This is the solution for BCIS 5140-HW2 Part2 by Srivyshnavi Tangellapelli,Fall 2022.

Setup

```
# Python ≥3.5 is required
import sys
assert sys.version_info >= (3, 5)

# Scikit-Learn ≥0.20 is required
import sklearn
assert sklearn.__version__ >= "0.20"

# Common imports
import numpy as np
import os

# to make this notebook's output stable across runs
np.random.seed(42)

# To plot pretty figures
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)

# Where to save the figures
PROJECT_ROOT_DIR = "."
CHAPTER_ID = "decision_trees"
IMAGES_PATH = os.path.join(PROJECT_ROOT_DIR, "images", CHAPTER_ID)
os.makedirs(IMAGES_PATH, exist_ok=True)

def save_fig(fig_id, tight_layout=True, fig_extension="png", resolution=300):
    path = os.path.join(IMAGES_PATH, fig_id + "." + fig_extension)
    print("Saving figure", fig_id)
    if tight_layout:
        plt.tight_layout()
    plt.savefig(path, format=fig_extension, dpi=resolution)
```

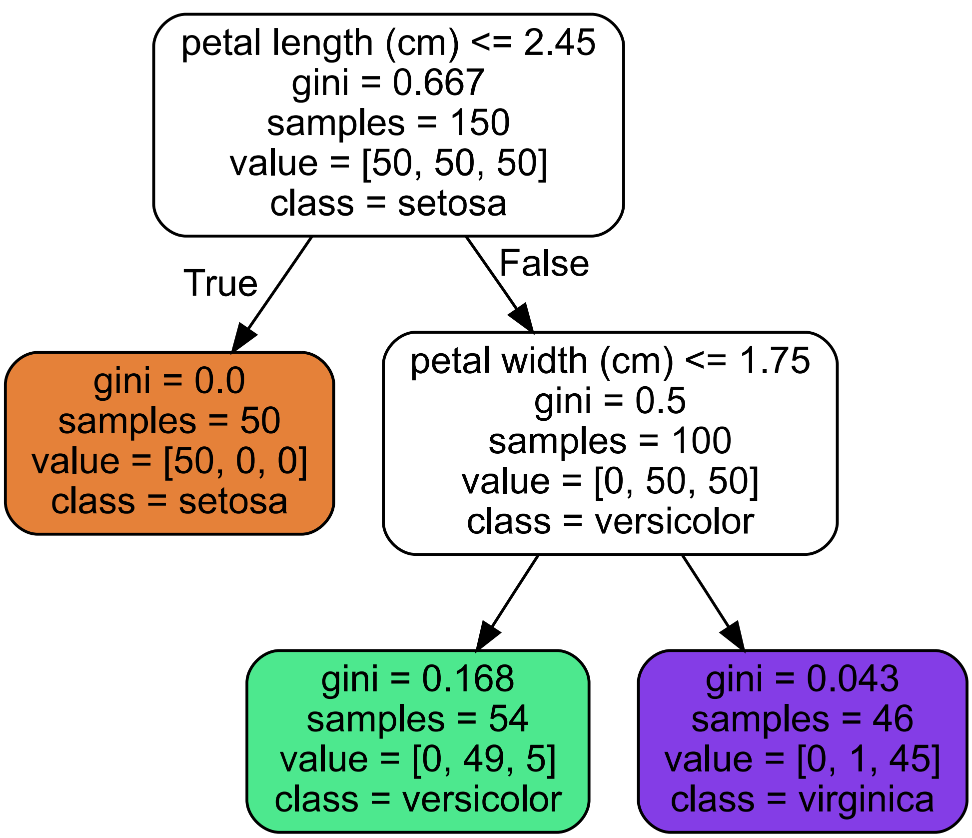
Training and Visualizing a Decision Tree

```
from sklearn.datasets import load_iris
```

```
from sklearn.tree import DecisionTreeClassifier

iris = load_iris()
X = iris.data[:, 2:] # petal length and width
y = iris.target

tree_clf = DecisionTreeClassifier(max_depth=2, random_state=42)
tree_clf.fit(X, y)
```

```
DecisionTreeClassifier(max_depth=2, random_state=42)
```

```
from graphviz import Source
from sklearn.tree import export_graphviz

export_graphviz(
        tree_clf,
        out_file=os.path.join(IMAGES_PATH, "iris_tree.dot"),
        feature_names=iris.feature_names[2:],
        class_names=iris.target_names,
        rounded=True,
        filled=True
    )

Source.from_file(os.path.join(IMAGES_PATH, "iris_tree.dot"))
```




```
from matplotlib.colors import ListedColormap
```

```
def plot_decision_boundary(clf, X, y, axes=[0, 7.5, 0, 3], iris=True, legend=False, plot_trai
    x1s = np.linspace(axes[0], axes[1], 100)
    x2s = np.linspace(axes[2], axes[3], 100)
    x1, x2 = np.meshgrid(x1s, x2s)
    X_new = np.c_[x1.ravel(), x2.ravel()]
    y_pred = clf.predict(X_new).reshape(x1.shape)
    custom_cmap = ListedColormap(['#fafab0','#9898ff','#a0faa0'])
    plt.contourf(x1, x2, y_pred, alpha=0.3, cmap=custom_cmap)
    if not iris:
        custom_cmap2 = ListedColormap(['#7d7d58','#4c4c7f','#507d50'])
        plt.contour(x1, x2, y_pred, cmap=custom_cmap2, alpha=0.8)
    if plot_training:
        plt.plot(X[:, 0][y==0], X[:, 1][y==0], "yo", label="Iris setosa")
        plt.plot(X[:, 0][y==1], X[:, 1][y==1], "bs", label="Iris versicolor")
        plt.plot(X[:, 0][y==2], X[:, 1][y==2], "g^", label="Iris virginica")
        plt.axis(axes)
    if iris:
        plt.xlabel("Petal length", fontsize=14)
        plt.ylabel("Petal width", fontsize=14)
    else:
        plt.xlabel(r"$x_1$", fontsize=18)
        plt.ylabel(r"$x_2$", fontsize=18, rotation=0)
    if legend:
        plt.legend(loc="lower right", fontsize=14)

plt.figure(figsize=(8, 4))
plot_decision_boundary(tree_clf, X, y)
plt.plot([2.45, 2.45], [0, 3], "k-", linewidth=2)
plt.plot([2.45, 7.5], [1.75, 1.75], "k--", linewidth=2)
plt.plot([4.95, 4.95], [0, 1.75], "k:", linewidth=2)
plt.plot([4.85, 4.85], [1.75, 3], "k:", linewidth=2)
plt.text(1.40, 1.0, "Depth=0", fontsize=15)
plt.text(3.2, 1.80, "Depth=1", fontsize=13)
plt.text(4.05, 0.5, "(Depth=2)", fontsize=11)

save_fig("decision_tree_decision_boundaries_plot")
plt.show()
```

```
Saving figure decision_tree_decision_boundaries_plot
```

Estimating Class Probabilities

```python
tree_clf.predict_proba([[5, 1.5]])
```

```
array([[0.        , 0.90740741, 0.09259259]])
```

```python
tree_clf.predict([[5, 1.5]])
```

```
array([1])
```

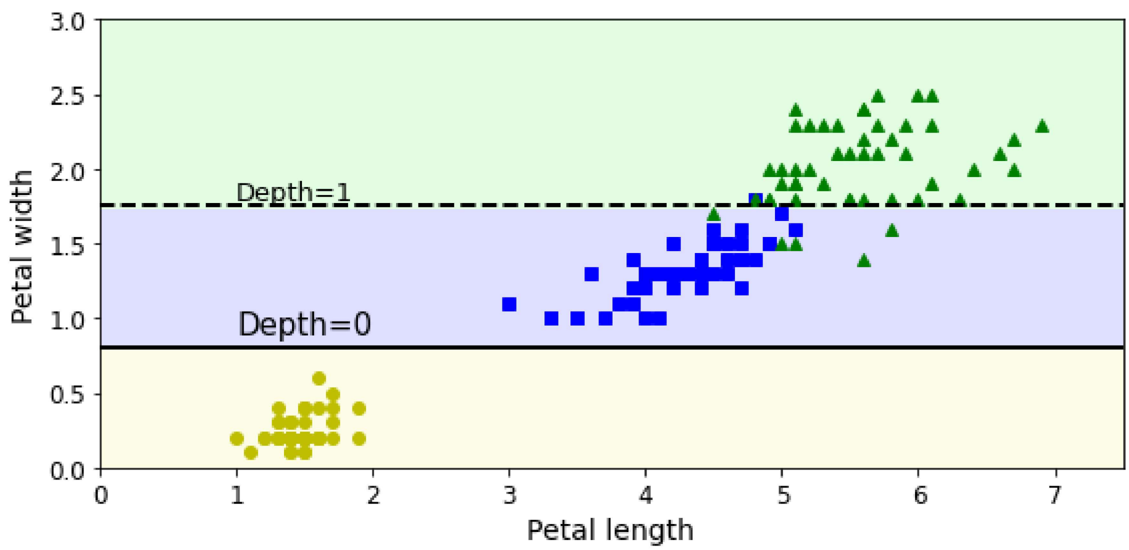
Petal length

```python
tree_clf_tweaked = DecisionTreeClassifier(max_depth=2, random_state=40)
tree_clf_tweaked.fit(X, y)
```

```
DecisionTreeClassifier(max_depth=2, random_state=40)
```

```python
plt.figure(figsize=(8, 4))
plot_decision_boundary(tree_clf_tweaked, X, y, legend=False)
plt.plot([0, 7.5], [0.8, 0.8], "k-", linewidth=2)
plt.plot([0, 7.5], [1.75, 1.75], "k--", linewidth=2)
plt.text(1.0, 0.9, "Depth=0", fontsize=15)
plt.text(1.0, 1.80, "Depth=1", fontsize=13)

save_fig("decision_tree_instability_plot")
plt.show()
```

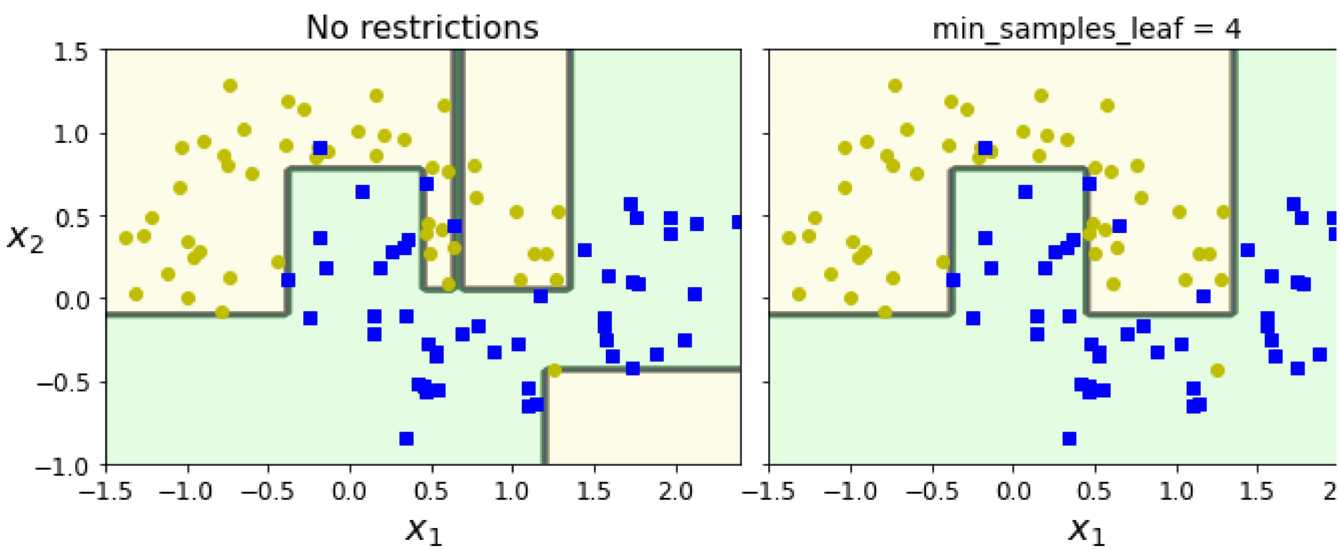
```
Saving figure decision_tree_instability_plot
```



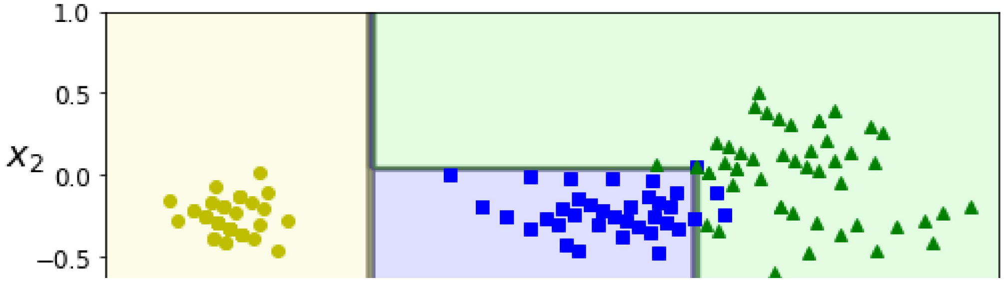

```python
from sklearn.datasets import make_moons
Xm, ym = make_moons(n_samples=100, noise=0.25, random_state=53)
```

```
deep_tree_clf1 = DecisionTreeClassifier(random_state=42)
deep_tree_clf2 = DecisionTreeClassifier(min_samples_leaf=4, random_state=42)
deep_tree_clf1.fit(Xm, ym)
deep_tree_clf2.fit(Xm, ym)

fig, axes = plt.subplots(ncols=2, figsize=(10, 4), sharey=True)
plt.sca(axes[0])
plot_decision_boundary(deep_tree_clf1, Xm, ym, axes=[-1.5, 2.4, -1, 1.5], iris=False)
plt.title("No restrictions", fontsize=16)
plt.sca(axes[1])
plot_decision_boundary(deep_tree_clf2, Xm, ym, axes=[-1.5, 2.4, -1, 1.5], iris=False)
plt.title("min_samples_leaf = {}".format(deep_tree_clf2.min_samples_leaf), fontsize=14)
plt.ylabel("")

save_fig("min_samples_leaf_plot")
plt.show()
```

```
Saving figure min_samples_leaf_plot
```

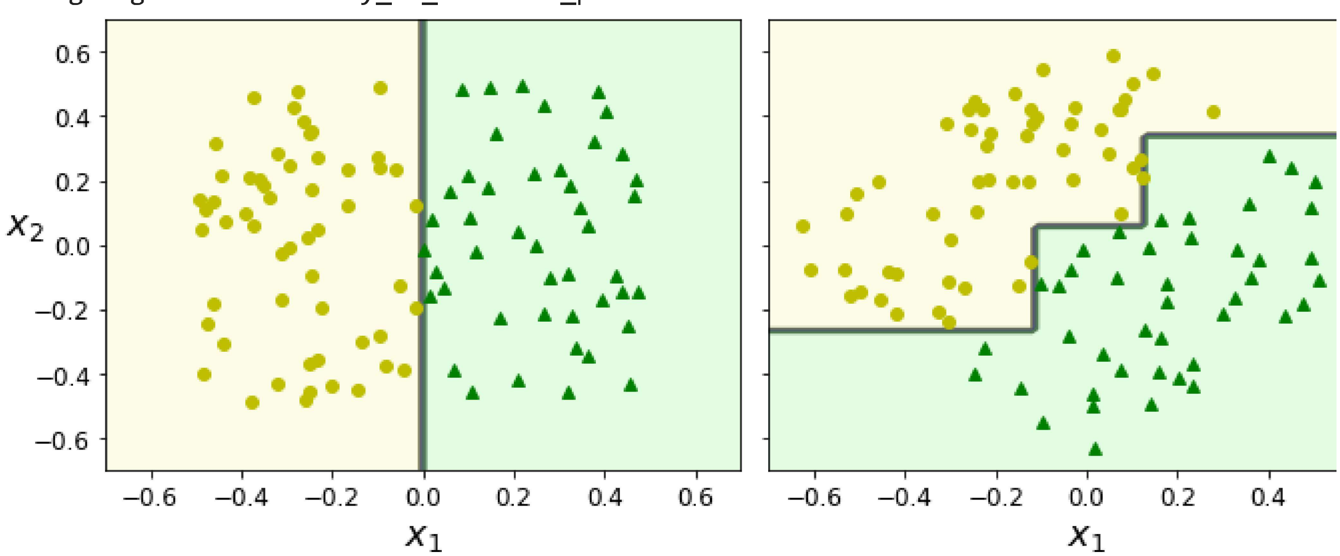



```
angle = np.pi / 180 * 20
rotation_matrix = np.array([[np.cos(angle), -np.sin(angle)], [np.sin(angle), np.cos(angle)]])
Xr = X.dot(rotation_matrix)

tree_clf_r = DecisionTreeClassifier(random_state=42)
tree_clf_r.fit(Xr, y)

plt.figure(figsize=(8, 3))
plot_decision_boundary(tree_clf_r, Xr, y, axes=[0.5, 7.5, -1.0, 1], iris=False)

plt.show()
```




```
np.random.seed(6)
Xs = np.random.rand(100, 2) - 0.5
ys = (Xs[:, 0] > 0).astype(np.float32) * 2

angle = np.pi / 4
rotation_matrix = np.array([[np.cos(angle), -np.sin(angle)], [np.sin(angle), np.cos(angle)]])
Xsr = Xs.dot(rotation_matrix)

tree_clf_s = DecisionTreeClassifier(random_state=42)
tree_clf_s.fit(Xs, ys)
tree_clf_sr = DecisionTreeClassifier(random_state=42)
tree_clf_sr.fit(Xsr, ys)

fig, axes = plt.subplots(ncols=2, figsize=(10, 4), sharey=True)
plt.sca(axes[0])
plot_decision_boundary(tree_clf_s, Xs, ys, axes=[-0.7, 0.7, -0.7, 0.7], iris=False)
plt.sca(axes[1])
plot_decision_boundary(tree_clf_sr, Xsr, ys, axes=[-0.7, 0.7, -0.7, 0.7], iris=False)
plt.ylabel("")

save_fig("sensitivity_to_rotation_plot")
plt.show()
```

```
Saving figure sensitivity_to_rotation_plot
```



Regression

```
# Quadratic training set + noise
np.random.seed(42)
m = 200
X = np.random.rand(m, 1)
y = 4 * (X - 0.5) ** 2
y = y + np.random.randn(m, 1) / 10
```

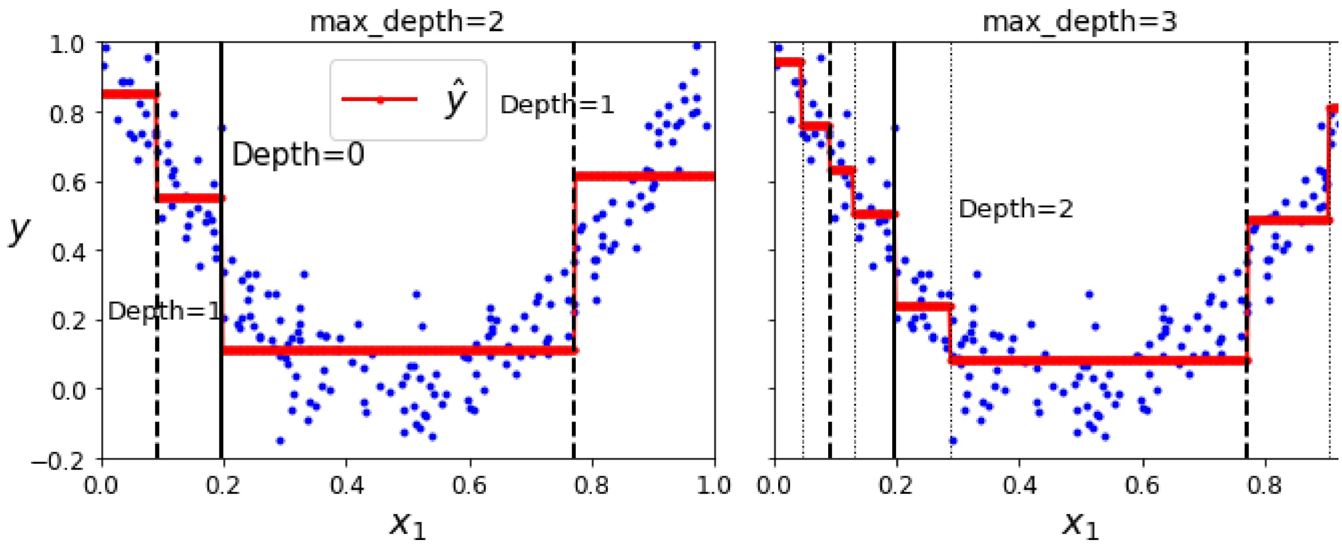
```
from sklearn.tree import DecisionTreeRegressor

tree_reg = DecisionTreeRegressor(max_depth=2, random_state=42)
tree_reg.fit(X, y)
```

```
DecisionTreeRegressor(max_depth=2, random_state=42)
```

```
from sklearn.tree import DecisionTreeRegressor

tree_reg1 = DecisionTreeRegressor(random_state=42, max_depth=2)
tree_reg2 = DecisionTreeRegressor(random_state=42, max_depth=3)
tree_reg1.fit(X, y)
tree_reg2.fit(X, y)

def plot_regression_predictions(tree_reg, X, y, axes=[0, 1, -0.2, 1], ylabel="$y$"):
    x1 = np.linspace(axes[0], axes[1], 500).reshape(-1, 1)
    y_pred = tree_reg.predict(x1)
    plt.axis(axes)
    plt.xlabel("$x_1$", fontsize=18)
    if ylabel:
        plt.ylabel(ylabel, fontsize=18, rotation=0)
    plt.plot(X, y, "b.")
    plt.plot(x1, y_pred, "r.-", linewidth=2, label=r"$\hat{y}$")

fig, axes = plt.subplots(ncols=2, figsize=(10, 4), sharey=True)
plt.sca(axes[0])
plot_regression_predictions(tree_reg1, X, y)
for split, style in ((0.1973, "k-"), (0.0917, "k--"), (0.7718, "k--")):
    plt.plot([split, split], [-0.2, 1], style, linewidth=2)
plt.text(0.21, 0.65, "Depth=0", fontsize=15)
plt.text(0.01, 0.2, "Depth=1", fontsize=13)
plt.text(0.65, 0.8, "Depth=1", fontsize=13)
plt.legend(loc="upper center", fontsize=18)
plt.title("max_depth=2", fontsize=14)

plt.sca(axes[1])
plot_regression_predictions(tree_reg2, X, y, ylabel=None)
for split, style in ((0.1973, "k-"), (0.0917, "k--"), (0.7718, "k--")):
    plt.plot([split, split], [-0.2, 1], style, linewidth=2)
for split in (0.0458, 0.1298, 0.2873, 0.9040):
    plt.plot([split, split], [-0.2, 1], "k:", linewidth=1)
plt.text(0.3, 0.5, "Depth=2", fontsize=13)
```

```
plt.title("max_depth=3", fontsize=14)

save_fig("tree_regression_plot")
plt.show()
```

```
Saving figure tree_regression_plot
```

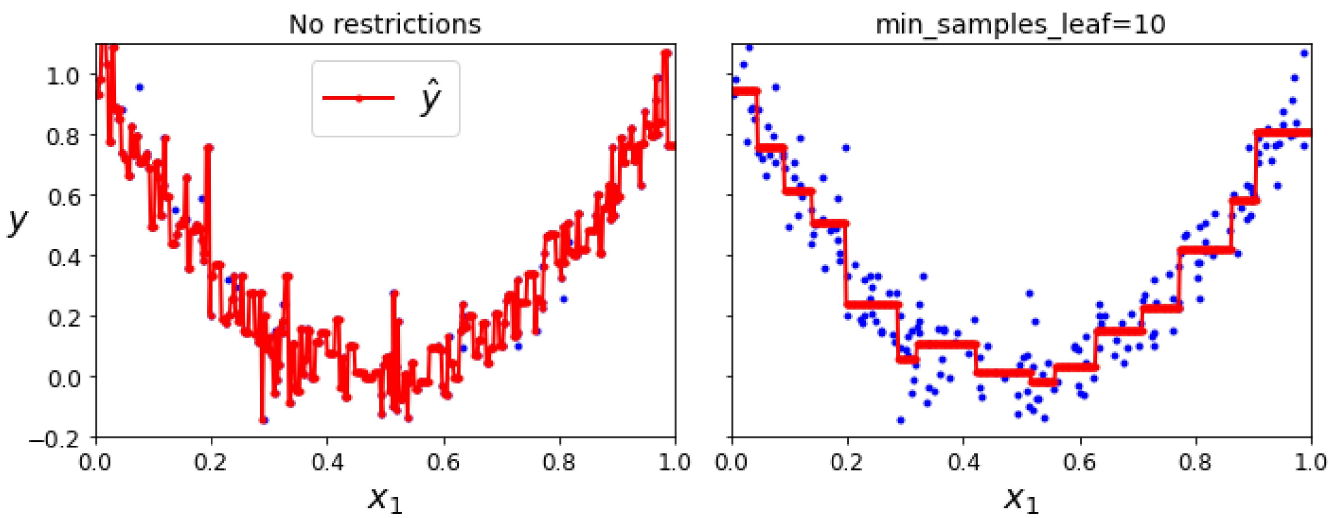



```
export_graphviz(
        tree_reg1,
        out_file=os.path.join(IMAGES_PATH, "regression_tree.dot"),
        feature_names=["x1"],
        rounded=True,
        filled=True
    )
```

```
Source.from_file(os.path.join(IMAGES_PATH, "regression_tree.dot"))
```

```
tree_reg1 = DecisionTreeRegressor(random_state=42)
tree_reg2 = DecisionTreeRegressor(random_state=42, min_samples_leaf=10)
tree_reg1.fit(X, y)
tree_reg2.fit(X, y)

x1 = np.linspace(0, 1, 500).reshape(-1, 1)
y_pred1 = tree_reg1.predict(x1)
y_pred2 = tree_reg2.predict(x1)

fig, axes = plt.subplots(ncols=2, figsize=(10, 4), sharey=True)

plt.sca(axes[0])
plt.plot(X, y, "b.")
plt.plot(x1, y_pred1, "r.-", linewidth=2, label=r"$\hat{y}$")
plt.axis([0, 1, -0.2, 1.1])
plt.xlabel("$x_1$", fontsize=18)
plt.ylabel("$y$", fontsize=18, rotation=0)
plt.legend(loc="upper center", fontsize=18)
plt.title("No restrictions", fontsize=14)

plt.sca(axes[1])
plt.plot(X, y, "b.")
plt.plot(x1, y_pred2, "r.-", linewidth=2, label=r"$\hat{y}$")
plt.axis([0, 1, -0.2, 1.1])
plt.xlabel("$x_1$", fontsize=18)
plt.title("min_samples_leaf={}".format(tree_reg2.min_samples_leaf), fontsize=14)

save_fig("tree_regression_regularization_plot")
plt.show()
```

```
Saving figure tree_regression_regularization_plot
```



Question and Answers

1. In Scikit learn, which estimator class can you use to fit a decision tree model if your goal is to predict a categorical variable? Write the code to import that class. (2 points)
We use DecisionTreeClassifier estimator from Scikit learn to fit a decision tree model when we try to predict the class i.e., when our target attribute is a categorical variable.
Code: from sklearn.tree import DecisionTreeClassifier

2.In Scikit learn, which estimator class can you use to fit a decision tree model if your goal is to predict a numerical value? Write the code to import that class. (2 points)
We use DecisionTreeRegressor estimator from Scikit learn to fit a decision tree model when we try to predict value instead of class.
Code: from sklearn.tree import DecisionTreeRegressor

3. Which estimator would you use to fit a model to predict employee attrition from your HW1? (1 point)
In the HW1 our target variable was Attrition, which is a categorical variable with two classes namely "Yes" class and "No" class. Hence, we use DecisionTreeClassifier estimator to fit a decision tree model.

4. What is the purpose of the max_depth hyperparameter? Find three more hyperparameters that can be manipulated when fitting a decision tree? (1 point)

1. Using max_depth hyperparameter, we can control the risk of overfitting of the model.So, reducing max_depth will regularize the model and reduce the risk of overfitting.
2. min_samples_leaf, max_leaf_nodes and max_features are few other hyperparameters that can be controlled to regularize the decision tree model. Increasing min type hyperparameters or reducing max type hyperparameters will regularize the model.

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