Chapter 7 – Ensemble Learning and Random Forests

This notebook contains all the sample code and solutions to the exercises in chapter 7.

Setup

This project requires Python 3.7 or above:

In [1]:
```
import sys

assert sys.version_info >= (3, 7)
```

It also requires Scikit-Learn ≥ 1.0.1:

In [2]:
```
from packaging import version
import sklearn

assert version.parse(sklearn.__version__) >= version.parse("1.0.1")
```

As we did in previous chapters, let's define the default font sizes to make the figures prettier:

In [3]:
```
import matplotlib.pyplot as plt

plt.rc('font', size=14)
plt.rc('axes', labelsize=14, titlesize=14)
plt.rc('legend', fontsize=14)
plt.rc('xtick', labelsize=10)
plt.rc('ytick', labelsize=10)
```

And let's create the `images/ensembles` folder (if it doesn't already exist), and define the `save_fig()` function which is used through this notebook to save the figures in high-res for the book:

In [4]:
```
from pathlib import Path

IMAGES_PATH = Path() / "images" / "ensembles"
IMAGES_PATH.mkdir(parents=True, exist_ok=True)

def save_fig(fig_id, tight_layout=True, fig_extension="png", resolution=300):
    path = IMAGES_PATH / f"{fig_id}.{fig_extension}"
    if tight_layout:
        plt.tight_layout()
    plt.savefig(path, format=fig_extension, dpi=resolution)
```

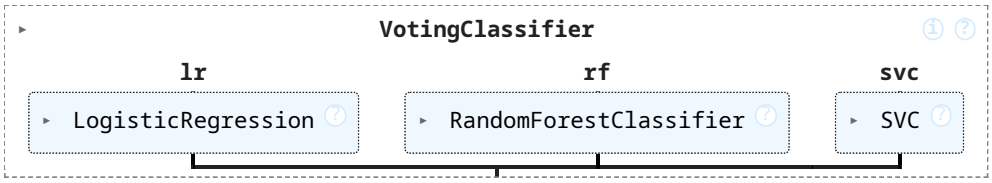
Voting Classifiers

Let's build a voting classifier:

In [5]:
```
from sklearn.datasets import make_moons
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC

X, y = make_moons(n_samples=500, noise=0.30, random_state=42)
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)

voting_clf = VotingClassifier(
    estimators=[
        ('lr', LogisticRegression(random_state=42)),
        ('rf', RandomForestClassifier(random_state=42)),
        ('svc', SVC(random_state=42))
    ]
```

```
)
voting_clf.fit(X_train, y_train)
```

Out[5]:



In [6]:
```
for name, clf in voting_clf.named_estimators_.items():
    print(name, "=", clf.score(X_test, y_test))
```

```
lr = 0.864
rf = 0.896
svc = 0.896
```

In [7]:
```
voting_clf.predict(X_test[:1])
```

Out[7]:
```
array([1])
```

In [8]:
```
[clf.predict(X_test[:1]) for clf in voting_clf.estimators_]
```

Out[8]:
```
[array([1]), array([1]), array([0])]
```

In [9]:
```
voting_clf.score(X_test, y_test)
```

Out[9]:
```
0.912
```

Now let's use soft voting:

In [10]:
```
voting_clf.voting = "soft"
voting_clf.named_estimators["svc"].probability = True
voting_clf.fit(X_train, y_train)
voting_clf.score(X_test, y_test)
```

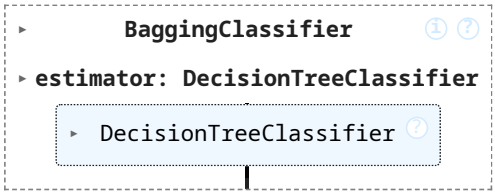
Out[10]:
```
0.92
```

Bagging and Pasting

Bagging and Pasting in Scikit-Learn

In [11]:
```
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier

bag_clf = BaggingClassifier(DecisionTreeClassifier(), n_estimators=500,
                            max_samples=100, n_jobs=-1, random_state=42)
bag_clf.fit(X_train, y_train)
```

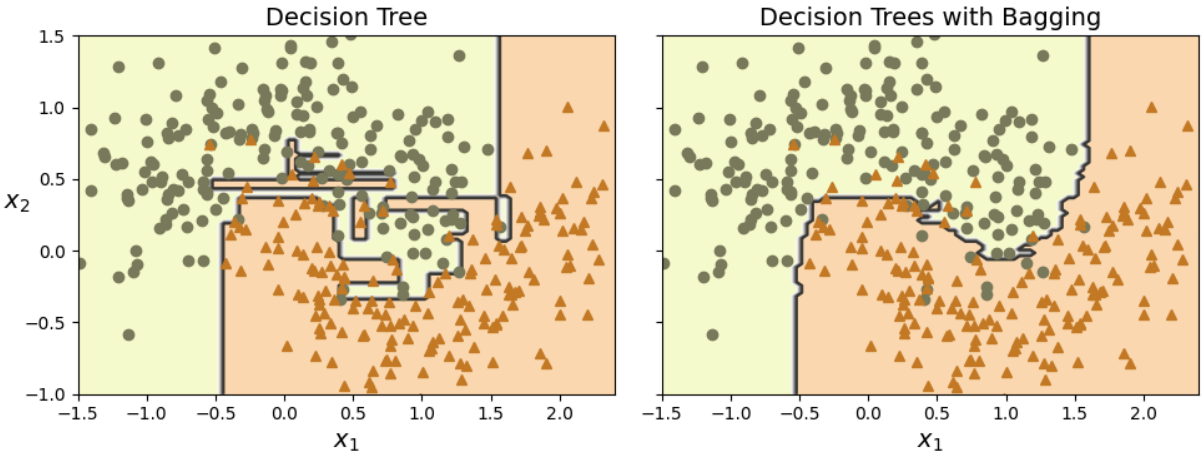
Out[11]:



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

In [13]:
```
# extra code – this cell generates and saves Figure 7–5

def plot_decision_boundary(clf, X, y, alpha=1.0):
    axes=[-1.5, 2.4, -1, 1.5]
    x1, x2 = np.meshgrid(np.linspace(axes[0], axes[1], 100),
                         np.linspace(axes[2], axes[3], 100))
    X_new = np.c_[x1.ravel(), x2.ravel()]
    y_pred = clf.predict(X_new).reshape(x1.shape)

    plt.contourf(x1, x2, y_pred, alpha=0.3 * alpha, cmap='Wistia')
    plt.contour(x1, x2, y_pred, cmap="Greys", alpha=0.8 * alpha)
```

```
    colors = ["#78785c", "#c47b27"]
    markers = ("o", "^")
    for idx in (0, 1):
        plt.plot(X[:, 0][y == idx], X[:, 1][y == idx],
                 color=colors[idx], marker=markers[idx], linestyle="none")
    plt.axis(axes)
    plt.xlabel(r"$x_1$")
    plt.ylabel(r"$x_2$", rotation=0)

tree_clf = DecisionTreeClassifier(random_state=42)
tree_clf.fit(X_train, y_train)

fig, axes = plt.subplots(ncols=2, figsize=(10, 4), sharey=True)
plt.sca(axes[0])
plot_decision_boundary(tree_clf, X_train, y_train)
plt.title("Decision Tree")
plt.sca(axes[1])
plot_decision_boundary(bag_clf, X_train, y_train)
plt.title("Decision Trees with Bagging")
plt.ylabel("")
save_fig("decision_tree_without_and_with_bagging_plot")
plt.show()
```



Out-of-Bag evaluation

In [14]:
```
bag_clf = BaggingClassifier(DecisionTreeClassifier(), n_estimators=500,
                            oob_score=True, n_jobs=-1, random_state=42)
bag_clf.fit(X_train, y_train)
bag_clf.oob_score_
```

Out[14]:
```
0.896
```

In [15]:
```
bag_clf.oob_decision_function_[:3]  # probas for the first 3 instances
```

Out[15]:
```
array([[0.32352941, 0.67647059],
       [0.3375    , 0.6625    ],
       [1.        , 0.        ]])
```

In [16]:
```
from sklearn.metrics import accuracy_score

y_pred = bag_clf.predict(X_test)
accuracy_score(y_test, y_pred)
```

Out[16]:
```
0.92
```

If you randomly draw one instance from a dataset of size m, each instance in the dataset obviously has probability $1/m$ of getting picked, and therefore it has a probability $1 – 1/m$ of *not* getting picked. If you draw m instances with replacement, all draws are independent and therefore each instance has a probability $(1 – 1/m)^m$ of *not* getting picked. Now let's use the fact that $\exp(x)$ is equal to the limit of $(1 + x/m)^m$ as m approaches infinity. So if m is large, the ratio of out-of-bag instances will be about $\exp(–1) \approx 0.37$. So roughly 63% (1 – 0.37) will be sampled.

In [17]:
```
# extra code – shows how to compute the 63% proba
print(1 - (1 - 1 / 1000) ** 1000)
print(1 - np.exp(-1))
```

```
0.6323045752290363
0.6321205588285577
```

Random Forests

In [18]:
```
from sklearn.ensemble import RandomForestClassifier

rnd_clf = RandomForestClassifier(n_estimators=500, max_leaf_nodes=16,
                                 n_jobs=-1, random_state=42)
rnd_clf.fit(X_train, y_train)
y_pred_rf = rnd_clf.predict(X_test)
```

A Random Forest is equivalent to a bag of decision trees:

In [19]:
```
bag_clf = BaggingClassifier(
    DecisionTreeClassifier(max_features="sqrt", max_leaf_nodes=16),
    n_estimators=500, n_jobs=-1, random_state=42)
```

In [20]:
```
# extra code – verifies that the predictions are identical
bag_clf.fit(X_train, y_train)
y_pred_bag = bag_clf.predict(X_test)
np.all(y_pred_bag == y_pred_rf)  # same predictions
```

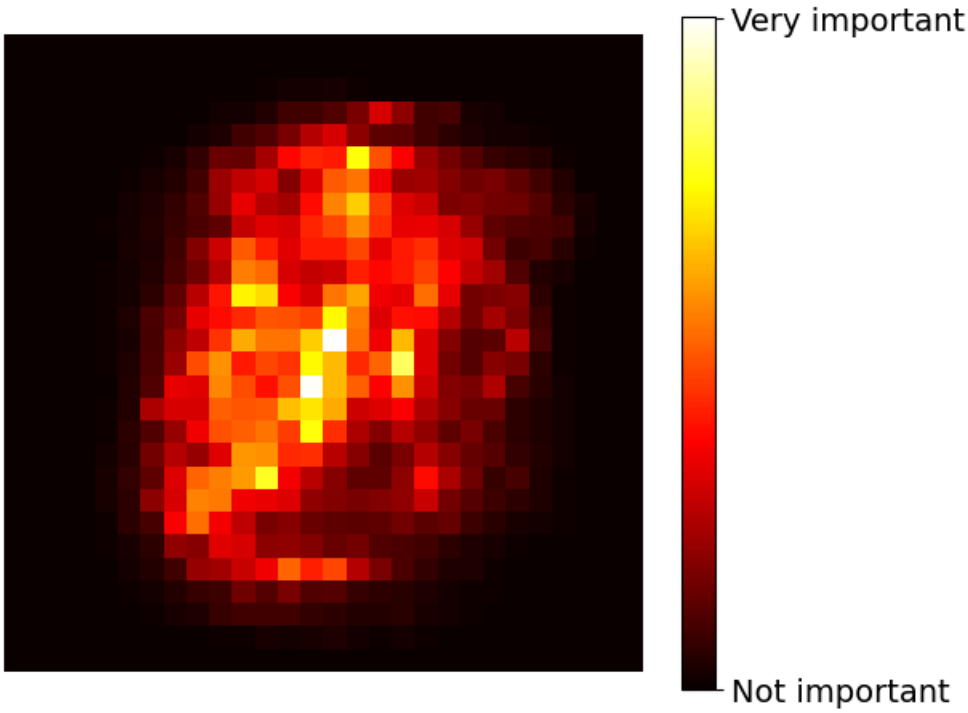
Out[20]:
```
np.True_
```

Feature Importance

In [21]:
```
from sklearn.datasets import load_iris

iris = load_iris(as_frame=True)
rnd_clf = RandomForestClassifier(n_estimators=500, random_state=42)
rnd_clf.fit(iris.data, iris.target)
for score, name in zip(rnd_clf.feature_importances_, iris.data.columns):
    print(round(score, 2), name)
```

```
0.11 sepal length (cm)
0.02 sepal width (cm)
0.44 petal length (cm)
0.42 petal width (cm)
```

In [22]:
```
# extra code – this cell generates and saves Figure 7–6

from sklearn.datasets import fetch_openml

X_mnist, y_mnist = fetch_openml('mnist_784', return_X_y=True, as_frame=False)

rnd_clf = RandomForestClassifier(n_estimators=100, random_state=42)
rnd_clf.fit(X_mnist, y_mnist)

heatmap_image = rnd_clf.feature_importances_.reshape(28, 28)
plt.imshow(heatmap_image, cmap="hot")
cbar = plt.colorbar(ticks=[rnd_clf.feature_importances_.min(),
                           rnd_clf.feature_importances_.max()])
cbar.ax.set_yticklabels(['Not important', 'Very important'], fontsize=14)
plt.axis("off")
save_fig("mnist_feature_importance_plot")
plt.show()
```


Very important
Not important