Modelación del aprendizaje con inteligencia artificial

Tutorial para el aprendizaje y evaluación de Árboles de Decisión y Bosques Aleatorios

In [ ]:
```
# importar la biblioteca para manipulación y tratamiento de datos
import pandas as pd
import numpy as np
import random
```

In [ ]:
```
# cargar y mostrar el conjunto de datos sobre cáncer de mama
data = pd.read_csv(r'C:\Users\Raul\OneDrive\Escritorio\CS\TC2034.101\data\salary.cs
data.head()
```

Out[ ]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	rac
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	Whit
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	Whit
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	Whit
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Blac
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Blac

In [ ]:
```
# obtener la información condensada de los predictores
data.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  salary          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [ ]:

```
for column in data.select_dtypes('object'):
  print("---------------")
  print(column)
  print(data[column].value_counts())
```

```
---------------
workclass
workclass
 Private             22696
 Self-emp-not-inc     2541
 Local-gov            2093
 ?                    1836
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: count, dtype: int64
---------------
education
education
 HS-grad         10501
 Some-college     7291
 Bachelors        5355
 Masters          1723
 Assoc-voc        1382
 11th             1175
 Assoc-acdm       1067
 10th              933
 7th-8th           646
 Prof-school       576
 9th               514
 12th              433
 Doctorate         413
 5th-6th           333
 1st-4th           168
 Preschool          51
Name: count, dtype: int64
---------------
marital-status
marital-status
 Married-civ-spouse       14976
 Never-married            10683
 Divorced                  4443
 Separated                 1025
 Widowed                    993
 Married-spouse-absent      418
 Married-AF-spouse           23
Name: count, dtype: int64
---------------
occupation
occupation
 Prof-specialty       4140
 Craft-repair         4099
 Exec-managerial      4066
 Adm-clerical         3770
 Sales                3650
 Other-service        3295
 Machine-op-inspct    2002
 ?                    1843
 Transport-moving     1597
```

```
 Handlers-cleaners    1370
 Farming-fishing       994
 Tech-support          928
 Protective-serv       649
 Priv-house-serv       149
 Armed-Forces            9
Name: count, dtype: int64
---------------
relationship
relationship
 Husband           13193
 Not-in-family      8305
 Own-child          5068
 Unmarried          3446
 Wife               1568
 Other-relative      981
Name: count, dtype: int64
---------------
race
race
 White                 27816
 Black                  3124
 Asian-Pac-Islander     1039
 Amer-Indian-Eskimo      311
 Other                   271
Name: count, dtype: int64
---------------
sex
sex
 Male      21790
 Female    10771
Name: count, dtype: int64
---------------
native-country
native-country
 United-States                 29170
 Mexico                          643
 ?                               583
 Philippines                     198
 Germany                         137
 Canada                          121
 Puerto-Rico                     114
 El-Salvador                     106
 India                           100
 Cuba                             95
 England                          90
 Jamaica                          81
 South                            80
 China                            75
 Italy                            73
 Dominican-Republic               70
 Vietnam                          67
 Guatemala                        64
 Japan                            62
 Poland                           60
 Columbia                         59
```

```
 Taiwan                           51
 Haiti                            44
 Iran                             43
 Portugal                         37
 Nicaragua                        34
 Peru                             31
 France                           29
 Greece                           29
 Ecuador                          28
 Ireland                          24
 Hong                             20
 Cambodia                         19
 Trinadad&Tobago                  19
 Laos                             18
 Thailand                         18
 Yugoslavia                       16
 Outlying-US(Guam-USVI-etc)       14
 Honduras                         13
 Hungary                          13
 Scotland                         12
 Holand-Netherlands                1
Name: count, dtype: int64
---------------
salary
salary
 <=50K    24720
 >50K      7841
Name: count, dtype: int64
```

In [ ]:

```
for column in data:
  print(column, ":", data[column].isna().sum())
  if data[column].dtype == 'object':
    data[column] = data[column].str.strip()

data.columns = data.columns.str.strip()
# Genial

data.head()
```

```
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
salary : 0
```

Out[ ]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	rac
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	Whit
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	Whit
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	Whit
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Blac
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Blac

In [ ]:

```
# from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustScaler
# scaler = MinMaxScaler((0,1))
# scaler = StandardScaler()
# # scaler = RobustScaler()

# temp = data.select_dtypes(exclude= 'object')

# scaler.fit(temp)

# temp = pd.DataFrame(scaler.transform(temp), columns = temp.columns)

# data = pd.concat([data.select_dtypes('object'), temp], axis = 1)

data.drop('native-country', axis=1, inplace= True)

data.head()
```

Out[ ]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	rac
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	Whit
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	Whit
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	Whit
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Blac
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Blac

In [ ]:

```
temp = pd.get_dummies(data)
print(temp.columns)
temp = temp.rename(columns= {'sex_Male':'sex', 'salary_>50K':'salary'})
temp.drop(['sex_Female', 'salary_<=50K'], axis=1, inplace=True)

print(temp.columns)
temp.head()
```

```
Index(['age', 'fnlwgt', 'education-num', 'capital-gain', 'capital-loss',
       'hours-per-week', 'workclass_?', 'workclass_Federal-gov',
       'workclass_Local-gov', 'workclass_Never-worked', 'workclass_Private',
       'workclass_Self-emp-inc', 'workclass_Self-emp-not-inc',
       'workclass_State-gov', 'workclass_Without-pay', 'education_10th',
       'education_11th', 'education_12th', 'education_1st-4th',
       'education_5th-6th', 'education_7th-8th', 'education_9th',
       'education_Assoc-acdm', 'education_Assoc-voc', 'education_Bachelors',
       'education_Doctorate', 'education_HS-grad', 'education_Masters',
       'education_Preschool', 'education_Prof-school',
       'education_Some-college', 'marital-status_Divorced',
       'marital-status_Married-AF-spouse', 'marital-status_Married-civ-spouse',
       'marital-status_Married-spouse-absent', 'marital-status_Never-married',
       'marital-status_Separated', 'marital-status_Widowed', 'occupation_?',
       'occupation_Adm-clerical', 'occupation_Armed-Forces',
       'occupation_Craft-repair', 'occupation_Exec-managerial',
       'occupation_Farming-fishing', 'occupation_Handlers-cleaners',
       'occupation_Machine-op-inspct', 'occupation_Other-service',
       'occupation_Priv-house-serv', 'occupation_Prof-specialty',
       'occupation_Protective-serv', 'occupation_Sales',
       'occupation_Tech-support', 'occupation_Transport-moving',
       'relationship_Husband', 'relationship_Not-in-family',
       'relationship_Other-relative', 'relationship_Own-child',
       'relationship_Unmarried', 'relationship_Wife',
       'race_Amer-Indian-Eskimo', 'race_Asian-Pac-Islander', 'race_Black',
       'race_Other', 'race_White', 'sex_Female', 'sex_Male', 'salary_<=50K',
       'salary_>50K'],
      dtype='object')
Index(['age', 'fnlwgt', 'education-num', 'capital-gain', 'capital-loss',
       'hours-per-week', 'workclass_?', 'workclass_Federal-gov',
       'workclass_Local-gov', 'workclass_Never-worked', 'workclass_Private',
       'workclass_Self-emp-inc', 'workclass_Self-emp-not-inc',
       'workclass_State-gov', 'workclass_Without-pay', 'education_10th',
       'education_11th', 'education_12th', 'education_1st-4th',
       'education_5th-6th', 'education_7th-8th', 'education_9th',
       'education_Assoc-acdm', 'education_Assoc-voc', 'education_Bachelors',
       'education_Doctorate', 'education_HS-grad', 'education_Masters',
       'education_Preschool', 'education_Prof-school',
       'education_Some-college', 'marital-status_Divorced',
       'marital-status_Married-AF-spouse', 'marital-status_Married-civ-spouse',
       'marital-status_Married-spouse-absent', 'marital-status_Never-married',
       'marital-status_Separated', 'marital-status_Widowed', 'occupation_?',
       'occupation_Adm-clerical', 'occupation_Armed-Forces',
       'occupation_Craft-repair', 'occupation_Exec-managerial',
       'occupation_Farming-fishing', 'occupation_Handlers-cleaners',
       'occupation_Machine-op-inspct', 'occupation_Other-service',
       'occupation_Priv-house-serv', 'occupation_Prof-specialty',
       'occupation_Protective-serv', 'occupation_Sales',
       'occupation_Tech-support', 'occupation_Transport-moving',
       'relationship_Husband', 'relationship_Not-in-family',
       'relationship_Other-relative', 'relationship_Own-child',
       'relationship_Unmarried', 'relationship_Wife',
       'race_Amer-Indian-Eskimo', 'race_Asian-Pac-Islander', 'race_Black',
       'race_Other', 'race_White', 'sex', 'salary'],
      dtype='object')
```

Out[ ]:

	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	workclass_?	workclass_Federal-gov	woı
0	39	77516	13	2174	0	40	False	False	
1	50	83311	13	0	0	13	False	False	
2	38	215646	9	0	0	40	False	False	
3	53	234721	7	0	0	40	False	False	
4	28	338409	13	0	0	40	False	False	

5 rows × 66 columns

In [ ]:

```
# crear los conjuntos de entrenamiento y prueba
from sklearn.model_selection import train_test_split

X = temp.drop('salary', axis=1)
y = temp['salary']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20)
```

In [ ]:

```
y_train.sum()
```

Out[ ]:

```
6258
```

In [ ]:

```
from imblearn.under_sampling import RandomUnderSampler
rus = RandomUnderSampler()
X_train, y_train = rus.fit_resample(X_train, y_train)

print(y_train.value_counts())
```

```
salary
False    6258
True     6258
Name: count, dtype: int64
```

In [ ]:

```
X_train.head()
```

Out[ ]:

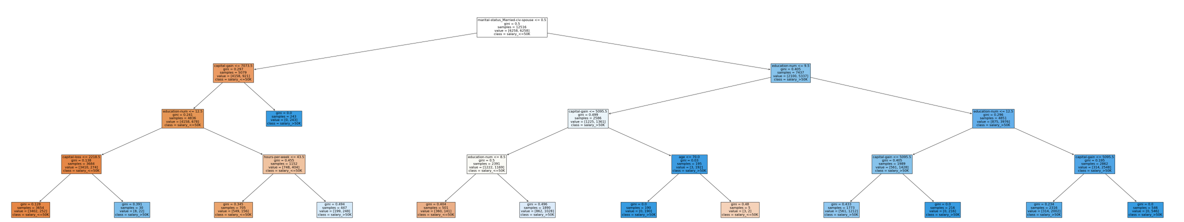
	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	workclass_?	workclass_Federal-gov
22460	48	278039	9	0	0	60	False	False
3658	21	342575	10	0	0	30	False	False
8274	56	172071	9	0	0	40	False	False
12932	60	83850	9	0	0	40	False	False
6006	33	93206	3	0	0	40	False	False

5 rows × 65 columns

In [ ]:
```
# Hyperparams
depth = 4
```

In [ ]:
```
# crear y entrenar un árbol de decisión para clasificación de cáncer
from sklearn.tree import DecisionTreeClassifier

dtc = DecisionTreeClassifier(max_depth=depth, )
dtc = dtc.fit(X_train, y_train)
```

In [ ]:
```
# crea un gráfico que muestre el árbol de decisión
from sklearn import tree
from matplotlib import pyplot as plt

fig = plt.figure(figsize=(80,15))
_ = tree.plot_tree(dtc,
                   feature_names=list(X_train.columns),
                   class_names=['salary_<=50K', 'salary_>50K'],
                   filled=True,
                   fontsize=12)
```



In [ ]:
```
# crear y entrenar un bosque aleatorio
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(n_estimators=200, max_depth=depth)
rfc = rfc.fit(X_train, y_train)
```

In [ ]:
```
# lista los hiperparámetros del árbol de decisión
dtc.get_params()
```

Out[ ]:
```
{'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': 4,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'random_state': None,
 'splitter': 'best'}
```

In [ ]:
```
# lista los hiperparámetros del bosque aleatorio
rfc.get_params()
```

Out[ ]:
```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': 4,
 'max_features': 'sqrt',
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 200,
 'n_jobs': None,
 'oob_score': False,
 'random_state': None,
 'verbose': 0,
 'warm_start': False}
```

In [ ]:
```
# evalua el aprendizaje de los datos de entrenamiento
dtc.score(X_train, y_train)
```

Out[ ]:
```
0.8006551613934164
```

In [ ]:
```
# evalua el aprendizaje de los datos de entrenamiento
rfc.score(X_train, y_train)
```

Out[ ]:
```
0.7897091722595079
```

In [ ]:
```
# evalua el aprendizaje de los datos de prueba
dtc.score(X_test, y_test)
```

Out[ ]:
```
0.7417472746814064
```

In [ ]:
```
# evalua el aprendizaje de los datos de prueba
rfc.score(X_test, y_test)
```

Out[ ]:
```
0.7448180561953017
```

In [ ]:
```
# obtén las predicciones para el conjunto de prueba
dtc_pred = dtc.predict(X_test)
dtc_pred
```

Out[ ]:
```
array([ True, False, False, ..., False,  True, False])
```

In [ ]:
```
# obtén las predicciones para el conjunto de prueba
rfc_pred = rfc.predict(X_test)
rfc_pred
```

Out[ ]:
```
array([ True, False, False, ..., False,  True, False])
```

In [ ]:
```
# cantidad de predicciones distintas
abs(dtc_pred*1 - rfc_pred*1).sum()
```

Out[ ]:
```
698
```

In [ ]:
```
# muestra la diferencia entre un árbol que no tiene criterios de paro y uno que si
dtc.predict_proba(X_test)[:10,:]
```

Out[ ]:
```
array([[0.31641286, 0.68358714],
       [0.93103448, 0.06896552],
       [0.93103448, 0.06896552],
       [0.93103448, 0.06896552],
       [0.13557858, 0.86442142],
       [0.13557858, 0.86442142],
       [0.45608466, 0.54391534],
       [0.13557858, 0.86442142],
       [0.93103448, 0.06896552],
       [0.93103448, 0.06896552]])
```

In [ ]:
```
# muestra la diferencia entre un árbol que no tiene criterios de paro y uno que si
rfc.predict_proba(X_test)[:10,:]
```

Out[ ]:
```
array([[0.34745878, 0.65254122],
       [0.8673643 , 0.1326357 ],
       [0.8087407 , 0.1912593 ],
       [0.92640375, 0.07359625],
       [0.32373128, 0.67626872],
       [0.22489224, 0.77510776],
       [0.38180455, 0.61819545],
       [0.22640813, 0.77359187],
       [0.76950062, 0.23049938],
       [0.92046582, 0.07953418]])
```

In [ ]:
```
# evalua y muestra las métricas de evaluación para el árbol
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

print('Exactitud:', accuracy_score(y_test, dtc_pred))
print('Precisión:', precision_score(y_test, dtc_pred))
print('Sensibilidad:', recall_score(y_test, dtc_pred))
print('F1 score:', f1_score(y_test, dtc_pred))
```

```
Exactitud: 0.7417472746814064
Precisión: 0.4834503510531595
Sensibilidad: 0.9134554643082754
F1 score: 0.6322693484914735
```

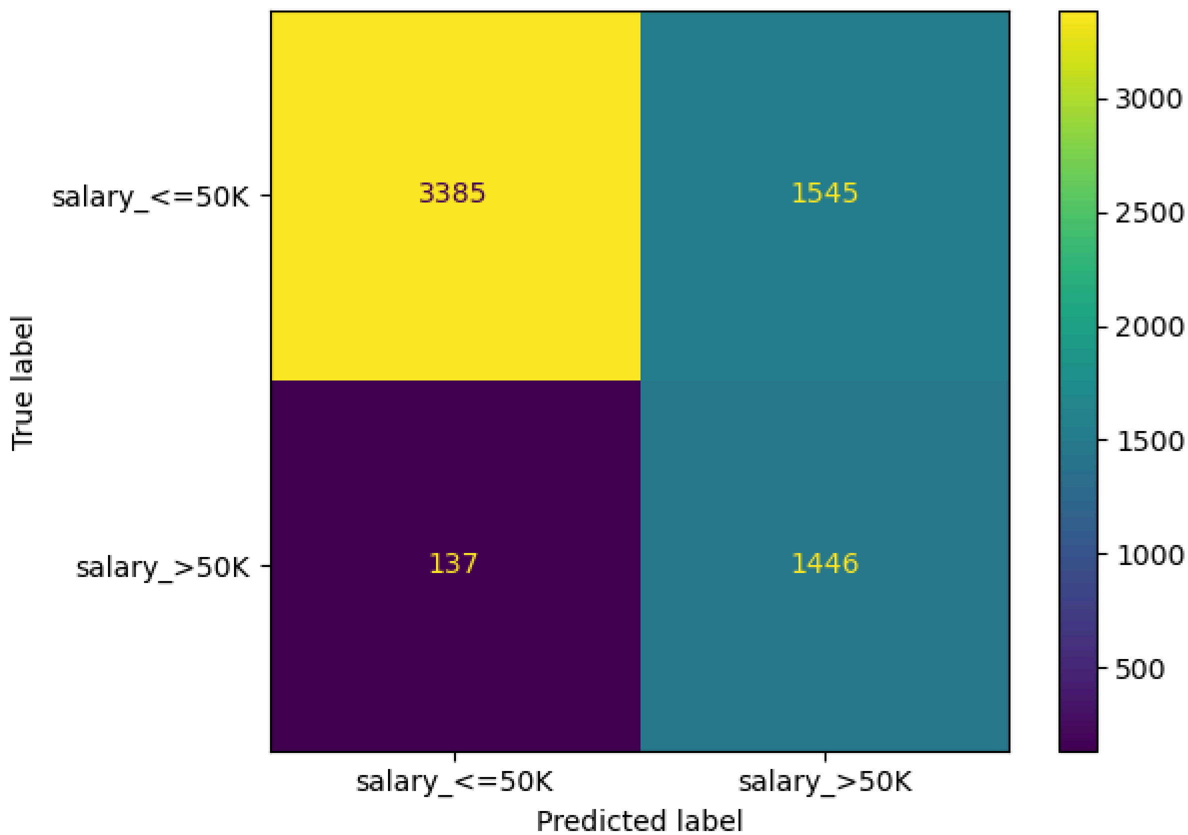
In [ ]:
```python
# Obten y muestra la matriz de confusión para el árbol
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, dtc_pred)
print(cm)
```

```
[[3385 1545]
 [ 137 1446]]
```

In [ ]:
```python
# calcula las métricas de evaluación para el árbol con las fórmulas
VN = cm[0,0]
FP = cm[0,1]
FN = cm[1,0]
VP = cm[1,1]

Exactitud = (VP + VN) / (VP + VN + FP + FN)
Precision = VP / (VP + FP)
Recall = VP / (VP + FN)
F1 = 2*VP / (2*VP + FP + FN )

print('Exactitud: ', Exactitud )
print('Precisión: ', Precision)
print('Sensibilidad: ', Recall)
print('F1-score: ', F1)
```

```
Exactitud:  0.7417472746814064
Precisión:  0.4834503510531595
Sensibilidad:  0.9134554643082754
F1-score:  0.6322693484914735
```

In [ ]:
```python
# calcula y muestra una gráfica de la matriz de confusión para el árbol
from sklearn.metrics import ConfusionMatrixDisplay

_ = ConfusionMatrixDisplay.from_predictions(y_test, dtc_pred, display_labels=['sala
```



In [ ]:
```python
# obten el reporte de clasificación completo para el árbol
from sklearn.metrics import classification_report

print(classification_report(y_test, dtc_pred, target_names=['salary_<=50K', 'salary
```

```
              precision    recall  f1-score   support

salary_<=50K       0.96      0.69      0.80      4930
 salary_>50K       0.48      0.91      0.63      1583

    accuracy                           0.74      6513
   macro avg       0.72      0.80      0.72      6513
weighted avg       0.85      0.74      0.76      6513
```

In [ ]:
```python
# calcula y muestra una gráfica de la matriz de confusión para el bosque

_ = ConfusionMatrixDisplay.from_predictions(y_test, rfc_pred, display_labels=['sala
```

In [ ]:

```
# obten el reporte de clasificación completo para el bosque

print(classification_report(y_test, rfc_pred, target_names=['salary_<=50K', 'salary
```

```
              precision    recall  f1-score   support

salary_<=50K       0.95      0.70      0.81      4930
 salary_>50K       0.49      0.88      0.63      1583

    accuracy                           0.74      6513
   macro avg       0.72      0.79      0.72      6513
weighted avg       0.83      0.74      0.76      6513
```

In [ ]:

```
# crea una lista con el nombre de las características
feature_names = X.columns
feature_names
```

Out[ ]:
```
Index(['age', 'fnlwgt', 'education-num', 'capital-gain', 'capital-loss',
       'hours-per-week', 'workclass_?', 'workclass_Federal-gov',
       'workclass_Local-gov', 'workclass_Never-worked', 'workclass_Private',
       'workclass_Self-emp-inc', 'workclass_Self-emp-not-inc',
       'workclass_State-gov', 'workclass_Without-pay', 'education_10th',
       'education_11th', 'education_12th', 'education_1st-4th',
       'education_5th-6th', 'education_7th-8th', 'education_9th',
       'education_Assoc-acdm', 'education_Assoc-voc', 'education_Bachelors',
       'education_Doctorate', 'education_HS-grad', 'education_Masters',
       'education_Preschool', 'education_Prof-school',
       'education_Some-college', 'marital-status_Divorced',
       'marital-status_Married-AF-spouse', 'marital-status_Married-civ-spouse',
       'marital-status_Married-spouse-absent', 'marital-status_Never-married',
       'marital-status_Separated', 'marital-status_Widowed', 'occupation_?',
       'occupation_Adm-clerical', 'occupation_Armed-Forces',
       'occupation_Craft-repair', 'occupation_Exec-managerial',
       'occupation_Farming-fishing', 'occupation_Handlers-cleaners',
       'occupation_Machine-op-inspct', 'occupation_Other-service',
       'occupation_Priv-house-serv', 'occupation_Prof-specialty',
       'occupation_Protective-serv', 'occupation_Sales',
       'occupation_Tech-support', 'occupation_Transport-moving',
       'relationship_Husband', 'relationship_Not-in-family',
       'relationship_Other-relative', 'relationship_Own-child',
       'relationship_Unmarried', 'relationship_Wife',
       'race_Amer-Indian-Eskimo', 'race_Asian-Pac-Islander', 'race_Black',
       'race_Other', 'race_White', 'sex'],
      dtype='object')
```

In [ ]:
```
# obten la importancia de las características para generar las predicciones con el
dtc.feature_importances_
```

Out[ ]:
```
array([0.00122618, 0.        , 0.1917574 , 0.16971268, 0.00918228,
       0.02127579, 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.60684567, 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ])
```

In [ ]:
```
# ordena las características por su importancia para las prediciones del árbol
dtc_feature_importance = pd.DataFrame(dtc.feature_importances_, index = feature_nam
dtc_feature_importance.columns = ['Feature Importance']
dtc_feature_importance
```

Out[ ]:

	Feature Importance
marital-status_Married-civ-spouse	0.606846
education-num	0.191757
capital-gain	0.169713
hours-per-week	0.021276
capital-loss	0.009182
...	...
education_Preschool	0.000000
education_Prof-school	0.000000
education_Some-college	0.000000
marital-status_Divorced	0.000000
sex	0.000000

65 rows × 1 columns

In [ ]:

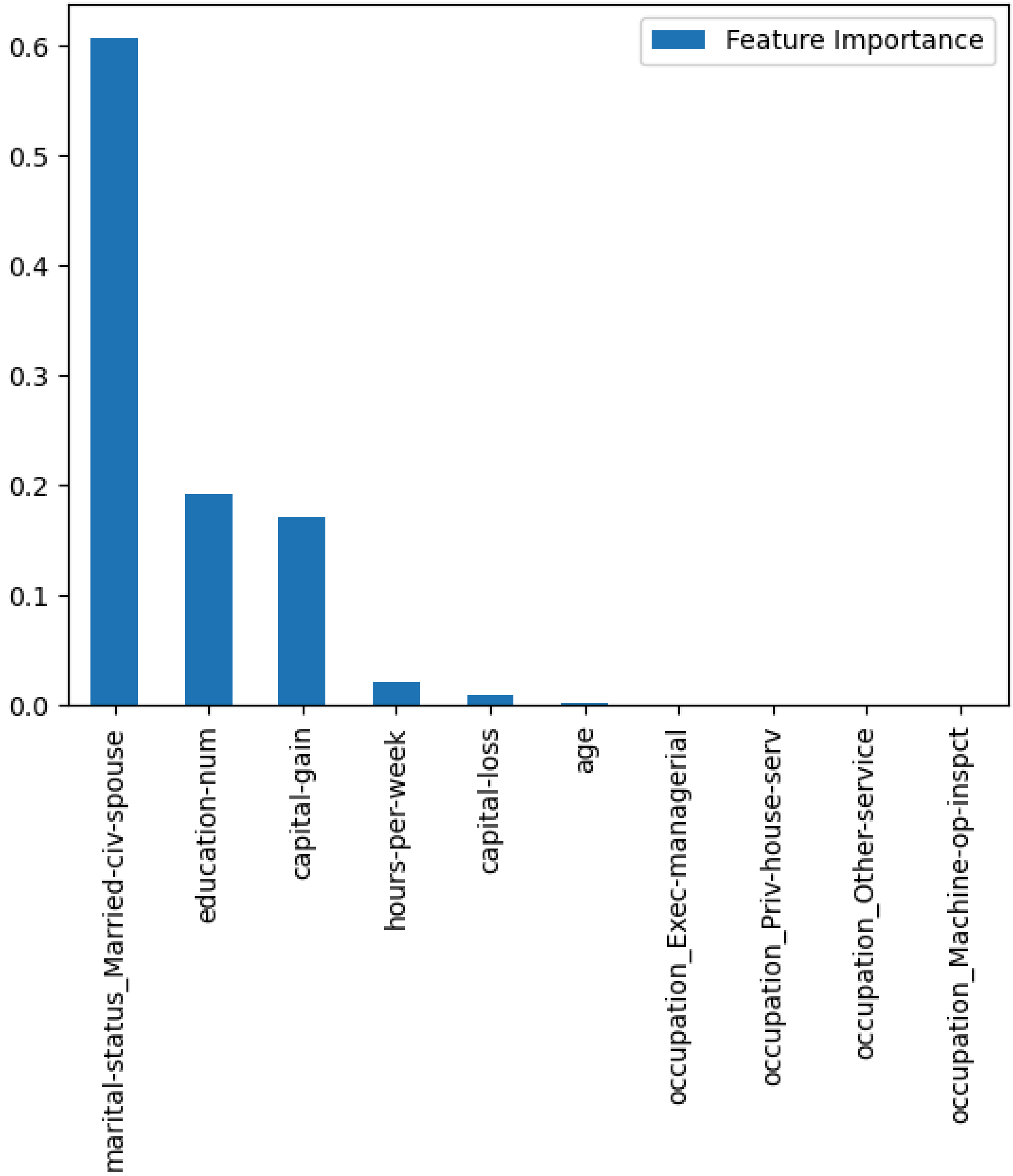
```
# obtén una lista solo con las características utilizadas
dtc_features = list(dtc_feature_importance[dtc_feature_importance['Feature Importan
dtc_features
```

Out[ ]:

```
['marital-status_Married-civ-spouse',
 'education-num',
 'capital-gain',
 'hours-per-week',
 'capital-loss',
 'age']
```

In [ ]:

```
# muestra las características importantes en una gráfica de barras
_ = dtc_feature_importance.head(10).plot(kind='bar')
```



In [ ]:

```
# Sigue el primer ejemplo del árbol para explicar el camino de decisión para la sal
X_test.head(10)
```

Out[ ]:

	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	workclass_?	workclass_Federal-gov
10855	48	195949	10	0	0	42	False	False
17074	17	176467	5	0	0	20	False	False
2400	32	117927	10	0	0	40	False	False
1389	17	46496	7	0	0	5	False	False
17999	27	137063	13	0	0	50	False	False
22257	50	172175	15	0	0	50	False	False
9180	54	329266	9	0	0	44	False	False
23498	53	58913	14	0	0	42	False	False
10830	47	152073	9	0	0	40	False	False
2059	20	176321	8	0	0	40	False	False

10 rows × 65 columns

In [ ]:

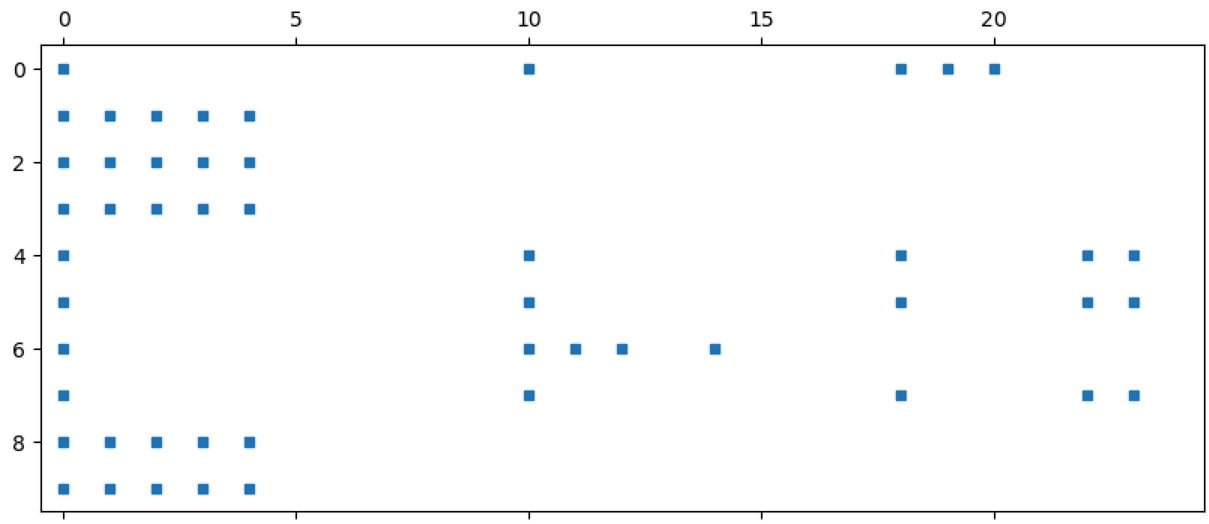
```
# crea una matriz con las rutas de decisión seguidas para los primeros 10 casos de
sparse = dtc.decision_path(X_test).toarray()[:10]
sparse
```

Out[ ]:

```
array([[1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0,
        0, 0, 0],
       [1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0],
       [1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0],
       [1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0],
       [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
        1, 1, 0],
       [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
        1, 1, 0],
       [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0],
       [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
        1, 1, 0],
       [1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0],
       [1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0]], dtype=int64)
```

In [ ]:

```
# muestra las rutas de decisión en una figura
plt.figure(figsize=(10, 10))
_ = plt.spy(sparse, markersize=5)
```



In [ ]:

```
# ordena las características por su importancia para las prediciones del bosque
rfc_feature_importance = pd.DataFrame(rfc.feature_importances_, index = feature_nam
rfc_feature_importance.columns = ['Feature Importance']
rfc_feature_importance
```

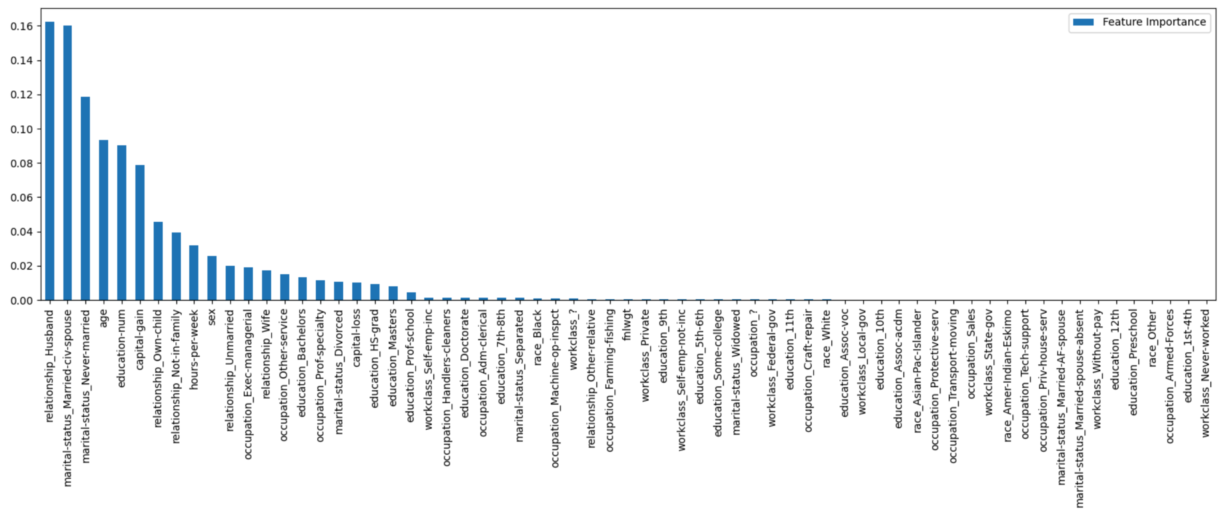
Out[ ]:

	Feature Importance
relationship_Husband	0.162250
marital-status_Married-civ-spouse	0.160335
marital-status_Never-married	0.118339
age	0.093449
education-num	0.090029
...	...
education_Preschool	0.000007
race_Other	0.000004
occupation_Armed-Forces	0.000000
education_1st-4th	0.000000
workclass_Never-worked	0.000000

65 rows × 1 columns

In [ ]:

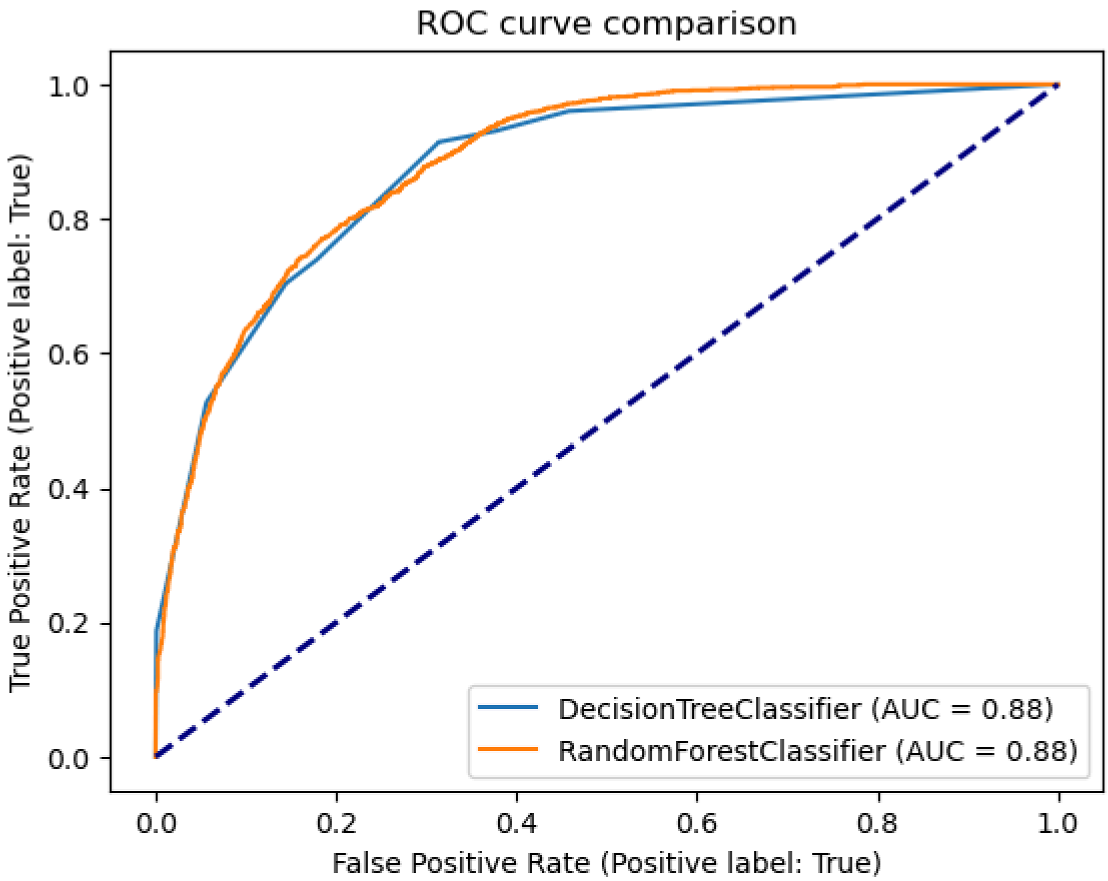
```
# muestra las características importantes en una gráfica de barras
fig, ax = plt.subplots(figsize=(20, 5))

_ = rfc_feature_importance.head(len(feature_names)).plot(kind='bar', ax=ax)

plt.show()
```



In [ ]:

```python
# calcular y mostrar las curvas ROC de cada modelo de aprendizaje
# y sus métricas de área bajo la curva (AUC)
from sklearn.metrics import RocCurveDisplay

plt.figure()
lw = 2
disp = RocCurveDisplay.from_estimator(dtc, X_test, y_test)
RocCurveDisplay.from_estimator(rfc, X_test, y_test, ax=disp.ax_)
plt.plot([0, 1], [0, 1], color="navy", lw=lw, linestyle="--")
plt.title("ROC curve comparison")
plt.legend(loc="lower right")
plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```



Conclusión: Para esta actividad, nosotros elegimos una base de datos que hacía la clasificación binaria de diferentes empleados alrededor del mundo, considerando variables como la educación, ocupasión, estado marital, edad, entre otros. Nosotros elegimos que para este trabajo nuestra variable a predecir sea el salario en donde se dividían en 2, salarios mayores a 50000 y salarios menores a 50000, que aunque no son la misma cantidad de numeros, se tuvo que hacer una limpieza y ajuste para que se pudiera llevar a cabo de la mejor manera. Tras llevar a cabo un análisis comparativo entre el árbol de decisión y el bosque aleatorio mediante representación gráfica utilizando una curva ROC, se ha observado que ambos modelos presentan curvas muy similares. Además, se logra observar que en las cifras presentadas, no se muestran diferencias significativas en el área bajo la curva, lo que indica que en este contexto específico ambos modelos son igualmente apropiados para tomar una decisión y sus diagnósticos tienen una precisión prácticamente idéntica. Este nos resulta muy interesante, ya que, a pesar de compartir la misma variable predictora principal, los modelos asignan niveles de importancia ligeramente diferentes a esta misma variable. Además, se destaca que, incluso cuando hay una ligera variación en las demás variables, la similitud en la eficacia de ambos modelos persiste. Esta característica de que haya una consistencia en la capacidad que los dos modelos tienen para predecir un resultado nos sirve como indicador de confiabilidad de los modelos, ya que se obtienen resultados similares mediante diferentes enfoques. Gracias a todo este proceso, pudimos darnos cuenta de que la elección entre un árbol de decisión y un bosque aleatorio en este escenario puede depender de otros factores, como la interpretabilidad del modelo o los recursos computacionales disponibles, ya que en términos de rendimiento predictivo no parece haber una ventaja clara de uno sobre el otro.

Raúl Correa Ocañas

Predictor: marital-status

In [ ]:
```
indices = random.sample(range(len(data)), 15)
print(data.iloc[indices][['salary']].value_counts())
print("----------------")
print(data.iloc[indices][['marital-status','salary']].value_counts())
```

```
salary
<=50K     14
>50K       1
Name: count, dtype: int64
----------------
marital-status      salary
Never-married       <=50K     7
Married-civ-spouse  <=50K     5
Divorced            <=50K     2
Married-civ-spouse  >50K      1
Name: count, dtype: int64
```

In [ ]:
```
def entropy(numlist):
    entropy = 0
    total = sum(numlist)
    for number in numlist:
        if number == 0:
            entropy += 0
        else:
            entropy += -number/total * np.log2(number/total)

    return entropy
```

In [ ]:
```
def gini(numlist):
    gini = 0
    total = sum(numlist)
    for number in numlist:
        gini += (number/total)**2

    return 1-gini
```

In [ ]:
```
entropy_metric = entropy([14,1])

entropy_metric
```

Out[ ]:
```
0.35335933502142136
```

In [ ]:
```
ig_metric = entropy_metric - (6/15 * entropy([5,1]) + 7/15 * entropy([7,0]) + 2/15

ig_metric
```

Out[ ]: 0.09335036636207972

In [ ]:
```
weighted_gini = 6/15 * gini([5,1]) + 7/15 * gini([7,0]) + 2/15 * gini([2,0])
weighted_gini
```

Out[ ]: 0.11111111111111108