Módulo 2. Uso de framework o biblioteca de aprendizaje máquina para la implementación de una solución. (Portafolio Implementación)

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Machine Learning: Decision Trees

Importamos librerias necesarias

In [ ]:
```
from sklearn import tree
from sklearn import preprocessing
from IPython.display import Image
import pydotplus
import matplotlib.pyplot as plt

from datetime import datetime

from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import confusion_matrix

import seaborn as sns
import numpy as np
import pandas as pd
```

Leemos base de datos: Iris.csv

In [ ]:
```
df_iris = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Iris.csv')
df_iris
```

Out[ ]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

Separamos las variables y etiquetas

In [ ]:
```
# Etiqueta
Y_iris = df_iris['Species']

# Variables
X_iris = df_iris.values[:, 1:5] # 5-1
```

Dividimos en training y test set

In [ ]:
```
X_train_iris, X_test_iris, y_train_iris, y_test_iris = train_test_split(X_iris,
```

Implementación del método DecisionTreeClassifier

In [ ]:
```
clf_tree_iris = tree.DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, cr
                       max_depth=None, 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')

# Train Decision Tree Classifer
clf_tree_iris = clf_tree_iris.fit(X_train_iris, y_train_iris)
```

Predict the response for test dataset

In [ ]:
```
test_pred_decision_tree = clf_tree_iris.predict(X_test_iris)
```

Verificación de predicciones

In [ ]:
```
#Predicción 1
print(clf_tree_iris.predict([[4.6, 3.2, 1.5, 0.3]]))
```

```
['Iris-setosa']
```

In [ ]:
```
#Predicción 2
print(clf_tree_iris.predict([[6.7, 2.5, 5.5, 1.4]]))
```

```
['Iris-virginica']
```

In [ ]:
```
#Predicción 3
print(clf_tree_iris.predict([[7.7, 4.0, 1.1, 2.1]]))
```

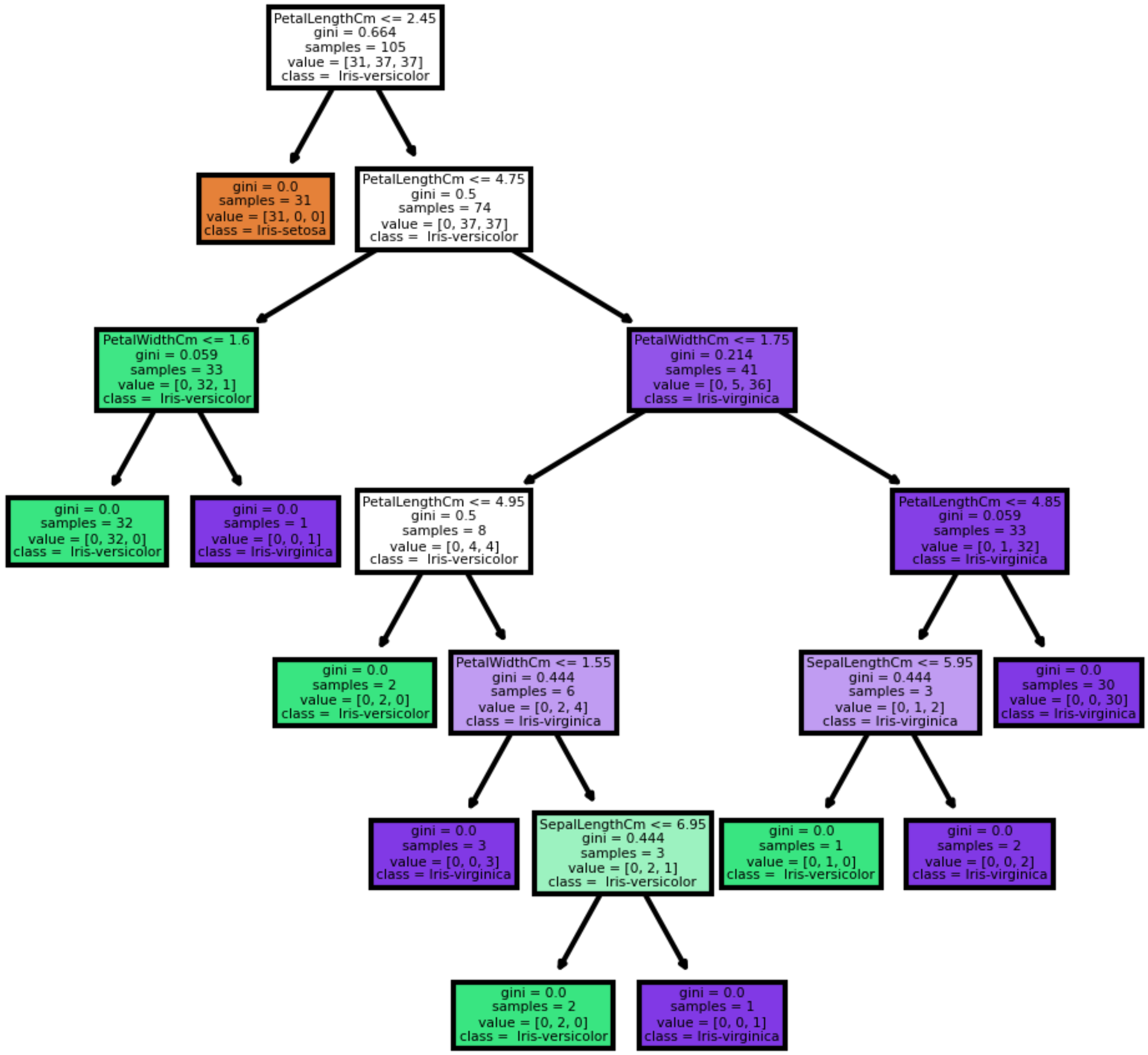
```
['Iris-setosa']
```

In [ ]:
```
feature_names = ['SepalLengthCm',        'SepalWidthCm', 'PetalLengthCm',
target_names = ['Iris-setosa', ' Iris-versicolor', 'Iris-virginica']

#Tamaño de los árboles
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)

# Crear los datos
tree.plot_tree(classifier, filled=True,
                          feature_names=feature_names,
                          class_names=target_names)

fig.savefig('imagename.png')
```



Matriz de confusión

In [ ]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test, test_pred_decision_tree)
```

Out[ ]:
```
array([[19,  0,  0],
       [ 0, 13,  0],
       [ 0,  0, 13]])
```

In [ ]:
```
from sklearn.metrics import accuracy_score
accuracy_score(y_test, test_pred_decision_tree)
```

Out[ ]:
```
1.0
```

Segunda implementación (debido a que sale un Accuracy perfecto en el dataset Iris)

Abrimos data set Wine

In [ ]:
```
import pandas as pd # importar libreria

columns = ["Classification", "Alcohol","Malic acid","Ash","Alcalinity of ash", "
        ,"Proanthocyanins", "Color intensity", "Hue", "OD280/OD315 of diluted wi

df1 = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Copia de wine.data', n
df1 = df1.drop(['index'], axis=1) # abrir el archivo de datos con los nombres da
df1.head()
```

Out[ ]:

	Classification	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols
0	1	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28
1	1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26
2	1	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30
3	1	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24
4	1	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39

Verificamos columna de clasificación

In [ ]:
```
df1['Classification']
```

Out[ ]:
```
0      1
1      1
2      1
3      1
4      1
      ..
173    3
174    3
175    3
176    3
177    3
Name: Classification, Length: 178, dtype: int64
```

Obtenemos valores únicos de la columna de clasificación

In [ ]:
```
df1.Classification.unique()
```

Out[ ]:
```
array([1, 2, 3])
```

Para una interpretación más sencilla se reemplazaron las clasificaciones numéricas a categóricas

In [ ]:
```
df1.Classification.replace([0, 1, 3], ['Cultivar 1', 'Cultivar 2', 'Cultivar 3']
df1.Classification
```

Out[ ]:
```
0      Cultivar 2
1      Cultivar 2
2      Cultivar 2
3      Cultivar 2
4      Cultivar 2
          ...
173    Cultivar 3
174    Cultivar 3
175    Cultivar 3
```

```
176    Cultivar 3
177    Cultivar 3
Name: Classification, Length: 178, dtype: object
```

In [ ]:

```
#df1['Classification'].astype(str)
```

Separamos las variables de la variable target

In [ ]:

```
df_x = df1.drop(["Classification"], axis=1)
df_y = df1["Classification"]


# Print df_x first 5
df_x
```

Out[ ]:

	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocya
0	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	
1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	
2	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	
3	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	
4	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	
...	...	...	...	...	...	...	...	...	
173	13.71	5.65	2.45	20.5	95	1.68	0.61	0.52	
174	13.40	3.91	2.48	23.0	102	1.80	0.75	0.43	
175	13.27	4.28	2.26	20.0	120	1.59	0.69	0.43	
176	13.17	2.59	2.37	20.0	120	1.65	0.68	0.53	
177	14.13	4.10	2.74	24.5	96	2.05	0.76	0.56	

178 rows × 13 columns

Separamos entre training y test set

In [ ]:

```
from sklearn.model_selection import train_test_split


X_train, X_test, y_train, y_test = train_test_split(df_x, df_y, test_size=0.2, r
```

Construimos el clasificador

In [ ]:

```
classifier = tree.DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, crite
                       max_depth=None, 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')

# Train Decision Tree Classifer
classifier = classifier.fit(X_train, y_train)
```

Generar predicción

In [ ]:
```
test_pred_decision_tree = classifier.predict(X_test)
```

Obtenemos columna

In [ ]:
```
df1.columns
```

Out[ ]:
```
Index(['Classification', 'Alcohol', 'Malic acid', 'Ash', 'Alcalinity of ash',
       'Magnesium', 'Total phenols', 'Flavanoids', 'Nonflavanoid phenols',
       'Proanthocyanins', 'Color intensity', 'Hue',
       'OD280/OD315 of diluted wines', 'Proline'],
      dtype='object')
```

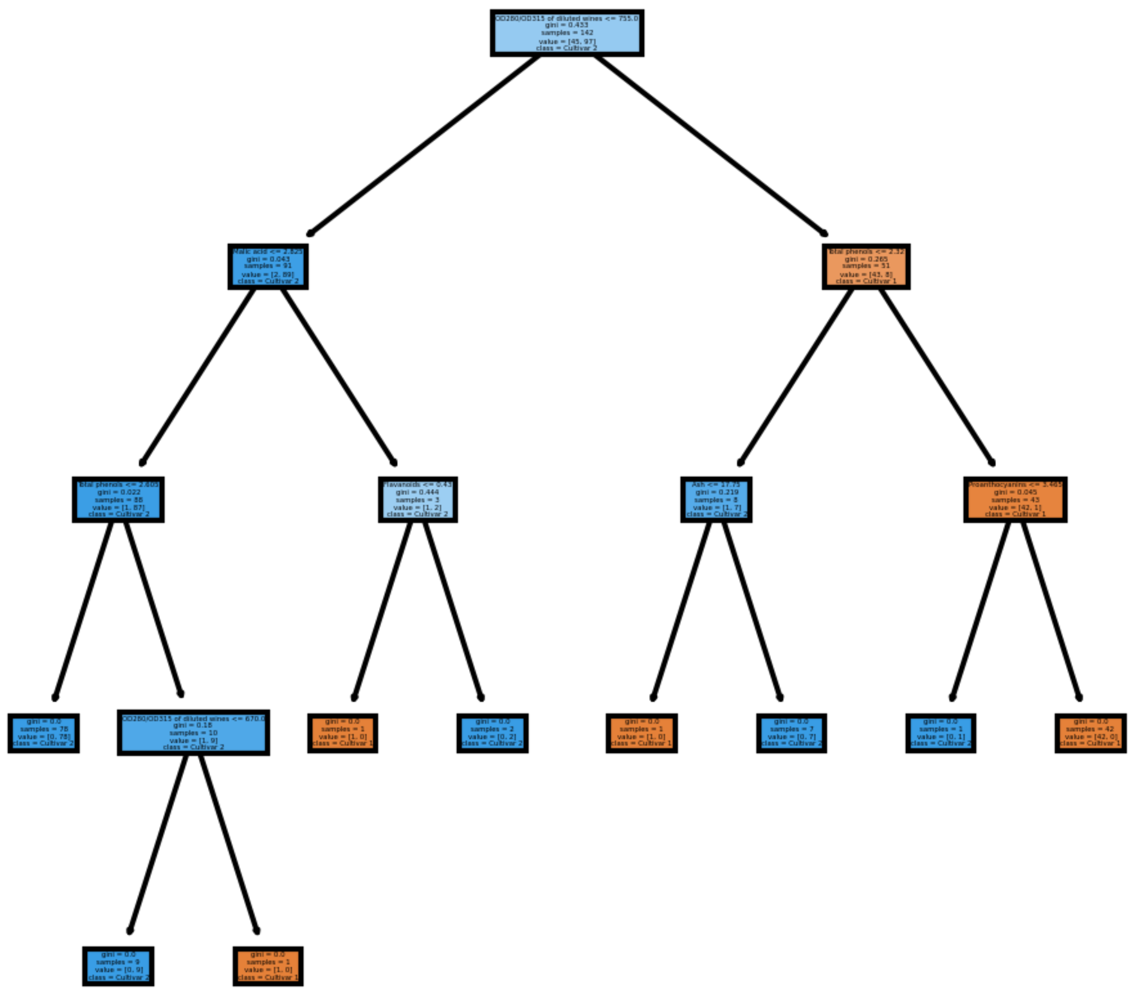
Graficamos el árbol de decisión

In [ ]:
```
feature_names = ['Classification', 'Alcohol', 'Malic acid', 'Ash', 'Alcalinity o
       'Magnesium', 'Total phenols', 'Flavanoids', 'Nonflavanoid phenols',
       'Proanthocyanins', 'Color intensity', 'Hue',
       'OD280/OD315 of diluted wines', 'Proline']
target_names = ['Cultivar 1', 'Cultivar 2', 'Cultivar 3']

#Tamaño de los árboles
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)

# Crear los datos
tree.plot_tree(classifier, filled=True,
                          feature_names=feature_names,
                          class_names=target_names)

fig.savefig('imagename.png')
```



Comparamos el valor actual con el predicho por el modelo

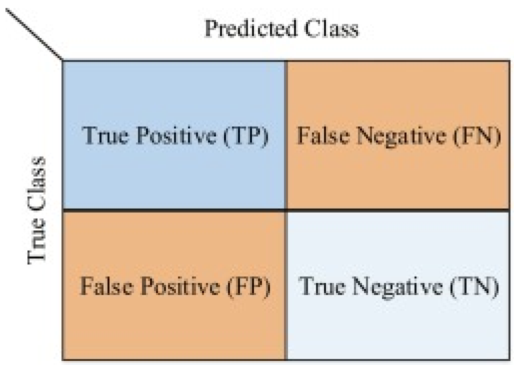
In [ ]:
```
test_pred_decision_tree_list = test_pred_decision_tree.tolist()
```

In [ ]:
```
for i in range(len(test_pred_decision_tree)):
  print('Real: ',test_pred_decision_tree_list[i],' | Pred: ', test_pred_decision
```

```
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
```

```
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 3  | Pred:  Cultivar 3
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 2  | Pred:  Cultivar 2
Real:  Cultivar 2  | Pred:  Cultivar 2
```

Obtenemos matriz de confusión



In [ ]:
```python
cf_matrix = confusion_matrix(y_test, test_pred_decision_tree)
cf_matrix
```

Out[ ]:
```
array([[14,  0],
       [ 3, 19]])
```

Métrica Accuracy

In [ ]:
```python
from sklearn.metrics import accuracy_score
accuracy_score(y_test, test_pred_decision_tree)
```

Out[ ]:
```
0.9166666666666666
```