

## ▼ Decision Tree for Iris Data

### Importing the Libs

```
!pip install plotly --upgrade
```

```
Requirement already satisfied: plotly in c:\users\novae\appdata\local\programs\python\python39\lib\site-packa
Requirement already satisfied: tenacity>=6.2.0 in c:\users\novae\appdata\local\programs\python\python39\lib\
Requirement already satisfied: six in c:\users\novae\appdata\local\programs\python\python39\lib\site-package:
WARNING: You are using pip version 21.2.3; however, version 22.0.4 is available.
You should consider upgrading via the 'C:\Users\novae\AppData\Local\Programs\Python\Python39\python.exe -m p:
```

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
```

## ▼ Base de dados de Iris

- Fonte (adaptado): <https://www.kaggle.com/datasets/arshid/iris-flower-dataset?select=IRIS.csv>

## ▼ Exploração dos Dados

```
base_Iris = pd.read_csv('./content/IRIS.csv')
```

```
base_Iris
```

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 5 columns

```
base_Iris.head(10)
```

```
base_Iris.describe()
```

```
base_Iris.shape  
  
(150, 5)
```

## ▼ Visualização dos Dados

```
sns.countplot(x = base_Iris['species']);
```

```
plt.hist(x = base_Iris['sepal_length']);
```

```
plt.hist(x = base_Iris['sepal_width']);
```

```
plt.hist(x = base_Iris['petal_length']);
```

```
plt.hist(x = base_Iris['petal_width']);
```

```
grafico = px.scatter_matrix(base_Iris, dimensions=['sepal_length', 'sepal_width', 'petal_length', 'petal_width'],
```

```
grafico.show();
```

```
plt.subplots(figsize=(16,12))  
sns.heatmap(  
    base_Iris.corr(),  
    annot=True,  
    square=True,  
    cbar=True  
)
```



## ▼ Tratamento de valores faltantes

```
base_Iris.isnull()
```

```
base_Iris.isnull().sum()
```

```
sepal_length    0  
sepal_width     0  
petal_length    0  
petal_width     0  
species         0  
dtype: int64
```



There are not missing values.

## ▼ Divisão entre previsores e classe

```
base_Iris.columns
```

```
Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width',  
      'species'],  
      dtype='object')
```

```
X_Iris = base_Iris.iloc[:, 0:4].values  
X_Iris
```

```
array([[5.1, 3.5, 1.4, 0.2],  
       [4.9, 3. , 1.4, 0.2],  
       [4.7, 3.2, 1.3, 0.2],  
       [4.6, 3.1, 1.5, 0.2],  
       [5. , 3.6, 1.4, 0.2],  
       [5.4, 3.9, 1.7, 0.4],  
       [4.6, 3.4, 1.4, 0.3],  
       [5. , 3.4, 1.5, 0.2],  
       [4.4, 2.9, 1.4, 0.2],  
       [4.9, 3.1, 1.5, 0.1],  
       [5.4, 3.7, 1.5, 0.2],  
       [4.8, 3.4, 1.6, 0.2],  
       [4.8, 3. , 1.4, 0.1],  
       [4.3, 3. , 1.1, 0.1],  
       [5.8, 4. , 1.2, 0.2],  
       [5.7, 4.4, 1.5, 0.4],  
       [5.4, 3.9, 1.3, 0.4],  
       [5.1, 3.5, 1.4, 0.3],  
       [5.7, 3.8, 1.7, 0.3],  
       [5.1, 3.8, 1.5, 0.3],  
       [5.4, 3.4, 1.7, 0.2],  
       [5.1, 3.7, 1.5, 0.4],  
       [4.6, 3.6, 1. , 0.2],  
       [5.1, 3.3, 1.7, 0.5],  
       [4.8, 3.4, 1.9, 0.2],
```

```
[5. , 3. , 1.6, 0.2],
[5. , 3.4, 1.6, 0.4],
[5.2, 3.5, 1.5, 0.2],
[5.2, 3.4, 1.4, 0.2],
[4.7, 3.2, 1.6, 0.2],
[4.8, 3.1, 1.6, 0.2],
[5.4, 3.4, 1.5, 0.4],
[5.2, 4.1, 1.5, 0.1],
[5.5, 4.2, 1.4, 0.2],
[4.9, 3.1, 1.5, 0.1],
[5. , 3.2, 1.2, 0.2],
[5.5, 3.5, 1.3, 0.2],
[4.9, 3.1, 1.5, 0.1],
[4.4, 3. , 1.3, 0.2],
[5.1, 3.4, 1.5, 0.2],
[5. , 3.5, 1.3, 0.3],
[4.5, 2.3, 1.3, 0.3],
[4.4, 3.2, 1.3, 0.2],
[5. , 3.5, 1.6, 0.6],
[5.1, 3.8, 1.9, 0.4],
[4.8, 3. , 1.4, 0.3],
[5.1, 3.8, 1.6, 0.2],
[4.6, 3.2, 1.4, 0.2],
[5.3, 3.7, 1.5, 0.2],
[5. , 3.3, 1.4, 0.2],
[7. , 3.2, 4.7, 1.4],
[6.4, 3.2, 4.5, 1.5],
[6.9, 3.1, 4.9, 1.5],
[5.5, 2.3, 4. , 1.3],
[6.5, 2.8, 4.6, 1.5],
[5.7, 2.8, 4.5, 1.3],
[6.3, 3.3, 4.7, 1.6],
[4.9, 2.4, 3.3, 1. ],
```

```
Y_Iris = base_Iris.iloc[:, 4].values
Y_Iris
```

```
array(['Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
      'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
      'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
      'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
      'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
```

[illegible]

## ▼ Tratamento de atributos categóricos

### ▼ LabelEncoder

```
from sklearn.preprocessing import LabelEncoder
Y_Iris = LabelEncoder().fit_transform(Y_Iris)
Y_Iris

array([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, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

### ▼ Escalonamento dos valores

```
from sklearn.preprocessing import MinMaxScaler
X_Iris = MinMaxScaler().fit_transform(X_Iris)
X_Iris

array([[0.22222222, 0.625      , 0.06779661, 0.04166667],
       [0.16666667, 0.41666667, 0.06779661, 0.04166667],
       [0.11111111, 0.5        , 0.05084746, 0.04166667],
       [0.08333333, 0.45833333, 0.08474576, 0.04166667],
       [0.19444444, 0.66666667, 0.06779661, 0.04166667],
       [0.30555556, 0.79166667, 0.11864407, 0.125      ],
       [0.08333333, 0.58333333, 0.06779661, 0.08333333],
       [0.19444444, 0.58333333, 0.08474576, 0.04166667],
       [0.02777778, 0.375      , 0.06779661, 0.04166667],
       [0.16666667, 0.45833333, 0.08474576, 0.        ],
       [0.30555556, 0.70833333, 0.08474576, 0.04166667],
```

```
[0.13888889, 0.58333333, 0.10169492, 0.04166667],
[0.13888889, 0.41666667, 0.06779661, 0.         ],
[0.         , 0.41666667, 0.01694915, 0.         ],
[0.41666667, 0.83333333, 0.03389831, 0.04166667],
[0.38888889, 1.         , 0.08474576, 0.125         ],
[0.30555556, 0.79166667, 0.05084746, 0.125         ],
[0.22222222, 0.625         , 0.06779661, 0.08333333],
[0.38888889, 0.75         , 0.11864407, 0.08333333],
[0.22222222, 0.75         , 0.08474576, 0.08333333],
[0.30555556, 0.58333333, 0.11864407, 0.04166667],
[0.22222222, 0.70833333, 0.08474576, 0.125         ],
[0.08333333, 0.66666667, 0.         , 0.04166667],
[0.22222222, 0.54166667, 0.11864407, 0.16666667],
[0.13888889, 0.58333333, 0.15254237, 0.04166667],
[0.19444444, 0.41666667, 0.10169492, 0.04166667],
[0.19444444, 0.58333333, 0.10169492, 0.125         ],
[0.25         , 0.625         , 0.08474576, 0.04166667],
[0.25         , 0.58333333, 0.06779661, 0.04166667],
[0.11111111, 0.5         , 0.10169492, 0.04166667],
[0.13888889, 0.45833333, 0.10169492, 0.04166667],
[0.30555556, 0.58333333, 0.08474576, 0.125         ],
[0.25         , 0.875         , 0.08474576, 0.         ],
[0.33333333, 0.91666667, 0.06779661, 0.04166667],
[0.16666667, 0.45833333, 0.08474576, 0.         ],
[0.19444444, 0.5         , 0.03389831, 0.04166667],
[0.33333333, 0.625         , 0.05084746, 0.04166667],
[0.16666667, 0.45833333, 0.08474576, 0.         ],
[0.02777778, 0.41666667, 0.05084746, 0.04166667],
[0.22222222, 0.58333333, 0.08474576, 0.04166667],
[0.19444444, 0.625         , 0.05084746, 0.08333333],
[0.05555556, 0.125         , 0.05084746, 0.08333333],
[0.02777778, 0.5         , 0.05084746, 0.04166667],
[0.19444444, 0.625         , 0.10169492, 0.20833333],
[0.22222222, 0.75         , 0.15254237, 0.125         ],
[0.13888889, 0.41666667, 0.06779661, 0.08333333],
[0.22222222, 0.75         , 0.10169492, 0.04166667],
[0.08333333, 0.5         , 0.06779661, 0.04166667],
[0.27777778, 0.70833333, 0.08474576, 0.04166667],
[0.19444444, 0.54166667, 0.06779661, 0.04166667],
[0.75         , 0.5         , 0.62711864, 0.54166667],
[0.58333333, 0.5         , 0.59322034, 0.58333333],
[0.72222222, 0.45833333, 0.66101695, 0.58333333],
```

```
[0.33333333, 0.125      , 0.50847458, 0.5      ],  
[0.61111111, 0.33333333, 0.61016949, 0.58333333],  
[0.38888889, 0.33333333, 0.59322034, 0.5      ],  
[0.55555556, 0.54166667, 0.62711864, 0.625     ],
```

## ▼ Divisão das bases em treinamento e teste

```
from sklearn.model_selection import train_test_split  
X_Iris_treinamento, X_Iris_teste, Y_Iris_treinamento, Y_Iris_teste = train_test_split(X_Iris, Y_Iris, test_size =  
  
X_Iris_treinamento.shape, Y_Iris_treinamento.shape  
  
((112, 4), (112,))  
  
X_Iris_teste.shape, Y_Iris_teste.shape  
  
((38, 4), (38,))
```

## ▼ Salvar as variáveis

```
import pickle  
with open('iris.pkl', mode = 'wb') as f:  
    pickle.dump([X_Iris_treinamento, Y_Iris_treinamento, X_Iris_teste, Y_Iris_teste], f)
```

## ▼ Training the Model with a Decision Tree 97,36% of precision

```
from sklearn.tree import DecisionTreeClassifier  
arvore_Iris = DecisionTreeClassifier(criterion='entropy')  
arvore_Iris.fit(X_Iris_treinamento, Y_Iris_treinamento)
```

```
DecisionTreeClassifier(criterion='entropy')

arvore_Iris.feature_importances_

array([0.          , 0.01832976, 0.29892117, 0.68274907])

arvore_Iris.classes_

array([0, 1, 2])

from sklearn import tree
previsores = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (20,20))
#figura, eixos = plt.subplots(nrows=1, ncols=1, figsize=(10,10)).make
tree.plot_tree(arvore_Iris, feature_names=previsores, class_names = ['0','1','2'], filled=True);
```

```
previsoes_Iris = arvore_Iris.predict(X_Iris_teste)
```

```
from sklearn.metrics import accuracy_score, classification_report  
accuracy_score(Y_Iris_teste, previsoes_Iris)
```

```
0.9736842105263158
```



```
from yellowbrick.classifier import ConfusionMatrix
cm = ConfusionMatrix(arvore_Iris)
cm.fit(X_Iris_treinamento, Y_Iris_treinamento)
cm.score(X_Iris_teste, Y_Iris_teste)
```

```
print(classification_report(Y_Iris_teste, previsoes_Iris))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	13
1	1.00	0.94	0.97	16
2	0.90	1.00	0.95	9
accuracy			0.97	38
macro avg	0.97	0.98	0.97	38
weighted avg	0.98	0.97	0.97	38

## ▼ Random Forest

```
from sklearn.ensemble import RandomForestClassifier
```

### ▼ With 2 trees 92,1%

```
random_forest_Iris2 = RandomForestClassifier(n_estimators=2, criterion='entropy', random_state = 0)
random_forest_Iris2.fit(X_Iris_treinamento, Y_Iris_treinamento)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=2, random_state=0)
```

```
previsoes2 = random_forest_Iris2.predict(X_Iris_teste)
accuracy_score(Y_Iris_teste, previsoes2)
```

```
0.9210526315789473
```

### ▼ With 5 Trees 97,36%

```
random_forest_Iris5 = RandomForestClassifier(n_estimators=5, criterion='entropy', random_state = 0)
random_forest_Iris5.fit(X_Iris_treinamento, Y_Iris_treinamento)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=5, random_state=0)
```

```
previsoes5 = random_forest_Iris5.predict(X_Iris_teste)
accuracy_score(Y_Iris_teste, previsoes5)
```

```
0.9736842105263158
```

### ▼ With 100 Trees 97,36%

```
random_forest_Iris100 = RandomForestClassifier(n_estimators=100, criterion='entropy', random_state = 0)
random_forest_Iris100.fit(X_Iris_treinamento, Y_Iris_treinamento)
```

```
RandomForestClassifier(criterion='entropy', random_state=0)
```

```
previsoes100 = random_forest_Iris100.predict(X_Iris_teste)
accuracy_score(Y_Iris_teste, previsoes100)
```

```
0.9736842105263158
```

```
from yellowbrick.classifier import ConfusionMatrix
cm = ConfusionMatrix(random_forest_Iris100)
cm.fit(X_Iris_treinamento, Y_Iris_treinamento)
cm.score(X_Iris_teste, Y_Iris_teste)
```

```
print(classification_report(Y_Iris_teste, previsoes100))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	13
1	1.00	0.94	0.97	16
2	0.90	1.00	0.95	9
accuracy			0.97	38
macro avg	0.97	0.98	0.97	38
weighted avg	0.98	0.97	0.97	38

