Árboles de desición para especies de flores

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [3]:
```
df = pd.read_csv("../../Data-Sets/datasets/iris/iris.csv")
```

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

Out[4]:

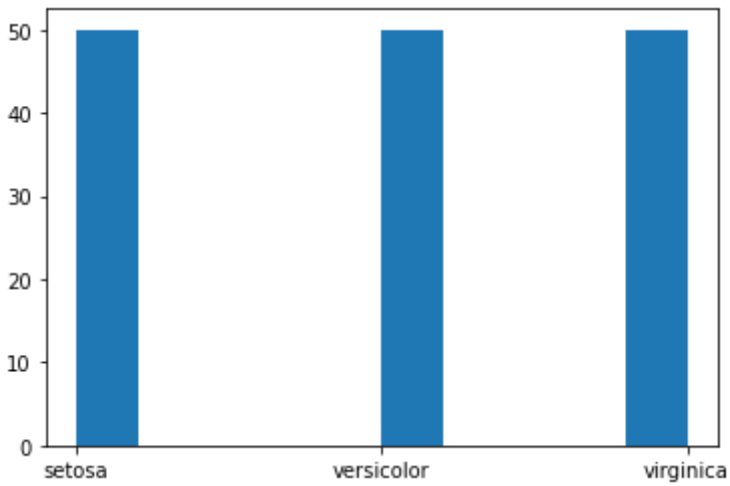
	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

In [7]:
```
df.shape
```

Out[7]:
```
(150, 5)
```

In [8]:
```
plt.hist(df.Species)
```

Out[8]:
```
(array([50.,  0.,  0.,  0.,  0., 50.,  0.,  0.,  0., 50.]),
 array([0. , 0.2, 0.4, 0.6, 0.8, 1. , 1.2, 1.4, 1.6, 1.8, 2. ]),
 <BarContainer object of 10 artists>)
```



In [9]:
```
df.Species.unique()
```

Out[9]:
```
array(['setosa', 'versicolor', 'virginica'], dtype=object)
```

In [10]:
```
colnames = df.columns.values.tolist()
colnames[4]
```

Out[10]:
```
'Species'
```

In [11]:
```
colnames = df.columns.values.tolist()
predictors = colnames[:4]
target = colnames[4]
```

In [12]:
```
import numpy as np
```

In [13]:
```
df["is_train"] = np.random.uniform(0,1,len(df))<0.75
```

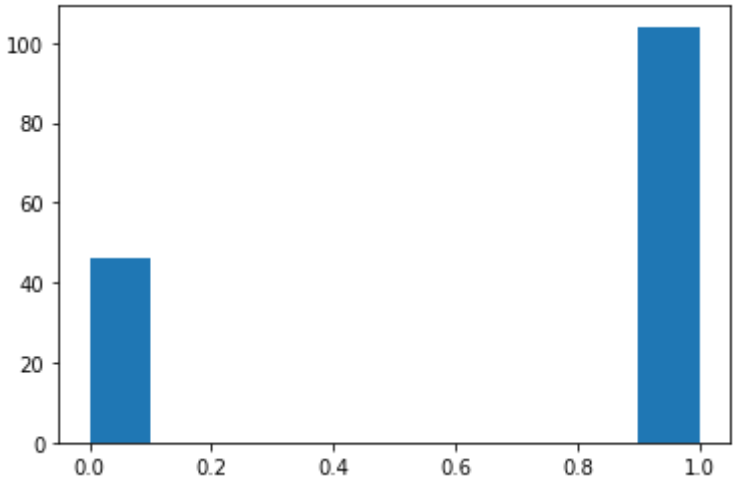
In [14]:
```
df.head()
```

Out[14]:

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species	is_train
0	5.1	3.5	1.4	0.2	setosa	True
1	4.9	3.0	1.4	0.2	setosa	False
2	4.7	3.2	1.3	0.2	setosa	True
3	4.6	3.1	1.5	0.2	setosa	True
4	5.0	3.6	1.4	0.2	setosa	True

In [15]:
```
plt.hist(df.is_train.astype(np.float32))
```

Out[15]:
```
(array([ 46.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0., 104.]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ],
       dtype=float32),
 <BarContainer object of 10 artists>)
```



In [16]:
```
train, test = df[df["is_train"]==True], df[df["is_train"]==False]
```

In [17]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [18]:
```
tree = DecisionTreeClassifier(criterion="entropy", min_samples_split=10, random_state=99)
tree.fit(train[predictors], train[target])
```

Out[18]:
```
DecisionTreeClassifier(criterion='entropy', min_samples_split=10,
                       random_state=99)
```

In [19]:
```
preds = tree.predict(test[predictors])
```

In [43]:
```
test.shape
```

Out[43]:
```
(46, 6)
```

In [20]:
```
pd.crosstab(test[target], preds, rownames=["Actual"], colnames=["Predictions"])
```

Out[20]:

Predictions	setosa	versicolor	virginica
Actual			
setosa	13	0	0
versicolor	0	19	0
virginica	0	1	13

Visualización del árbol de desición

In [21]:
```
from sklearn.tree import export_graphviz
```

In [22]:
```
with open("../../Data-Sets/notebooks/resources/iris_dtree.dot", "w") as dotfile:
    export_graphviz(tree, out_file=dotfile, feature_names=predictors)
    dotfile.close()
```

In [23]:
```
import os
os.environ["PATH"] += os.pathsep + r'C:\Program Files\Graphviz\bin'
from graphviz import Source
```

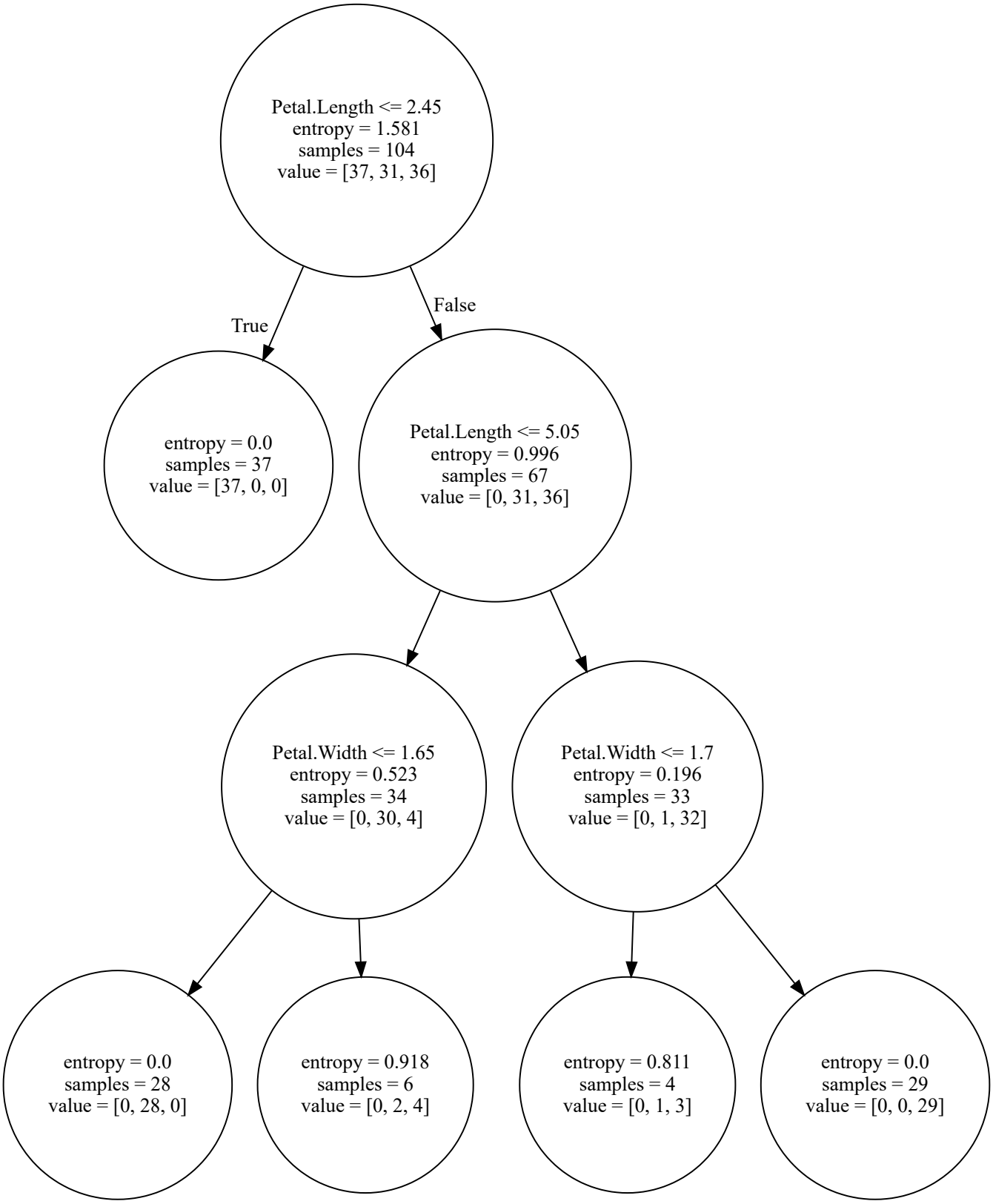
In [24]:
```
file = open("../../Data-Sets/notebooks/resources/iris_dtree.dot", "r")
text = file.read()
text
```

Out[24]:
```
'digraph Tree {\nnode [shape=box] ;\n0 [label="Petal.Length <= 2.45\\nentropy = 1.581\\nsampl
es = 104\\nvalue = [37, 31, 36]"] ;\n1 [label="entropy = 0.0\\nsamples = 37\\nvalue = [37, 0,
0]"] ;\n0 -> 1 [labeldistance=2.5, labelangle=45, headlabel="True"] ;\n2 [label="Petal.Length
<= 5.05\\nentropy = 0.996\\nsamples = 67\\nvalue = [0, 31, 36]"] ;\n0 -> 2 [labeldistance=2.
5, labelangle=-45, headlabel="False"] ;\n3 [label="Petal.Width <= 1.65\\nentropy = 0.523\\nsa
mples = 34\\nvalue = [0, 30, 4]"] ;\n2 -> 3 ;\n4 [label="entropy = 0.0\\nsamples = 28\\nvalue
= [0, 28, 0]"] ;\n3 -> 4 ;\n5 [label="entropy = 0.918\\nsamples = 6\\nvalue = [0, 2, 4]"] ;\n
3 -> 5 ;\n6 [label="Petal.Width <= 1.7\\nentropy = 0.196\\nsamples = 33\\nvalue = [0, 1, 3
2]"] ;\n2 -> 6 ;\n7 [label="entropy = 0.811\\nsamples = 4\\nvalue = [0, 1, 3]"] ;\n6 -> 7 ;\n
8 [label="entropy = 0.0\\nsamples = 29\\nvalue = [0, 0, 29]"] ;\n6 -> 8 ;\n}'
```

In [44]:
```
text2='digraph Tree {\nnode [shape=circle] ;\n0 [label="Petal.Length <= 2.45\\nentropy = 1.58
```

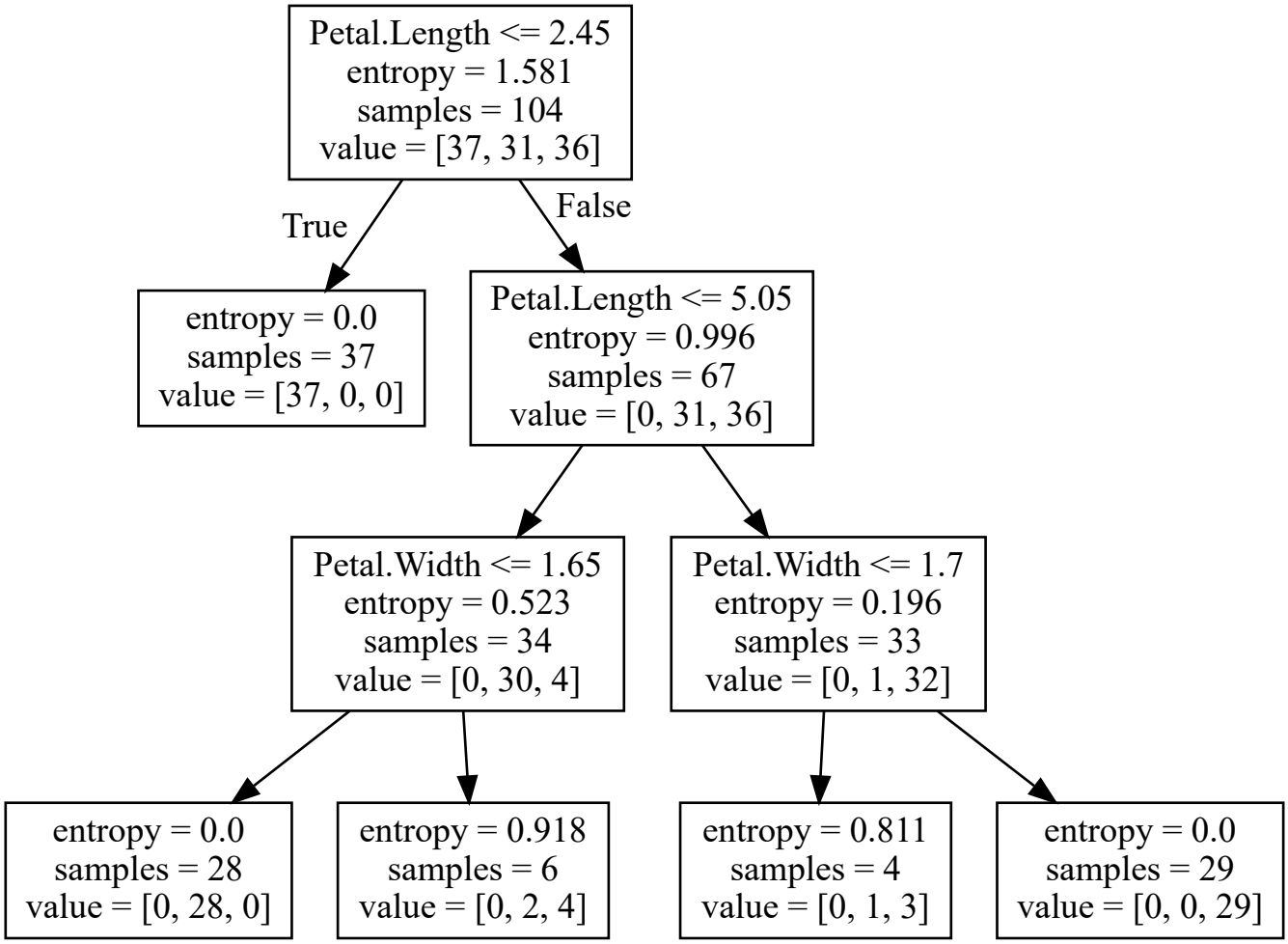
In [45]:
```
Source(text2)
```

Out[45]:



In [25]:
```
Source(text)
```

Out[25]:



In [46]:
```
predictors
```

Out[46]:
```
['Sepal.Length', 'Sepal.Width', 'Petal.Length', 'Petal.Width']
```

Cross Validation para la poda

In [26]:
```
X = df[predictors]
Y = df[target]
```

In [27]:
```
tree = DecisionTreeClassifier(criterion="entropy", max_depth=5, min_samples_split=20, random_
tree.fit(X,Y)
```

Out[27]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=5, min_samples_split=20,
                       random_state=99)
```

In [29]:
```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
```

In [32]:
```
cv = KFold(n_splits=10, shuffle=True, random_state=1)
```

In [33]:
```
from sklearn.model_selection import cross_val_score
```

In [36]:
```
scores = cross_val_score(tree, X, Y, scoring="accuracy", cv=cv, n_jobs=1)
scores
```

```
array([1.        , 0.93333333, 0.93333333, 0.93333333, 1.        ,
```

Out[36]:
```
       0.93333333, 1.        , 0.86666667, 0.93333333, 0.8       ])
```

In [37]:
```
score = np.mean(scores)
```

In [38]:
```
score
```

Out[38]:
```
0.9333333333333333
```

Un score de 0.9333 nos dice que el modelo tiene un 93% de presición a la hora de realizar este tipo de clasificación.

In [40]:
```
for i in range(1,11):
    tree = DecisionTreeClassifier(criterion="entropy", max_depth=i, min_samples_split=20, ra
    tree.fit(X,Y)
    cv = KFold(n_splits=10, shuffle=True, random_state=1)
    scores = cross_val_score(tree, X, Y, scoring="accuracy", cv=cv, n_jobs=1)
    score = np.mean(scores)
    print("Score para i= " , i , "es de", score)
    print("   ", tree.feature_importances_)
```

```
Score para i=  1 es de 0.5666666666666667
    [0. 0. 1. 0.]
Score para i=  2 es de 0.9200000000000002
    [0.         0.         0.66620285 0.33379715]
Score para i=  3 es de 0.9400000000000001
    [0.         0.         0.68976981 0.31023019]
Score para i=  4 es de 0.9333333333333333
    [0.         0.         0.66869158 0.33130842]
Score para i=  5 es de 0.9333333333333333
    [0.         0.         0.66869158 0.33130842]
Score para i=  6 es de 0.9333333333333333
    [0.         0.         0.66869158 0.33130842]
Score para i=  7 es de 0.9333333333333333
    [0.         0.         0.66869158 0.33130842]
Score para i=  8 es de 0.9333333333333333
    [0.         0.         0.66869158 0.33130842]
Score para i=  9 es de 0.9333333333333333
    [0.         0.         0.66869158 0.33130842]
Score para i=  10 es de 0.9333333333333333
    [0.         0.         0.66869158 0.33130842]
```

El máximo rendimiento se alcanza para i = 3, o sea para una profundidad del árbol de desición igual a 3.

In [41]:
```
predictors
```

Out[41]:
```
['Sepal.Length', 'Sepal.Width', 'Petal.Length', 'Petal.Width']
```

Con tree.feature*importances* tenemos los 4 predictores y su relevancia en el árbol, si sólo tuviéramos que elegir un solo clasificador, entonces probablemente nos quedaríamos con Petal.Length. En el caso de elegir 2, el 66% de la influencia se la lleva Petal.Length y Petal.Width con un 33% y así suscesivamente. Los **sépalos** no pintan nada al parecer.