

Tree

A tree algorithm with forward pruning.

Inputs

- Data: input dataset
- Preprocessor: preprocessing method(s)

Outputs

- Learner: decision tree learning algorithm
- Model: trained model

Tree is a simple algorithm that splits the data into nodes by class purity. It is a precursor to **Random Forest**. Tree in Orange is designed in-house and can handle both discrete and continuous datasets.

It can also be used for both classification and regression tasks.

Tree

Name

Tree

Parameters

☒ Induce binary tree

☒ Min. number of instances in leaves: 2

☒ Do not split subsets smaller than: 5

1. The learner can be given a name under which it will appear in other widgets. The default name is “Tree”.
2. Tree parameters:
 - **Induce binary tree**: build a binary tree (split into two child nodes)
 - **Min. number of instances in leaves**: if checked, the algorithm will never construct a split which would put less than the specified number of training examples into any of the branches.
 - **Do not split subsets smaller than**: forbids the algorithm to split the nodes with less than the given number of instances.
 - **Limit the maximal tree depth**: limits the depth of the classification tree to the specified number of node levels.
3. **Stop when majority reaches [%]**: stop splitting the nodes after a specified majority threshold is reached
4. Produce a report. After changing the settings, you need to click *Apply*, which will put the new learner on the output and, if the training examples are given, construct a new classifier and output it as well. Alternatively, tick the box on the left and changes will be communicated automatically.

Examples

There are two typical uses for this widget. First, you may want to induce a model and check what it looks like in [Tree Viewer](#).

The screenshot displays the Orange Data Mining interface with a workflow consisting of three widgets: File, Tree, and Tree Viewer. The Tree widget is configured with the following parameters:

- Name:** Tree
- Parameters:**
 - ☒ Induce binary tree
 - ☒ Min. number of instances in leaves: 2
 - ☒ Do not split subsets smaller than: 5
 - ☒ Limit the maximal tree depth to: 100
- Classification:**
 - ☒ Stop when majority reaches [%]: 95
- Buttons:** Report, Apply Automatically

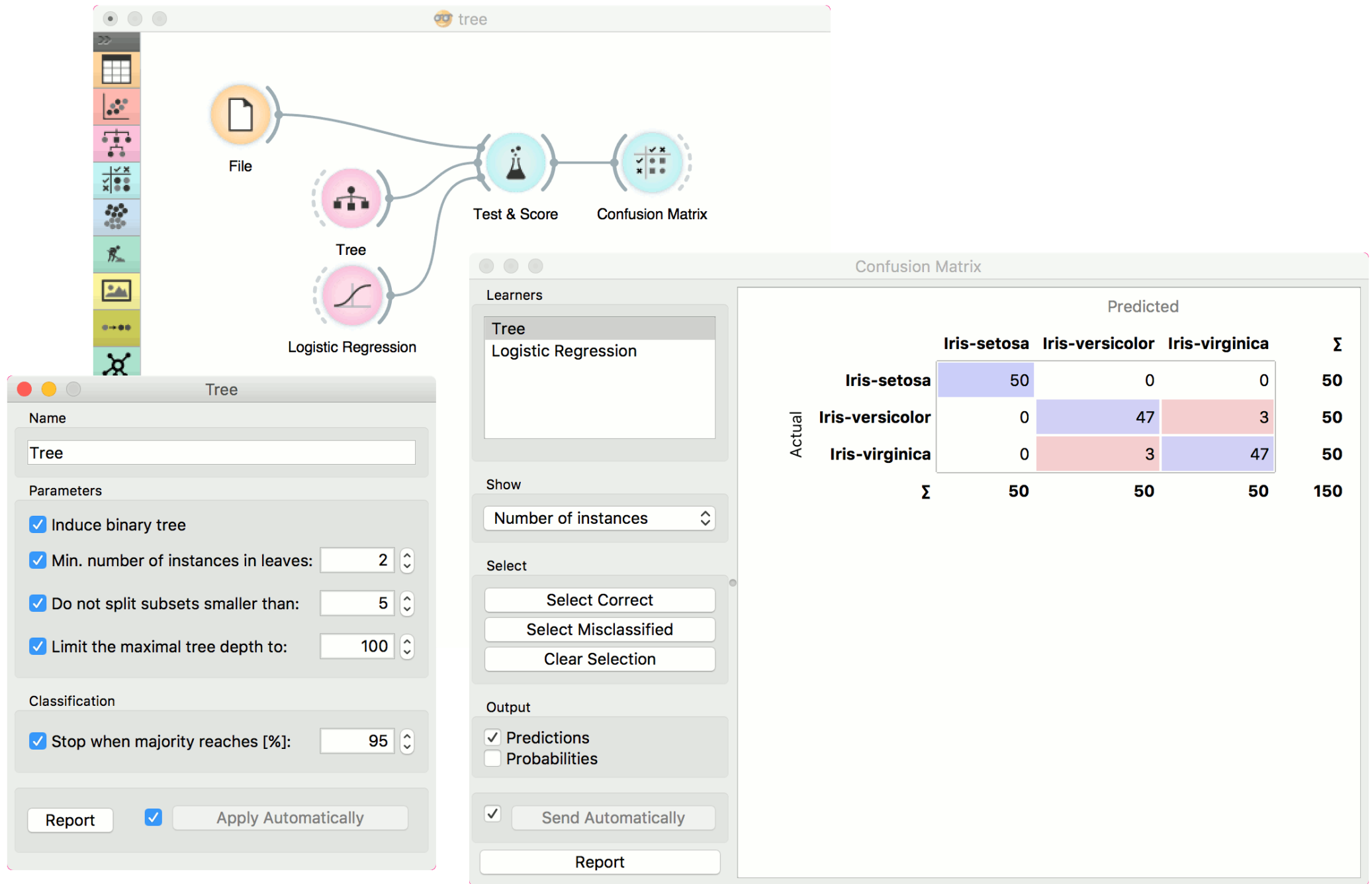
The Tree Viewer widget displays the resulting decision tree structure:

```

graph TD
    Root["Iris-setosa  
33.3%, 50/150  
petal length"]
    Root -- "≤ 1.900" --> L["Iris-setosa  
100%, 50/50"]
    Root -- "> 1.900" --> R["Iris-versicolor  
50.0%, 50/100  
petal width"]
    R -- "≤ 1.700" --> RL["Iris-versicolor  
90.7%, 49/54  
petal length"]
    R -- "> 1.700" --> RR["Iris-virginica  
97.8%, 45/46"]
  
```

The tree structure shows a root node splitting on 'petal length'. The left branch (≤ 1.900) leads to a leaf node 'Iris-setosa' with 100% accuracy (50/50). The right branch (> 1.900) leads to a node splitting on 'petal width'. The left sub-branch (≤ 1.700) leads to a leaf node 'Iris-versicolor' with 90.7% accuracy (49/54), and the right sub-branch (> 1.700) leads to a leaf node 'Iris-virginica' with 97.8% accuracy (45/46).

The second schema trains a model and evaluates its performance against **Logistic Regression**.



We used the *iris* dataset in both examples. However, **Tree** works for regression tasks as well. Use *housing* dataset and pass it to **Tree**. The selected tree node from **Tree Viewer** is presented in the **Scatter Plot** and we can see that the selected examples exhibit the same features.

