Lab 8

Decision Trees

Introduction

Objectives

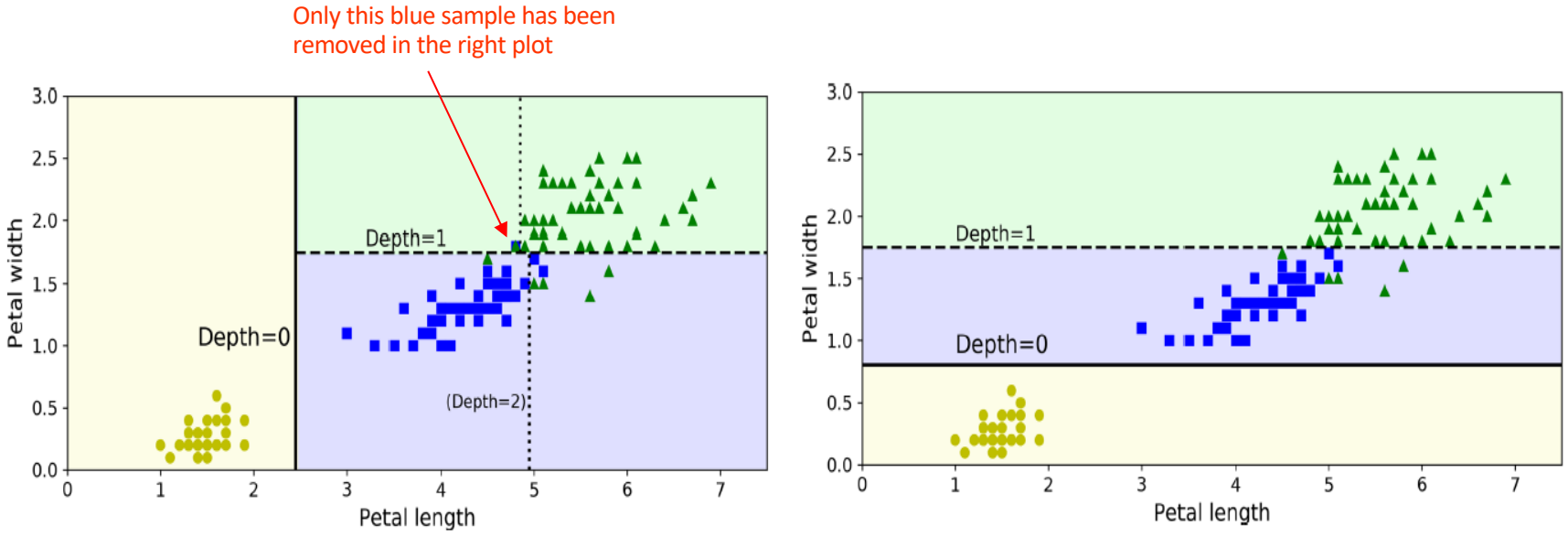
- Learn how to use decision trees to solve a classification problem
- Learn to prune a decision tree
- Learn to train a random forest classifier
- Solve the Ionosphere classification problem with decision trees and random forests
- Solve the MNIST classification problem with random forests.

Bias and variance

Decision trees are large variance predictors: a slight modification in the dataset can dramatically change the decision boundaries.

They are prone to overfitting -> control growing (min samples at leaf node, max depth, etc) / pruning

Trees may be biased if there is class imbalance



Decision Trees in sklearn

Class: `DecisionTreeClassifier`

Scikit-Learn uses the **CART algorithm**, which produces only binary tres. CART constructs binary trees using the feature and threshold that yield the largest information gain at each node.

The main parameters are:

criterion: The function to measure the quality of a split. Supported criteria are “gini” (default) for the Gini impurity and “entropy” for the information gain.

max_depth: The maximum depth of the tree. If None (default), then nodes are expanded until all leaves are pure or until all leaves contain less than **min_samples_split** samples.

min_samples_split: The minimum number of samples required to split an internal node (default=2)

min_samples_leaf The minimum number of samples required to be at a leaf node (default 1). A split point at any depth will only be considered if it leaves at least min_samples_leaf training samples in each of the left and right branches. This may have the effect of smoothing the model, especially in regression.

class_weight Weights associated with classes (default None).

Decision Trees in sklearn

```
clf = sklearn.tree.DecisionTreeClassifier(criterion='entropy' )
clf.fit(X, y)
```

#Plot the tree
```
sklearn.tree.plot_tree(clf, ax=fig.subplots());
```

#Export in textual format
```
t = export_text(clf)
```

#Check parameters used
```
clf.get_params()
```

#Feature importances
```
clf.feature_importances_
```

#Parameters for regularization
```
max_depth
min_simples_split
min_simples_leaf
min_weight_fraction_leaf
max_leaf_nodes
max_features
```

#Parameters for pruning
```
ccp_alpha
```

Complexity param: the subtree with the largest cost complexity that is smaller than ccp_alpha will be chosen. By default, no pruning is performed

Random Forests in sklearn

To improve the predictive accuracy and control over-fitting, multiple decision tree classifiers can be trained and later combined.

In random forests, randomness is introduced in the classifier construction by :

1. Each tree is built from a **sample drawn with replacement from the training set**.
2. When splitting each node during the construction of a tree, the best split is found from a **random subset from the input features**.

Random forests achieve a reduced variance by combining diverse trees, sometimes at the cost of a slight increase in bias. In practice the variance reduction is often significant hence yielding an overall better model

Random Forests in sklearn

Random foeste class: `RandomForestClassifier`

```
clf =
sklearn.ensemble.RandomForestClassifier(criterion='entropy',min_sam
ples_leaf=5)
clf.fit(X, y)
```

Default parameters:

```
n_estimators = 100
criterion = 'gini'
max_depth = None
min_samples_split =2
min_samples_leaf = 1
ccp_alpha = 0
```