Random Forest

Predict using an ensemble of decision trees.

Inputs

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

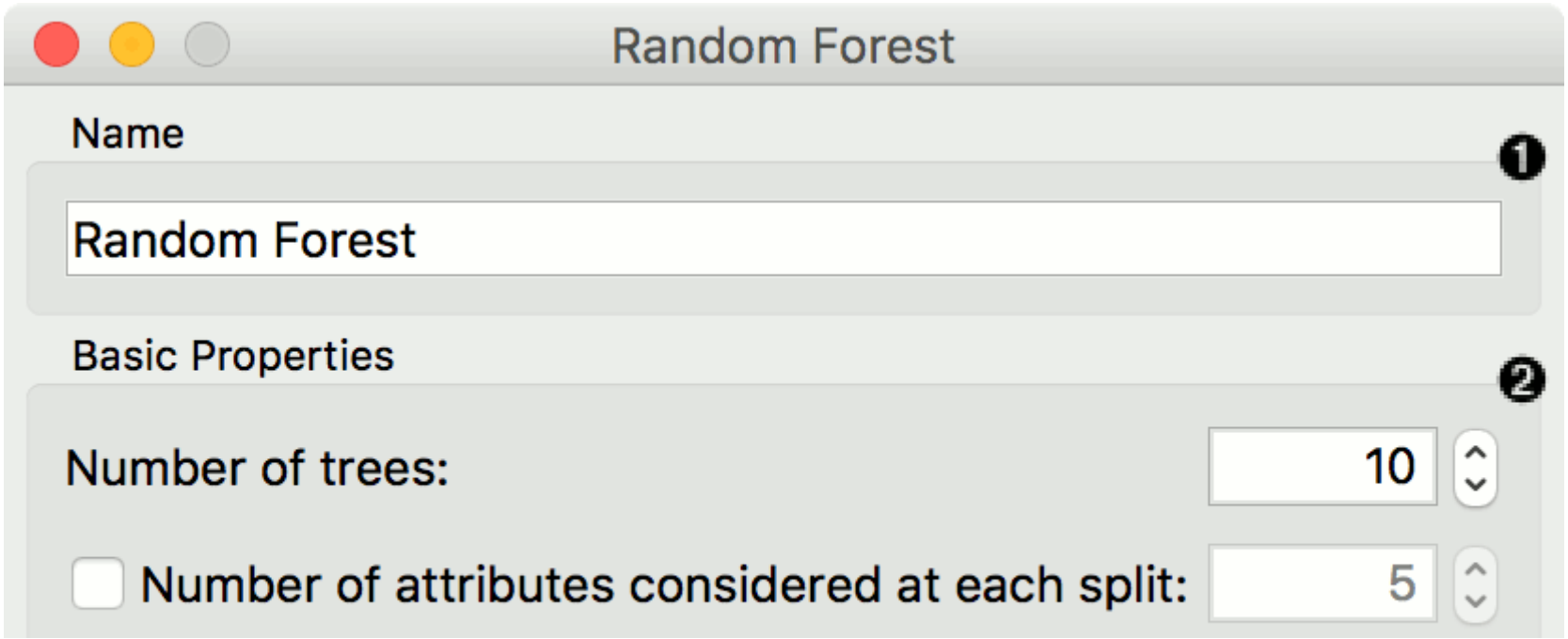
Outputs

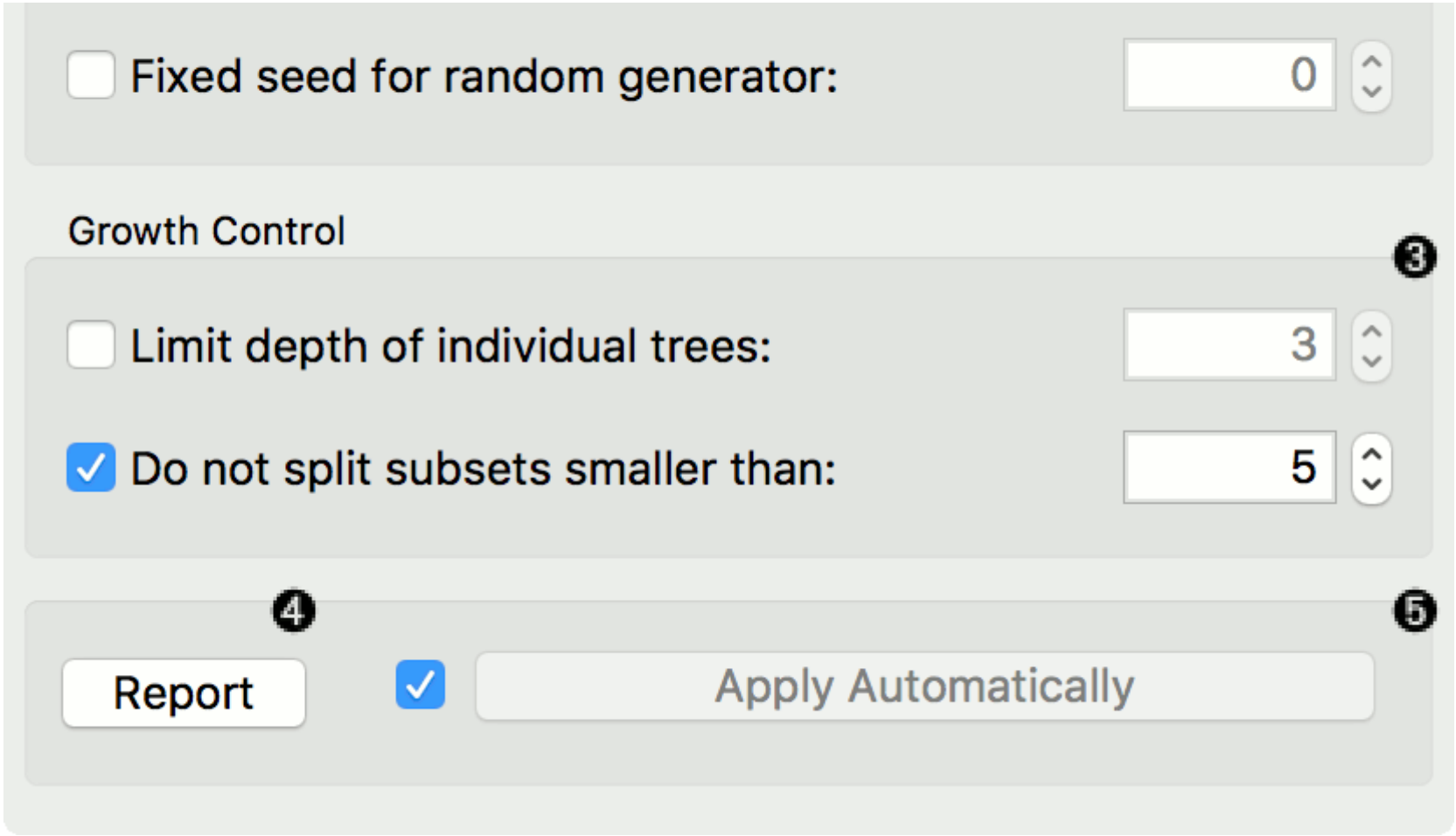
- Learner: random forest learning algorithm
- Model: trained model

Random forest is an ensemble learning method used for classification, regression and other tasks. It was first proposed by Tin Kam Ho and further developed by Leo Breiman (Breiman, 2001) and Adele Cutler.

Random Forest builds a set of decision trees. Each tree is developed from a bootstrap sample from the training data. When developing individual trees, an arbitrary subset of attributes is drawn (hence the term “Random”), from which the best attribute for the split is selected. The final model is based on the majority vote from individually developed trees in the forest.

Random Forest works for both classification and regression tasks.

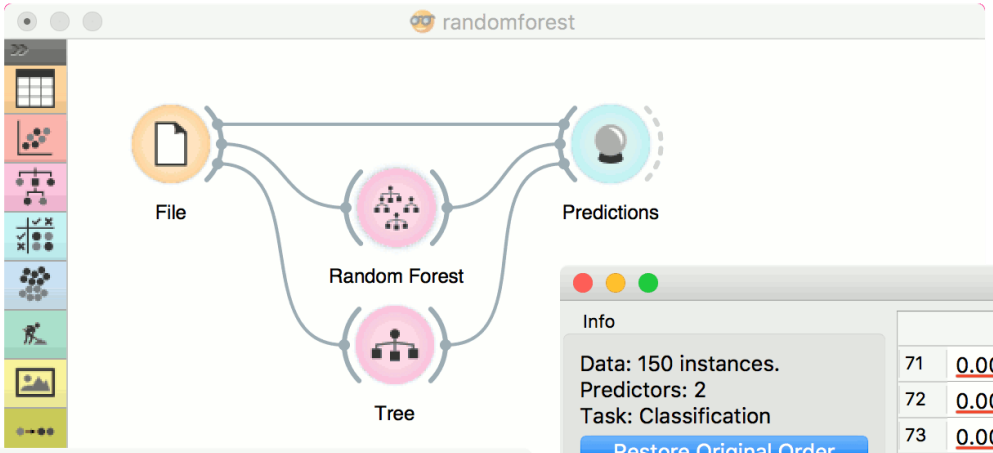


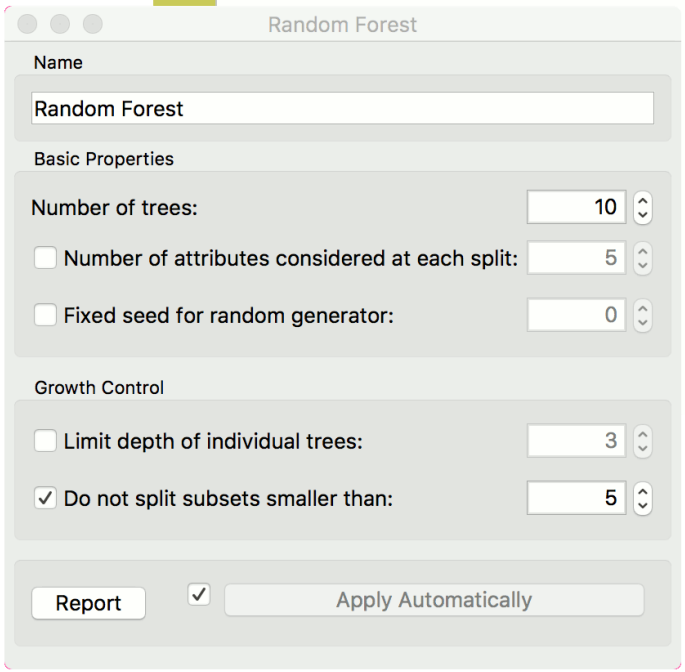


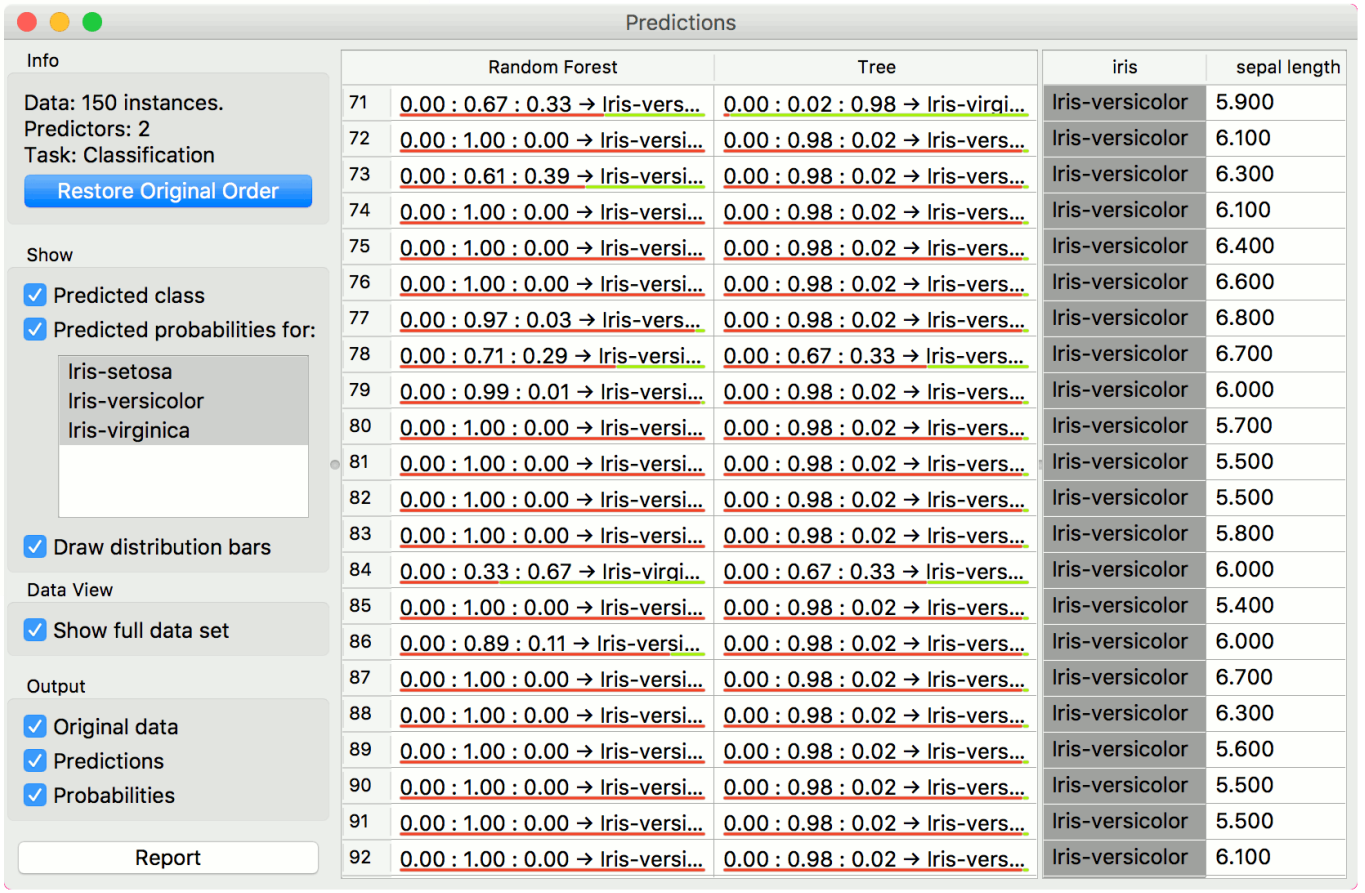
1. Specify the name of the model. The default name is “Random Forest”.
2. Specify how many decision trees will be included in the forest (*Number of trees in the forest*), and how many attributes will be arbitrarily drawn for consideration at each node. If the latter is not specified (option *Number of attributes…* left unchecked), this number is equal to the square root of the number of attributes in the data. You can also choose to fix the seed for tree generation (*Fixed seed for random generator*), which enables replicability of the results.
3. Original Breiman’s proposal is to grow the trees without any pre-pruning, but since pre-pruning often works quite well and is faster, the user can set the depth to which the trees will be grown (*Limit depth of individual trees*). Another pre-pruning option is to select the smallest subset that can be split (*Do not split subsets smaller than*).
4. Produce a report.
5. Click *Apply* to communicate the changes to other widgets. Alternatively, tick the box on the left side of the *Apply* button and changes will be communicated automatically.

Examples

For classification tasks, we use *iris* dataset. Connect it to Predictions. Then, connect Fileto **Random Forest** and Tree and connect them further to Predictions. Finally, observe the predictions for the two models.

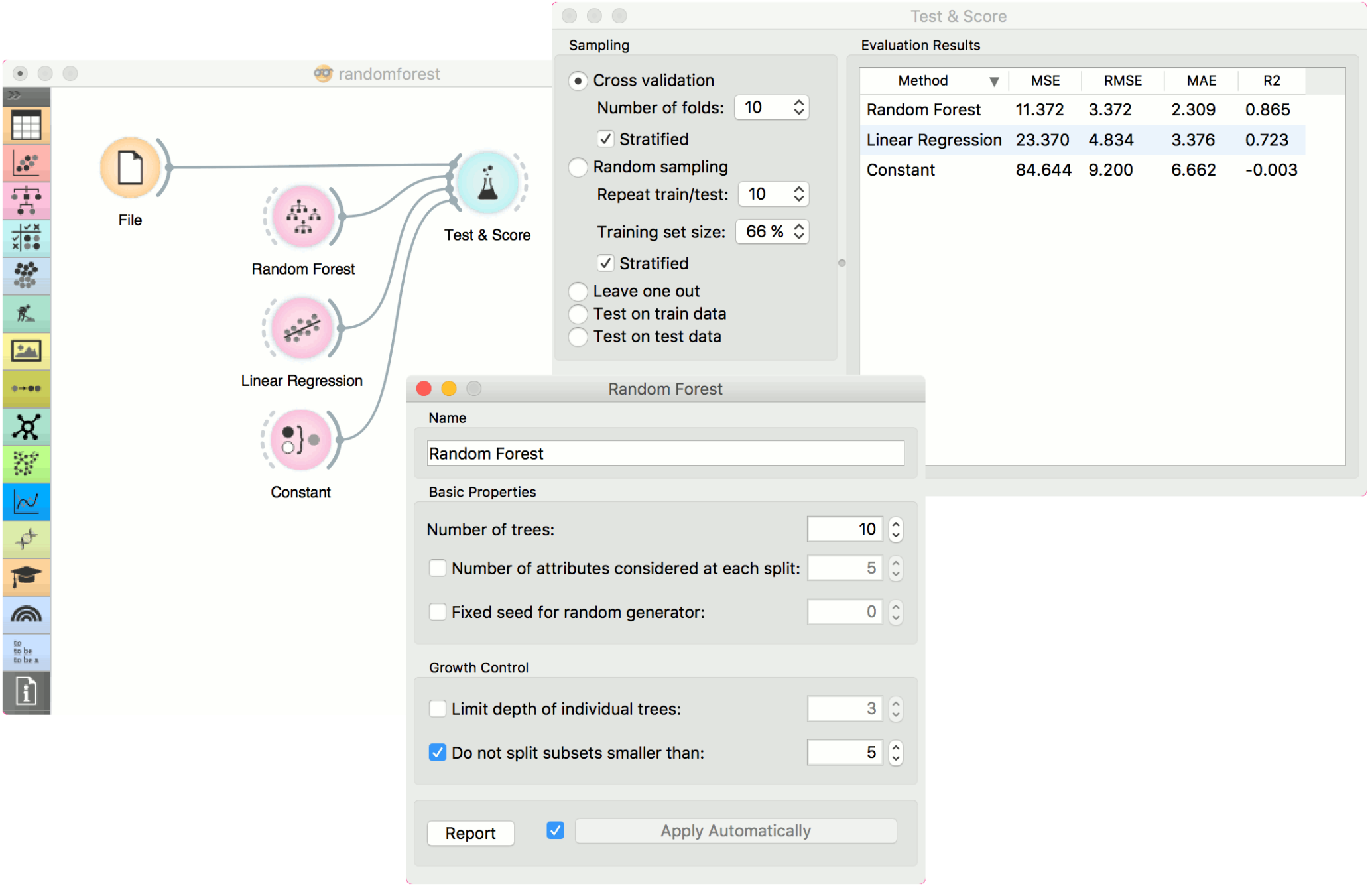






	Random Forest	Tree	iris	sepal length
71	0.00 : 0.67 : 0.33 → Iris-vers...	0.00 : 0.02 : 0.98 → Iris-virgi...	Iris-versicolor	5.900
72	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	6.100
73	0.00 : 0.61 : 0.39 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	6.300
74	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	6.100
75	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	6.400
76	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	6.600
77	0.00 : 0.97 : 0.03 → Iris-vers...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	6.800
78	0.00 : 0.71 : 0.29 → Iris-versi...	0.00 : 0.67 : 0.33 → Iris-vers...	Iris-versicolor	6.700
79	0.00 : 0.99 : 0.01 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	6.000
80	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	5.700
81	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	5.500
82	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	5.500
83	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	5.800
84	0.00 : 0.33 : 0.67 → Iris-virgi...	0.00 : 0.67 : 0.33 → Iris-vers...	Iris-versicolor	6.000
85	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	5.400
86	0.00 : 0.89 : 0.11 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	6.000
87	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	6.700
88	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	6.300
89	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	5.600
90	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	5.500
91	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	5.500
92	0.00 : 1.00 : 0.00 → Iris-versi...	0.00 : 0.98 : 0.02 → Iris-vers...	Iris-versicolor	6.100

For regressions tasks, we will use *housing* data. Here, we will compare different models, namely **Random Forest**, Linear Regression and Constant, in the Test & Score widget.


randomforest
File
Random Forest
Linear Regression
Constant
Test & Score
Test & Score
Sampling
Cross validation
Number of folds: 10
Stratified
Random sampling
Repeat train/test: 10
Training set size: 66 %
Stratified
Leave one out
Test on train data
Test on test data
Evaluation Results
Method MSE RMSE MAE R2
Random Forest 11.372 3.372 2.309 0.865
Linear Regression 23.370 4.834 3.376 0.723
Constant 84.644 9.200 6.662 -0.003
Random Forest
Name
Random Forest
Basic Properties
Number of trees: 10
Number of attributes considered at each split: 5
Fixed seed for random generator: 0
Growth Control
Limit depth of individual trees: 3
Do not split subsets smaller than: 5
Report
Apply Automatically

References

Breiman, L. (2001). Random Forests. In Machine Learning, 45(1), 5-32. Available here.