------------------
KNN :

Lista de ACC: [0.789376727049432, 0.788083538083538, 0.788083538083538, 0.78
71621621621622, 0.7917690417690417, 0.7813267813267813, 0.7994471744471745,
0.7794840294840295, 0.789004914004914, 0.7862407862407862]

Maior ACC: 79.94471744471745 %

Menor ACC: 77.94840294840296 %

Média ACC: 78.79978692651397 %

Desvio Padrão: 0.005467205528439763
-----------------------------------
MLP :

Lista de ACC: [0.8130181148295977, 0.8114250614250614, 0.8230958230958231,
0.808968058968059, 0.812960687960688, 0.8132678132678133, 0.823402948402948
4, 0.8111179361179361, 0.8286240786240786, 0.8114250614250614]

Maior ACC: 82.86240786240786 %

Menor ACC: 80.8968058968059 %

Média ACC: 81.57305584117067 %

Desvio Padrão: 0.006704331049663252
-----------------------------------
```

In [43]:

```python
df_compare = pd.DataFrame(lst_1, columns= ['Model', 'Maior ACC', 'Menor ACC'
df_compare
```

Out[43]:

	Model	Maior ACC	Menor ACC	Média ACC	Desvio Padrão
0	Decision Tree	81.756757	78.624079	80.522685	0.008316
1	KNN	79.944717	77.948403	78.799787	0.005467
2	MLP	82.862408	80.896806	81.573056	0.006704

6) Técnicas de ajuste de hiperparâmetros

- https://scikit-learn.org/stable/modules/grid_search.html#
- Abordagens disponíveis no scikit-learn:
  - GridSearchCV: considera exaustivamente todas as combinações de parâmetros;
  - RandomizedSearchCV: pesquisa aleatória de parâmetros, em que cada configuração é amostrada a partir de uma distribuição de possíveis valores de parâmetro.

In [44]:
```
models.pop(2)
```

Out[44]:
```
['MLP',
 MLPClassifier(hidden_layer_sizes=(10, 5), max_iter=800, random_state=3,
               solver='sgd')]
```

In [45]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
```

In [46]:
```
def grid_search(estimator, param_grid, cv, return_train_score):
  return GridSearchCV(estimator=estimator, param_grid=param_grid, refit=True
```

In [47]:
```
def randomized_search(estimator, param_grid, cv, return_train_score):
  return RandomizedSearchCV(estimator=estimator, param_distributions=param_g
```

In [48]:
```
estimators = []
estimators.append(['GridSearchCV', grid_search])
estimators.append(['RandomizedSearchCV', randomized_search])
```

In [49]:
```
models_param_grid = {
    'Decision Tree' : {'criterion': ['gini', 'entropy', 'log_loss']},
    'KNN': {'n_neighbors': [3,5,7,9], 'metric':['euclidean', 'manhattan', 'c
    'MLP': {'hidden_layer_sizes': [(10,30,10),(20,)], 'activation': ['tanh',
}
```

In [50]:
```
lst_1= []

for m in range(len(models)):
  model = models[m][1]
  print(models[m][0],':')
  for n in range(len(estimators)):
    lst_2= []
    estimator = estimators[n][1]
    e_search = estimator(model, models_param_grid[models[m][0]], 10, False)
    sm = SMOTE()
    x_train_oversampled, y_train_oversampled = sm.fit_resample(X_train, y_tr
    e_search.fit(x_train_oversampled, y_train_oversampled)
    print('-------')
    print(estimators[n][0],':')
    print(e_search.best_params_)
```

```
        print(e_search.best_score_)
        print(e_search.best_index_)
        print(e_search.cv_results_.keys())
        g_results =  pd.DataFrame(e_search.cv_results_)
        # Obtém a média das acurácias (10 folds) referente ao conjunto treino
        mean_test_score = g_results.loc[e_search.best_index_,'mean_test_score']
        print(mean_test_score)
        # Avalia o conjunto teste  com o melhor conjunto de parâmetros encontrad
        # best_estimator_ .Para tanto, o parâmetro refit precisa ser igual a Tru
        model = e_search.best_estimator_
        score = model.score(X_test,y_test)
        print(score)
        print('-------')
        lst_2.append(f'{models[m][0]}({estimators[n][0]})')
        lst_2.append(e_search.best_params_)
        lst_2.append(e_search.best_score_)
        lst_2.append(e_search.best_index_)
        lst_2.append(mean_test_score)
        lst_2.append(score)
        lst_1.append(lst_2)
    print('------------------------------------')
```

```
Decision Tree :
-------
GridSearchCV :
{'criterion': 'log_loss'}
0.8599296911710306
2
dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_ti
me', 'param_criterion', 'params', 'split0_test_score', 'split1_test_score',
'split2_test_score', 'split3_test_score', 'split4_test_score', 'split5_test_
score', 'split6_test_score', 'split7_test_score', 'split8_test_score', 'spli
t9_test_score', 'mean_test_score', 'std_test_score', 'rank_test_score'])
0.8599296911710306
0.8037670181185382
-------
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:3
05: UserWarning:

The total space of parameters 3 is smaller than n_iter=10. Running 3 iterati
ons. For exhaustive searches, use GridSearchCV.
```

```
-------
RandomizedSearchCV :
{'criterion': 'log_loss'}
0.858342697846162
2
dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_ti
me', 'param_criterion', 'params', 'split0_test_score', 'split1_test_score',
'split2_test_score', 'split3_test_score', 'split4_test_score', 'split5_test_
score', 'split6_test_score', 'split7_test_score', 'split8_test_score', 'spli
t9_test_score', 'mean_test_score', 'std_test_score', 'rank_test_score'])
0.858342697846162
0.8085781553894974
-------
-----------------------------------
KNN :
-------
GridSearchCV :
{'metric': 'manhattan', 'n_neighbors': 3}
0.8858752903498861
4
dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_ti
me', 'param_metric', 'param_n_neighbors', 'params', 'split0_test_score', 'sp
lit1_test_score', 'split2_test_score', 'split3_test_score', 'split4_test_sco
re', 'split5_test_score', 'split6_test_score', 'split7_test_score', 'split8_
test_score', 'split9_test_score', 'mean_test_score', 'std_test_score', 'rank
_test_score'])
0.8858752903498861
0.8064284983109837
-------
-------
RandomizedSearchCV :
{'n_neighbors': 3, 'metric': 'manhattan'}
0.8848647144490102
0
dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_ti
me', 'param_n_neighbors', 'param_metric', 'params', 'split0_test_score', 'sp
lit1_test_score', 'split2_test_score', 'split3_test_score', 'split4_test_sco
re', 'split5_test_score', 'split6_test_score', 'split7_test_score', 'split8_
test_score', 'split9_test_score', 'mean_test_score', 'std_test_score', 'rank
_test_score'])
0.8848647144490102
0.8057119459514792
-------
-----------------------------------
```

In [51]:
```
df_compare = pd.DataFrame(lst_1, columns= ['Model', 'best_params_', 'best_sc
df_compare
```

Out[51]:

	Model	best_params_	best_score_	best_index_	mean_test_score
0	Decision Tree(GridSearchCV)	{'criterion': 'log_loss'}	0.859930	2	0.859930
1	Decision Tree(RandomizedSearchCV)	{'criterion': 'log_loss'}	0.858343	2	0.858343
2	KNN(GridSearchCV)	{'metric': 'manhattan', 'n_neighbors': 3}	0.885875	4	0.885875
3	KNN(RandomizedSearchCV)	{'n_neighbors': 3, 'metric': 'manhattan'}	0.884865	0	0.884865

In [51]: