

Understanding Decision Tree Workflow

▼ Importing Relevant Libraries

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

▼ Loading Iris Dataset

```
from sklearn import datasets

iris = datasets.load_iris()
data=pd.DataFrame(iris.data, columns=iris.feature_names)
data.head()
```

```
↗
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

It's always better to check for anomalies beforehand. Let's do the same :)

```
data.isnull().sum()
```

```
↗ sepal length (cm)    0
  sepal width (cm)     0
  petal length (cm)    0
  petal width (cm)     0
  dtype: int64
```

▼ Fixing Target Variable

```
y=iris.target
y
```

```
↳ 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])
```

▼ Creating Decision Tree Classifier Model

```
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
```

```
X_train,X_valid,y_train,y_valid=train_test_split(data,y,train_size=0.8,test_size=0.2,random_s
```

```
clf=DecisionTreeClassifier(random_state=0)
model=clf.fit(X_train,y_train)
```

▼ Visualizing D-Tree Rules Of The Model

Text Representation is actually used in real-time to keep log of information about the model into a text file.

It comes is handy while working with applications without User Interface.

```
text_representation = tree.export_text(clf)
print(text_representation)
```

```
↳
```

```

|--- feature_3 <= 0.80
|   |--- class: 0
|--- feature_3 > 0.80
|   |--- feature_3 <= 1.75
|   |   |--- feature_2 <= 4.95
|   |   |   |--- feature_3 <= 1.65
|   |   |   |   |--- class: 1
|   |   |   |   |--- feature_3 > 1.65
|   |   |   |   |   |--- class: 2
|   |   |--- feature_2 > 4.95
|   |   |   |--- feature_3 <= 1.55
|   |   |   |   |--- class: 2
|   |   |   |   |--- feature_3 > 1.55
|   |   |   |   |   |--- feature_2 <= 5.45

```

pip install dtreeviz

```

[+] Requirement already satisfied: dtreeviz in /usr/local/lib/python3.6/dist-packages (1.0)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.6/dist-packages (1.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (1.16.2)
Requirement already satisfied: graphviz>=0.9 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (0.10.1)
Requirement already satisfied: xgboost in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (0.90)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (3.0.3)
Requirement already satisfied: pytest in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (3.6.1)
Requirement already satisfied: colour in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (0.1.5)
Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (0.23.4)
Requirement already satisfied: scipy>=0.17.0 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (1.2.1)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (0.12.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (1.0.1)
Requirement already satisfied: cycloper>=0.10 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (0.10)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (2.6.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (2.4.2)
Requirement already satisfied: more-itertools>=4.0.0 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (4.2.0)
Requirement already satisfied: pluggy<0.8,>=0.5 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (0.7.0)
Requirement already satisfied: py>=1.5.0 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (1.9.0)
Requirement already satisfied: atomicwrites>=1.0 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (1.2)
Requirement already satisfied: setuptools in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (44.0.0)
Requirement already satisfied: attrs>=17.4.0 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (19.1.0)
Requirement already satisfied: six>=1.10.0 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (1.12.0)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from dtreeviz) (2019.1)

```

There are multiple ways to visualize the workflow of a Decision Tree.

For an instance, through libraries like tree, Graphviz or Dtreeviz.

I chose dtreeviz because of the following reasons:

- It represents distribution of class(here, Species) in each leaf of D-Tree
- It represents distribution of decision feature in each node of D-Tree
- Class color matching legends are clearly distinguishable

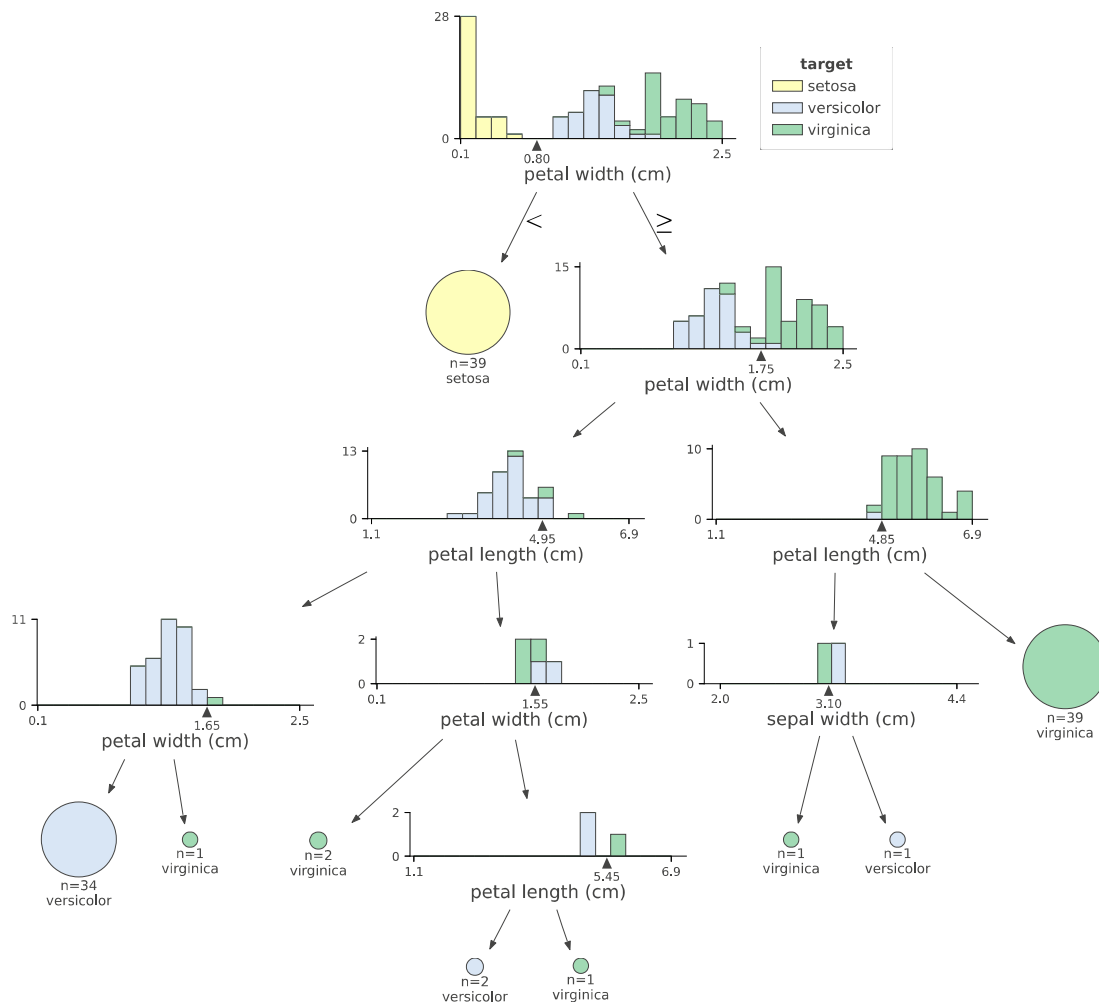
```
from dtreeviz.trees import dtreeviz
```

```
viz = dtreeviz(clf, X_train, y_train,
```



```
viz = DecisionTreeVisualizer(x_train, y_train,
                             target_name="target",
                             feature_names=iris.feature_names,
                             class_names=list(iris.target_names))
```

viz



```
viz.save("decision_tree.svg")
```

Well, Work done is never complete without testing it. So, Shall we?

```
predictions=model.predict(X_valid)
predictions
```

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

▼ Let's Evaluate The Results!

```
from sklearn.metrics import mean_absolute_error
```

```
MAE=mean_absolute_error(predictions,y_valid)
print('Mean Absolute Error: ',MAE)
```

```
↳ Mean Absolute Error: 0.0
```

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
```

```
results = confusion_matrix(y_valid,predictions)
```

```
print('Confusion Matrix :')
results
```

```
↳ Confusion Matrix :
array([[11,  0,  0],
       [ 0, 13,  0],
       [ 0,  0,  6]])
```

```
print('Accuracy Score :')
accuracy_score(y_valid, predictions)
```

```
↳ Accuracy Score :
1.0
```

```
print ('Report :',classification_report(y_valid, predictions) )
```

```
↳ Report :
```

		precision	recall	f1-score	support
	0	1.00	1.00	1.00	11
	1	1.00	1.00	1.00	13
	2	1.00	1.00	1.00	6
	accuracy			1.00	30
	macro avg	1.00	1.00	1.00	30
	weighted avg	1.00	1.00	1.00	30

So Far So Good. Happy Learning :)