Ávore de Decisão

Mini-projeto 2 - Sistemas Inteligentes

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Equipe 6

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⚙️ Setup

Importando dependências, conectando Google Drive, lendo datasets e criando os respectivos dataframes.

Dependências

In [1]:

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import classification_report, accuracy_score, precision_score, rec
all_score, f1_score, roc_auc_score, confusion_matrix
```

Drive

In [2]:

```
from google.colab import drive
drive.mount('/content/drive')

base_path = '/content/drive/MyDrive/'
```

```
Mounted at /content/drive
```

IRIS Dataset - https://www.kaggle.com/datasets/arshid/iris-flower-dataset (https://www.kaggle.com/datasets/arshid/iris-flower-dataset)

In [3]:

```
iris_dataset_path = base_path + 'IRIS.csv'
```

Titanic Dataset - [https://www.kaggle.com/c/titanic/data (https://www.kaggle.com/c/titanic/data)](https://www.kaggle.com/c/titanic/data)

In [4]:

```
titanic_train_dataset_path = base_path + 'titanic/train.csv'
titanic_test_dataset_path = base_path + 'titanic/test.csv'
```

Lower Back Pain Symptoms Dataset - [https://www.kaggle.com/datasets/sammy123/lower-back-pain-symptoms-dataset (https://www.kaggle.com/datasets/sammy123/lower-back-pain-symptoms-dataset)](https://www.kaggle.com/datasets/sammy123/lower-back-pain-symptoms-dataset)

In [5]:

```
pain_dataset_path = base_path + 'Dataset_spine.csv'
```

Lendo datasets

In [6]:

```
iris_df = pd.read_csv(iris_dataset_path)
```

In [7]:

```
titanic_df = pd.read_csv(titanic_train_dataset_path)
titanic_test_df = pd.read_csv(titanic_test_dataset_path) # Não possui a coluna de class
ificação (Survived)
```

In [8]:

```
pain_df = pd.read_csv(pain_dataset_path)
pain_df = pain_df.drop(pain_df.columns[[13]], axis=1) # Removendo a coluna 13
```

Funções

In [190]:

```
def predict_and_report(title, classifier, x_test, y_test, y_train, x_train):
  y_pred = classifier.predict(x_test)
  report = classification_report(y_test, y_pred)
  print(title + "- base de teste")
  print(report)
  plot_confusion_matrix(y_test, y_pred)
  print("-------------------------------------------------------")
  y_pred = classifier.predict(x_train)
  report = classification_report(y_train, y_pred)
  print(title + "- base de treino")
  print(report)
```

In [9]:

```
def plot_confusion_matrix(y_test, y_pred):
  cm = confusion_matrix(y_test, y_pred)
  fig, ax = plt.subplots(figsize=(2,2))
  sns.heatmap(cm, annot=True, fmt='d')
```

🧪 Experimento: Iris Flower Dataset

🔎 Análise do Dataset

In [10]:

```
iris_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

In [11]:

```
iris_df['species'].unique()
```

Out[11]:

```
array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

In [12]:

```
iris_df['species'].value_counts()
```

Out[12]:

```
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: species, dtype: int64
```

In [13]:

```
#iris_df.describe()
```

In [14]:

```
#sns.pairplot(iris_df, hue ='species')
```

In [15]:

```
#iris_df.hist(bins=50, figsize=(5,5))
#plt.show()
```

In [16]:

```
#sns.set_style("whitegrid")
#data = np.random.normal(size=(20, 6)) + np.arange(6) / 2
#sns.set(rc={'figure.figsize':(7,4)})
#sns.boxplot(data = iris_df.iloc[:,:-1])
```

🛠 Criando modelo

In [17]:

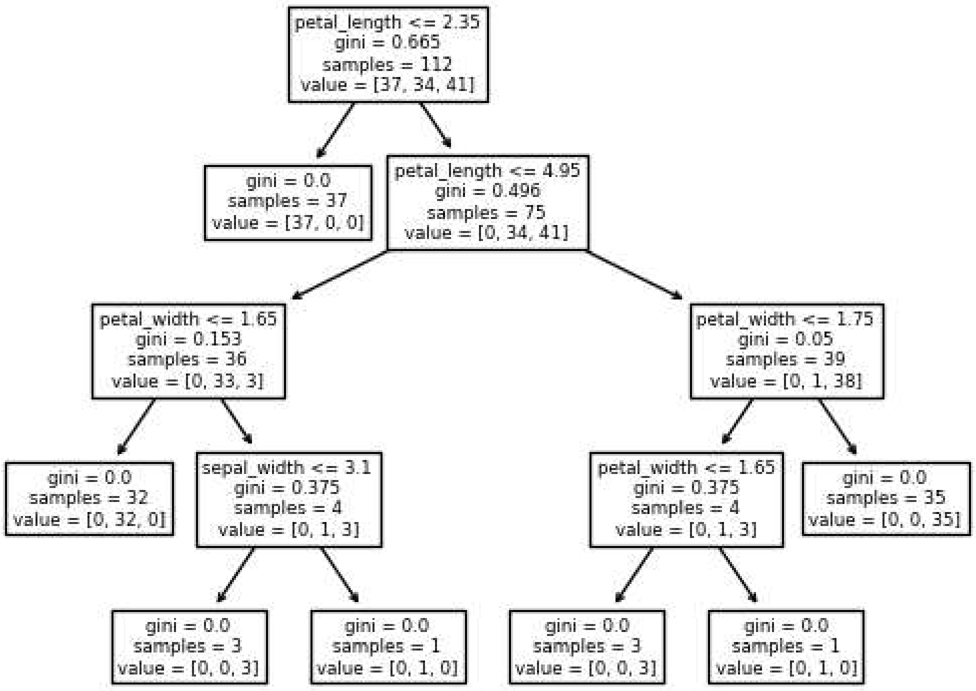
```
iris_x = iris_df.iloc[:, :-1]
iris_y = iris_df.iloc[:, -1]
iris_x_train, iris_x_test, iris_y_train, iris_y_test = train_test_split(iris_x, iris_y,
test_size = 0.25, random_state = 0)
```

In [ ]:

```
classifier = DecisionTreeClassifier()
classifier.fit(iris_x_train, iris_y_train)
```

In [19]:

```
plot_tree(classifier, feature_names=iris_df.columns[: -1])
plt.show()
```



In [20]:

```
iris_y_pred = classifier.predict(iris_x_test)
```

In [21]:

```
report = classification_report(iris_y_test, iris_y_pred)
```

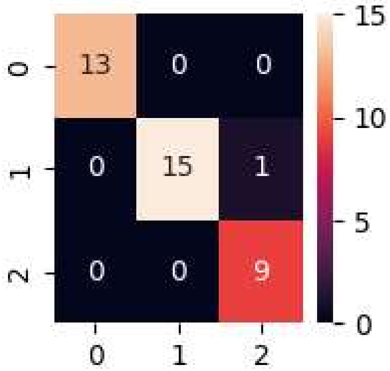
In [22]:

```
print(report)
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        13
Iris-versicolor       1.00      0.94      0.97        16
 Iris-virginica       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
```

In [23]:

```
plot_confusion_matrix(iris_y_test, iris_y_pred)
```



🚢 Projeto: Titanic Dataset

🔎 Análise e limpeza do Dataset

Valores faltantes

A primeira análise feita é verificar os valores faltantes. **Três colunas possuem valores nulos: Age, Cabin e Embarked.** Cada coluna terá um tratamento apropriado.

In [24]:

```
titanic_df.shape
```

Out[24]:

```
(891, 12)
```

In [25]:

```
#titanic_df.info()
titanic_df.isnull().sum()
```

Out[25]:

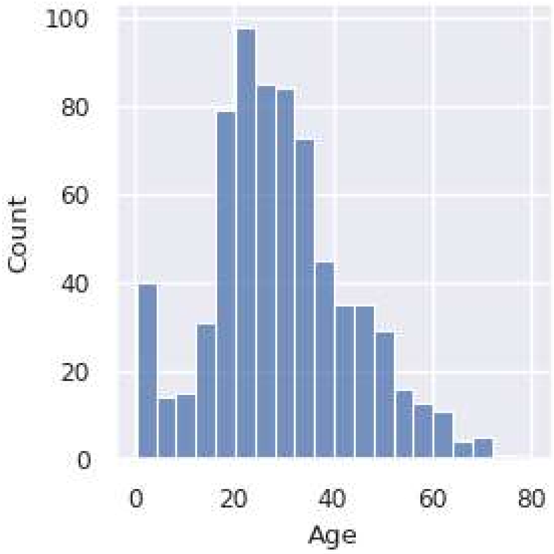
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

Age

- Como é uma coluna de valores numéricos, que a maioria dos valores não é nulo e que acreditamos ter grande relevância para a sobrevivência ou não, será utilizado um método de substituir os valores nulos por um outro valor.
- No plot vemos que se aproxima de uma distribuição assimétrica para a direita, então, então podemos **substituir os valores faltantes pela mediana**. [1] (https://vitalflux.com/pandas-impute-missing-values-mean-median-mode/#How_to_decide_which_imputation_technique_to_use)
- 🚩 **Idealmente, deveríamos analisar a correlação entre a idade e outras features, observando a existência de uma correlação, então os valores nulos deveriam ser substituídos pela mediana do subconjunto (separado pelas outras features correlacionadas).** Não fizemos isso por não achar necessário para o escopo do projeto.

In [26]:

```
sns.set(font_scale=0.8)
sns.displot(titanic_df['Age'], height=3)
plt.show()
```



In [27]:

```
titanic_df['Age'] = titanic_df['Age'].fillna(titanic_df['Age'].median())
```

Cabin

- A maioria dos valores são nulos (687 de 891), não são numéricos e possuem muitos valores únicos.
- Poderia ser feita uma tentativa de extrair informações relevantes dos dados que existem, visto que as strings consistem de uma letra seguida por um ou dois números, podemos deduzir que está relacionada a posição da cabine no navio, podendo então influenciar na sobrevivência de um passageiro. [2] (https://www.kaggle.com/code/ccastleberry/titanic-cabin-features/notebook)
- Entretanto, optaremos por **descartar a coluna** devido a quantidade de valores faltantes.

In [28]:

```
titanic_df['Cabin'].value_counts()
```

Out[28]:

```
B96 B98        4
G6             4
C23 C25 C27    4
C22 C26        3
F33            3
              ..
E34            1
C7             1
C54            1
E36            1
C148           1
Name: Cabin, Length: 147, dtype: int64
```

In [29]:

```
titanic_df = titanic_df.drop(columns=['Cabin'])
```

Embarked

- Como se tratam de valores categóricos, os dois valores faltantes serão subsituídos pela moda.

In [30]:

```
titanic_df['Embarked'].value_counts()
```

Out[30]:

```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

In [31]:

```
titanic_df['Embarked'] = titanic_df['Embarked'].fillna(titanic_df['Embarked'].mode()
[0])
```

In [32]:

```
titanic_df['Embarked'].value_counts()
```

Out[32]:

```
S    646
C    168
Q     77
Name: Embarked, dtype: int64
```

Colunas consideradas irrelevantes

Algumas colunas possuem informações irrelevantes: identificadores que não apresentam relação direta com algo que possa definir a sobrevivência ou são valores aleatórios:

- PassengerId
- Ticket

In [33]:

```
titanic_df = titanic_df.drop(columns=['PassengerId'])
titanic_df = titanic_df.drop(columns=['Ticket'])
```

Substituição dos valores categóricos por numéricos

Name

- Essa coluna é composta apenas de valores únicos, mas todos os indivíduos possuem títulos (Mr., Mrs., Miss., etc).
- É possível extrair a informação do título do passageiro e criar uma nova coluna.

In [34]:

```
titanic_df['Name'].unique().size
```

Out[34]:

```
891
```

In [35]:

```
titles = titanic_df.Name.str.extract(' ([A-Za-z]+)\.', expand=False)
print(titles.size)
titles.value_counts()
```

```
891
```

Out[35]:

```
Mr          517
Miss        182
Mrs         125
Master       40
Dr            7
Rev           6
Mlle          2
Major         2
Col           2
Countess      1
Capt          1
Ms            1
Sir           1
Lady          1
Mme           1
Don           1
Jonkheer      1
Name: Name, dtype: int64
```

- Como Mr, Miss, Mrs e Master são os únicos títulos que se repetem mais de dez vezes, vamos optar por substituir o restante por 'Other'. E outros títulos que equivalem a esses títulos também serão subsituídos.
- O seguinte mapeamento será feito:
  - Mr = 0, Mrs = 1, Miss = 2, Master = 3, Other = 4

In [36]:

```
titles = titles.replace(['Lady', 'Countess','Capt', 'Col', 'Don', 'Dr', 'Major', 'Rev',
'Sir', 'Jonkheer', 'Dona'], 'Other')
titles = titles.replace('Mlle', 'Miss')
titles = titles.replace('Ms', 'Miss')
titles = titles.replace('Mme', 'Mrs')
titles = titles.map({"Mr": 0, "Mrs": 1, "Miss": 2, "Master": 3, "Other": 4})
titles.value_counts()
```

Out[36]:

```
0    517
2    185
1    126
3     40
4     23
Name: Name, dtype: int64
```

In [37]:

```
titanic_df = titanic_df.drop(columns=['Name'])
```

In [38]:

```
titanic_df['Title'] = titles
```

Outras colunas

In [39]:

```
titanic_df['Sex'].unique()
```

Out[39]:

```
array(['male', 'female'], dtype=object)
```

In [40]:

```
titanic_df['Embarked'].unique()
```

Out[40]:

```
array(['S', 'C', 'Q'], dtype=object)
```

Antes de treinar o modelo, é necessário converter algumas colunas de uma string para um valor numérico.

- Sex (male = 0, female = 1)
- Embarked (S = 0, C = 1, Q = 2)

In [41]:

```
titanic_df['Sex'] = titanic_df['Sex'].map({'male': 0, 'female': 1})
```

In [42]:

```
titanic_df['Embarked'] = titanic_df['Embarked'].map({'S': 0, 'C': 1, 'Q': 2})
```

Combinar colunas

- Podemos combinar as colunas Sibsp e Parch para ter uma coluna representando o tamanho da família.
- Fizemos alguns testes combinando as colunas e não houve melhoria significativa nos scores.

In [43]:

```
#family = titanic_df['SibSp'] + titanic_df['Parch']
#titanic_df['Family'] = family
```

In [44]:

```
#titanic_df = titanic_df.drop(columns=['SibSp', 'Parch'])
```

Dataset após limpeza

In [161]:

```
titanic_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 9 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Survived  891 non-null    int64  
 1   Pclass    891 non-null    int64  
 2   Sex       891 non-null    int64  
 3   Age       891 non-null    float64
 4   SibSp     891 non-null    int64  
 5   Parch     891 non-null    int64  
 6   Fare      891 non-null    float64
 7   Embarked  891 non-null    int64  
 8   Title     891 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 62.8 KB
```

🛠️ Criando modelo

In [47]:

```
titanic_x = titanic_df.drop(columns=['Survived'])
titanic_y = titanic_df['Survived']

titanic_x_train, titanic_x_test, titanic_y_train, titanic_y_test = train_test_split(tit
anic_x, titanic_y, test_size = 0.2)
```

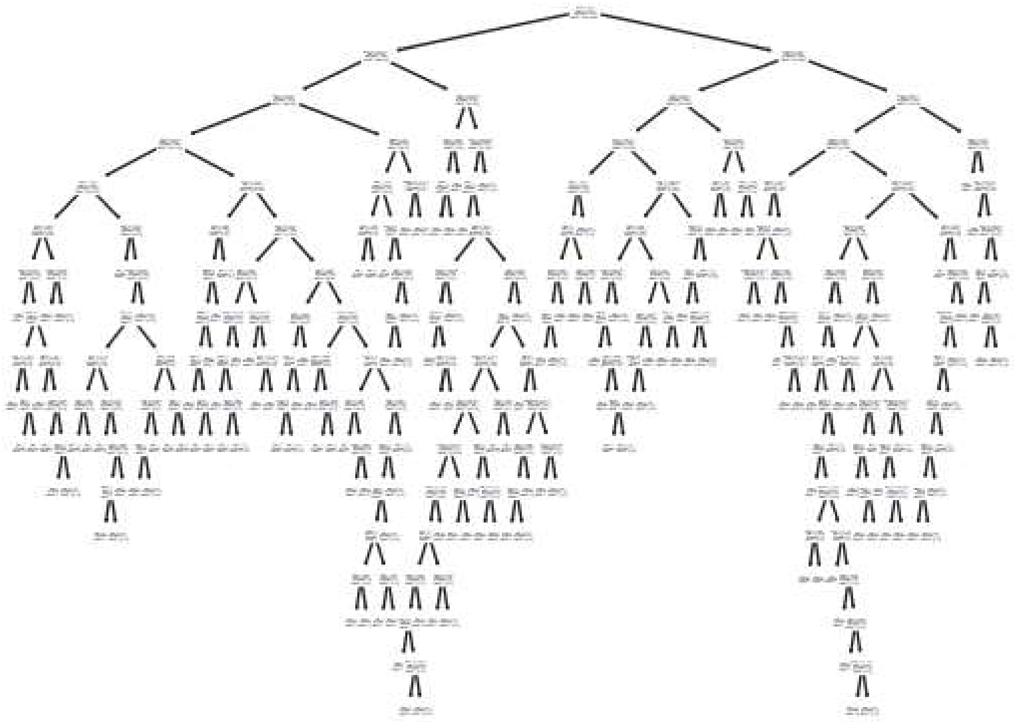
1. Classificador com parâmetros default

In [ ]:

```
classifier1 = DecisionTreeClassifier()
classifier1.fit(titanic_x_train, titanic_y_train)
```

In [112]:

```
plot_tree(classifier1, feature_names=titanic_df.drop(columns=['Survived']).columns)
plt.show()
```



In [183]:

```
titanic_y_pred = classifier1.predict(titanic_x_test)
titanic_report = classification_report(titanic_y_test, titanic_y_pred)
print(titanic_report)
```

```
              precision    recall  f1-score   support

           0       0.79      0.85      0.82       105
           1       0.76      0.68      0.71        74

    accuracy                           0.78       179
   macro avg       0.77      0.76      0.77       179
weighted avg       0.78      0.78      0.77       179
```

2. Utilizando GridSearchCV

In [117]:

```
parameters1 = {
    'criterion': ["gini", "entropy", "log_loss"],
    'splitter': ["best", "random"],
    'max_depth': [3, 10, 30, None],
    'max_features': ["sqrt", "log2", None],
    'min_samples_split': [2, 16, 32],
    'max_leaf_nodes': [5, 10, 40, None],
    'random_state': [13]
}
```

In [ ]:

```
grid = GridSearchCV(estimator = DecisionTreeClassifier(), param_grid = parameters1)
grid.fit(titanic_x_train, titanic_y_train)
```

In [119]:

```
print(grid.best_score_)
print(grid.best_params_)
```

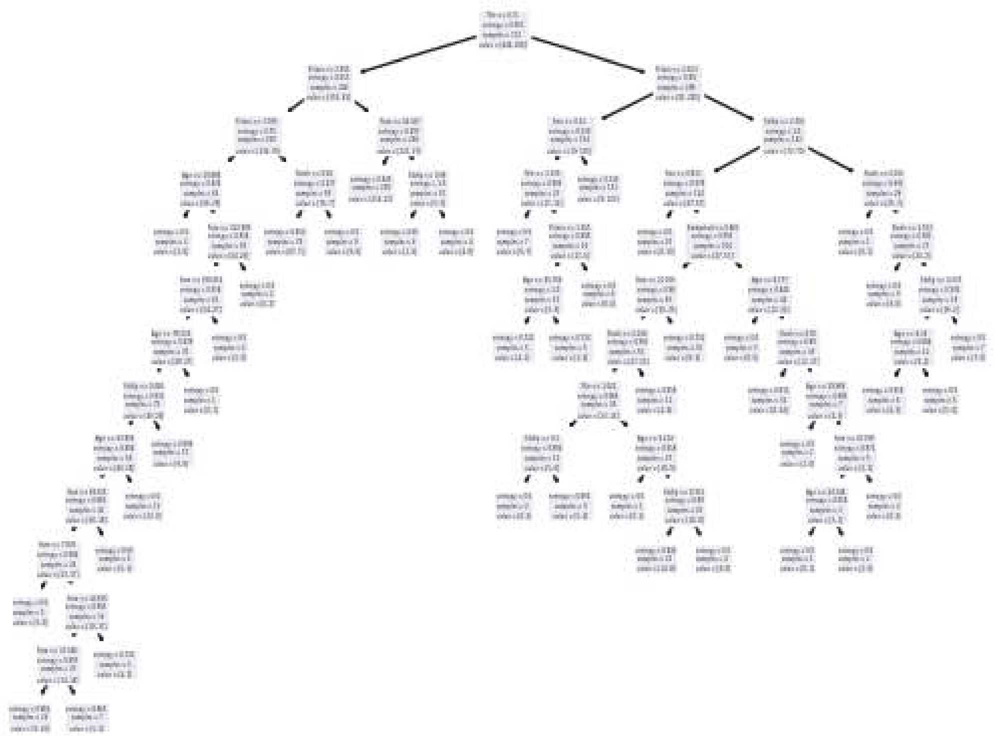
```
0.8385403329065302
{'criterion': 'entropy', 'max_depth': 30, 'max_features': None, 'max_leaf_
nodes': 40, 'min_samples_split': 2, 'random_state': 13, 'splitter': 'rando
m'}
```

In [ ]:

```
classifier2 = DecisionTreeClassifier(criterion=grid.best_params_['criterion'],
                                    max_depth=grid.best_params_['max_depth'],
                                    max_features=grid.best_params_['max_features'],
                                    max_leaf_nodes=grid.best_params_['max_leaf_nodes'],
                                    min_samples_split=grid.best_params_['min_samples_sp
lit'],
                                    random_state=grid.best_params_['random_state'],
                                    splitter=grid.best_params_['splitter'])
classifier2.fit(titanic_x_train, titanic_y_train)
```

In [121]:

```
plot_tree(classifier2, feature_names=titanic_df.drop(columns=['Survived']).columns)
plt.show()
```



In [182]:

```
titanic_y_pred = classifier2.predict(titanic_x_test)
titanic_report = classification_report(titanic_y_test, titanic_y_pred)
print(titanic_report)
```

```
              precision    recall  f1-score   support

           0       0.82      0.90      0.85       105
           1       0.83      0.72      0.77        74

    accuracy                           0.82       179
   macro avg       0.82      0.81      0.81       179
weighted avg       0.82      0.82      0.82       179
```

3. Tentando obter uma árvore menor com score similar

In [124]:

```
parameters2 = {
    'criterion': ["gini", "entropy", "log_loss"],
    'splitter': ["best", "random"],
    'max_depth': [2, 4, 6],
    'max_features': ["sqrt", "log2", None],
    'min_samples_split': [2, 4, 8],
    'max_leaf_nodes': [4, 7, 10],
    'random_state': [13]
}
```

In [ ]:

```
grid2 = GridSearchCV(estimator = DecisionTreeClassifier(), param_grid = parameters2)
grid2.fit(titanic_x_train, titanic_y_train)
```

In [126]:

```
print(grid2.best_score_)
print(grid2.best_params_)
```

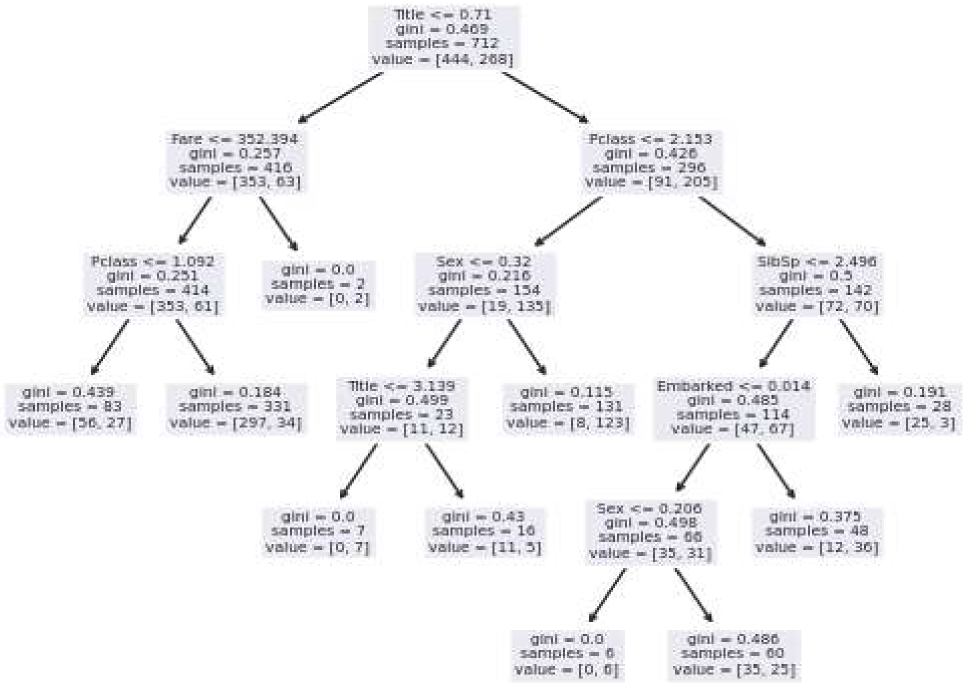
```
0.8357234314980794
{'criterion': 'gini', 'max_depth': 6, 'max_features': None, 'max_leaf_node
s': 10, 'min_samples_split': 2, 'random_state': 13, 'splitter': 'random'}
```

In [ ]:

```
classifier3 = DecisionTreeClassifier(criterion=grid2.best_params_['criterion'],
                                     max_depth=grid2.best_params_['max_depth'],
                                     max_features=grid2.best_params_['max_features'],
                                     max_leaf_nodes=grid2.best_params_['max_leaf_node
s'],
                                     min_samples_split=grid2.best_params_['min_samples_s
plit'],
                                     random_state=grid2.best_params_['random_state'],
                                     splitter=grid2.best_params_['splitter'])
classifier3.fit(titanic_x_train, titanic_y_train)
```

In [128]:

```
plot_tree(classifier3, feature_names=titanic_df.drop(columns=['Survived']).columns)
plt.show()
```



In [181]:

```
titanic_y_pred = classifier3.predict(titanic_x_test)
titanic_report = classification_report(titanic_y_test, titanic_y_pred)
print(titanic_report)
```

	precision	recall	f1-score	support
0	0.80	0.94	0.87	105
1	0.89	0.68	0.77	74
accuracy			0.83	179
macro avg	0.85	0.81	0.82	179
weighted avg	0.84	0.83	0.83	179

🎲 Utilizando Random Forests

Aplicando o RandomForestClassifier com a configuração default no problema Titanic.

In [131]:

```
parameters3 = {
    'criterion': ["gini", "entropy", "log_loss"],
    'n_estimators': [10, 50, 100], # Novo
    'max_depth': [2, 4, 6],
    'max_features': ["sqrt", "log2", None],
    'min_samples_split': [2, 4, 8],
    'max_leaf_nodes': [4, 7, 10],
    'random_state': [13]
}
```

In [ ]:

```
grid3 = GridSearchCV(estimator = RandomForestClassifier(), param_grid = parameters3)
grid3.fit(titanic_x_train, titanic_y_train)
```

In [133]:

```
print(grid3.best_score_)
print(grid3.best_params_)
```

```
0.8413473850093569
{'criterion': 'gini', 'max_depth': 6, 'max_features': 'sqrt', 'max_leaf_no
des': 10, 'min_samples_split': 4, 'n_estimators': 10, 'random_state': 13}
```

In [ ]:

```
classifier4 = RandomForestClassifier(criterion=grid3.best_params_['criterion'],
                                     max_depth=grid3.best_params_['max_depth'],
                                     max_features=grid3.best_params_['max_features'],
                                     max_leaf_nodes=grid3.best_params_['max_leaf_node
s'],
                                     min_samples_split=grid3.best_params_['min_samples_s
plit'],
                                     random_state=grid3.best_params_['random_state'],
                                     n_estimators=grid3.best_params_['n_estimators'])
classifier4.fit(titanic_x_train, titanic_y_train)
```

In [184]:

```
titanic_y_pred = classifier4.predict(titanic_x_test)
titanic_report = classification_report(titanic_y_test, titanic_y_pred)
print(titanic_report)
```

```
              precision    recall  f1-score   support

           0       0.82      0.92      0.87       105
           1       0.87      0.72      0.79        74

    accuracy                           0.84       179
   macro avg       0.85      0.82      0.83       179
weighted avg       0.84      0.84      0.83       179
```

Utilizando AD no problema de Detecção de Lombalgia

In [142]:

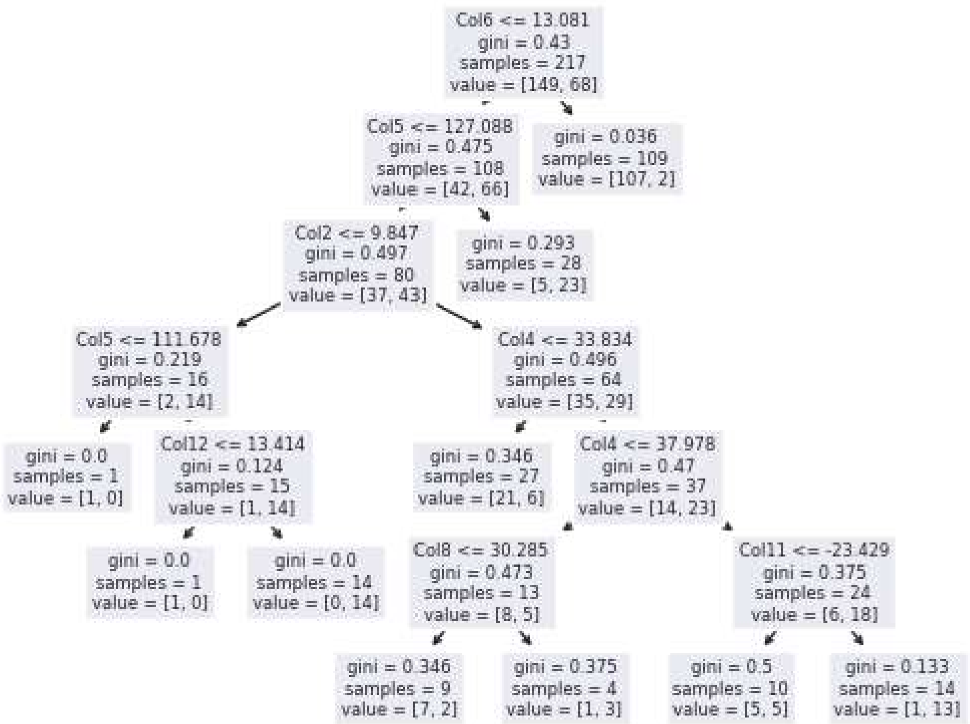
```
pain_x = pain_df.drop(columns=['Class_att'])
pain_y = pain_df['Class_att']

pain_x_train, pain_x_test, pain_y_train, pain_y_test = train_test_split(pain_x, pain_y,
test_size = 0.3)
```

In [ ]:

```
classifier5 = DecisionTreeClassifier(criterion=grid2.best_params_['criterion'],
                                      max_depth=grid2.best_params_['max_depth'],
                                      max_features=grid2.best_params_['max_features'],
                                      max_leaf_nodes=grid2.best_params_['max_leaf_node
s'],
                                      min_samples_split=grid2.best_params_['min_samples_s
plit'],
                                      random_state=grid2.best_params_['random_state'],
                                      splitter=grid2.best_params_['splitter'])
classifier5.fit(pain_x_train, pain_y_train)
```

In [158]:

```
plot_tree(classifier5, feature_names=pain_df.drop(columns=['Class_att']).columns)
plt.show()
```



In [198]:

```
pain_y_pred = classifier5.predict(pain_x_test)
pain_report = classification_report(pain_y_test, pain_y_pred)
print(pain_report)
```

```
              precision    recall  f1-score   support

    Abnormal       0.81      0.92      0.86        61
      Normal       0.79      0.59      0.68        32

    accuracy                           0.81        93
   macro avg       0.80      0.76      0.77        93
weighted avg       0.80      0.81      0.80        93
```

✏️ Conclusão

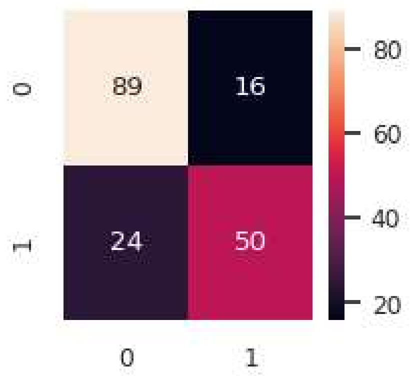
Titanic

- Configuração padrão teve os menores scores e houve overfitting.

In [192]:

```
predict_and_report("AD - Configuração padrão", classifier1, titanic_x_test, titanic_y_test, titanic_y_train, titanic_x_train)
```

```
AD - Configuração padrão- base de teste
              precision    recall  f1-score   support

           0       0.79      0.85      0.82       105
           1       0.76      0.68      0.71        74

    accuracy                           0.78       179
   macro avg       0.77      0.76      0.77       179
weighted avg       0.78      0.78      0.77       179

------------------------------------------------------
AD - Configuração padrão- base de treino
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       444
           1       0.99      0.96      0.98       268

    accuracy                           0.98       712
   macro avg       0.98      0.98      0.98       712
weighted avg       0.98      0.98      0.98       712
```



- Configuração 1 teve melhoria nos scores.

In [189]:

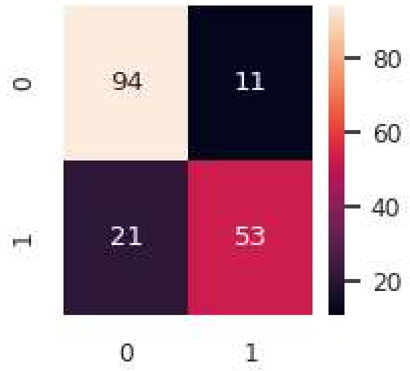
```
print(grid.best_params_)
```

```
{'criterion': 'entropy', 'max_depth': 30, 'max_features': None, 'max_leaf_nodes': 40, 'min_samples_split': 2, 'random_state': 13, 'splitter': 'random'}
```

In [193]:

```
predict_and_report("AD - Configuração 1", classifier2, titanic_x_test, titanic_y_test,
titanic_y_train, titanic_x_train)
```

```
AD - Configuração 1- base de teste
              precision    recall  f1-score   support

           0       0.82      0.90      0.85       105
           1       0.83      0.72      0.77        74

    accuracy                           0.82       179
   macro avg       0.82      0.81      0.81       179
weighted avg       0.82      0.82      0.82       179

------------------------------------------------------
AD - Configuração 1- base de treino
              precision    recall  f1-score   support

           0       0.88      0.93      0.90       444
           1       0.87      0.78      0.83       268

    accuracy                           0.88       712
   macro avg       0.87      0.86      0.86       712
weighted avg       0.87      0.88      0.87       712
```



- Configuração 2 teve scores similares (mas é uma árvore consideravelmente menor)

In [188]:

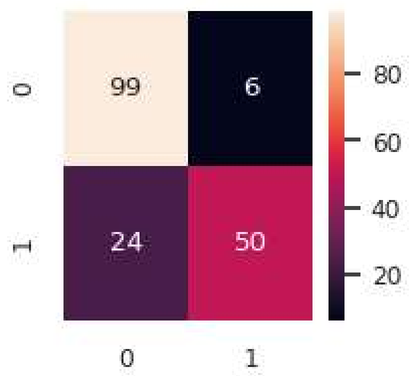
```
print(grid2.best_params_)
```

```
{'criterion': 'gini', 'max_depth': 6, 'max_features': None, 'max_leaf_node
s': 10, 'min_samples_split': 2, 'random_state': 13, 'splitter': 'random'}
```

In [194]:

```
predict_and_report("AD - Configuração 2", classifier3, titanic_x_test, titanic_y_test,
titanic_y_train, titanic_x_train)
```

```
AD - Configuração 2- base de teste
              precision    recall  f1-score   support

           0       0.80      0.94      0.87       105
           1       0.89      0.68      0.77        74

    accuracy                           0.83       179
   macro avg       0.85      0.81      0.82       179
weighted avg       0.84      0.83      0.83       179

-----------------------------------------------------
AD - Configuração 2- base de treino
              precision    recall  f1-score   support

           0       0.82      0.95      0.88       444
           1       0.90      0.65      0.75       268

    accuracy                           0.84       712
   macro avg       0.86      0.80      0.82       712
weighted avg       0.85      0.84      0.83       712
```

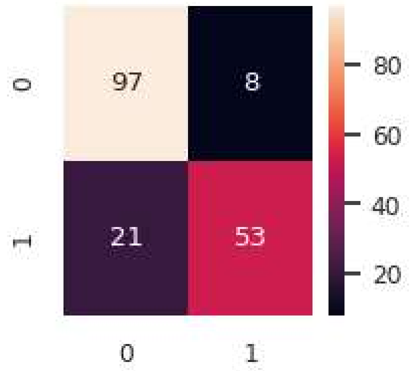


- RF apresentou scores similares.

In [195]:

```
predict_and_report("RF - Configuração 1", classifier4, titanic_x_test, titanic_y_test,
titanic_y_train, titanic_x_train)
```

```
RF - Configuração 1- base de teste
              precision    recall  f1-score   support

           0       0.82      0.92      0.87       105
           1       0.87      0.72      0.79        74

    accuracy                           0.84       179
   macro avg       0.85      0.82      0.83       179
weighted avg       0.84      0.84      0.83       179

------------------------------------------------------
RF - Configuração 1- base de treino
              precision    recall  f1-score   support

           0       0.84      0.93      0.88       444
           1       0.86      0.71      0.78       268

    accuracy                           0.85       712
   macro avg       0.85      0.82      0.83       712
weighted avg       0.85      0.85      0.84       712
```

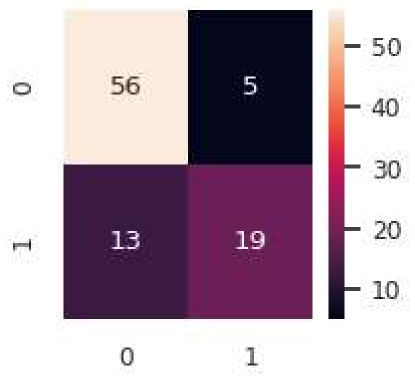


Detecção de Lombalgia

In [197]:

```
predict_and_report("AD - Configuração 1", classifier5, pain_x_test, pain_y_test, pain_y
_train, pain_x_train)
```

```
AD - Configuração 1- base de teste
              precision    recall  f1-score   support

    Abnormal       0.81      0.92      0.86        61
      Normal       0.79      0.59      0.68        32

    accuracy                           0.81        93
   macro avg       0.80      0.76      0.77        93
weighted avg       0.80      0.81      0.80        93

------------------------------------------------------
AD - Configuração 1- base de treino
              precision    recall  f1-score   support

    Abnormal       0.90      0.95      0.93       149
      Normal       0.88      0.78      0.83        68

    accuracy                           0.90       217
   macro avg       0.89      0.87      0.88       217
weighted avg       0.90      0.90      0.90       217
```



- Acurácia com MLP: 0.82
- Acurácia com AD (configuração 2): 0.81
- Testando outras configurações considerando esse dataset poderíamos obter resultados melhores.