

Table of Contents

- [1 Exercise 14.1. Growing deep trees by addition](#)
- [2 Exercise 14.2. Fitting the parameters of a simple regression tree](#)
- [3 Exercise 14.3. Code up a regression tree](#)
- [4 Exercise 14.4. Code up a two-class classification tree](#)
- [5 Exercise 14.5. Code up a multi-class classification tree](#)
- [6 Exercise 14.6. Gradient boosting for regression](#)
- [7 Exercise 14.7. Gradient boosting for classification](#)
- [8 Exercise 14.8. Random forests](#)
- [9 Exercise 14.9. Limitation of trees outside their training range](#)
- [10 Exercise 14.10. Naive cross-validation](#)

```
In [5]: # imports from custom library
import sys
sys.path.append('../')
import autograd.numpy as np
import matplotlib.pyplot as plt
import copy
datapath = '../mlrefined_datasets/nonlinear_superlearn_datasets/'

# import custom libraries
from mlrefined_libraries import nonlinear_superlearn_library as nonlib

# this is needed to compensate for %matplotlib notebook's tendency to blow up images when plotted inline
from matplotlib import rcParams
rcParams['figure.autolayout'] = True
%matplotlib notebook
```

The autoreload extension is already loaded. To reload it, use:
`%reload_ext autoreload`

Exercise 14.1. Growing deep trees by addition

Adding $2^D - 1$ one-dimensional stumps (if they do not share any split points) create $2^D - 1$ unique split points. Now take the midpoint. It creates two branches, one to its left and the other two its right. So far we have accounted for 1 split point and a depth 1 tree. We then take the midpoint on each branch, creating a depth 2 tree with a total of $1 + 2$ split points. Following this pattern we will end up using all $1 + 2 + 4 + \dots + 2^k$ split points and create a depth $k + 1$ tree.

All left to do is express k in terms of D :

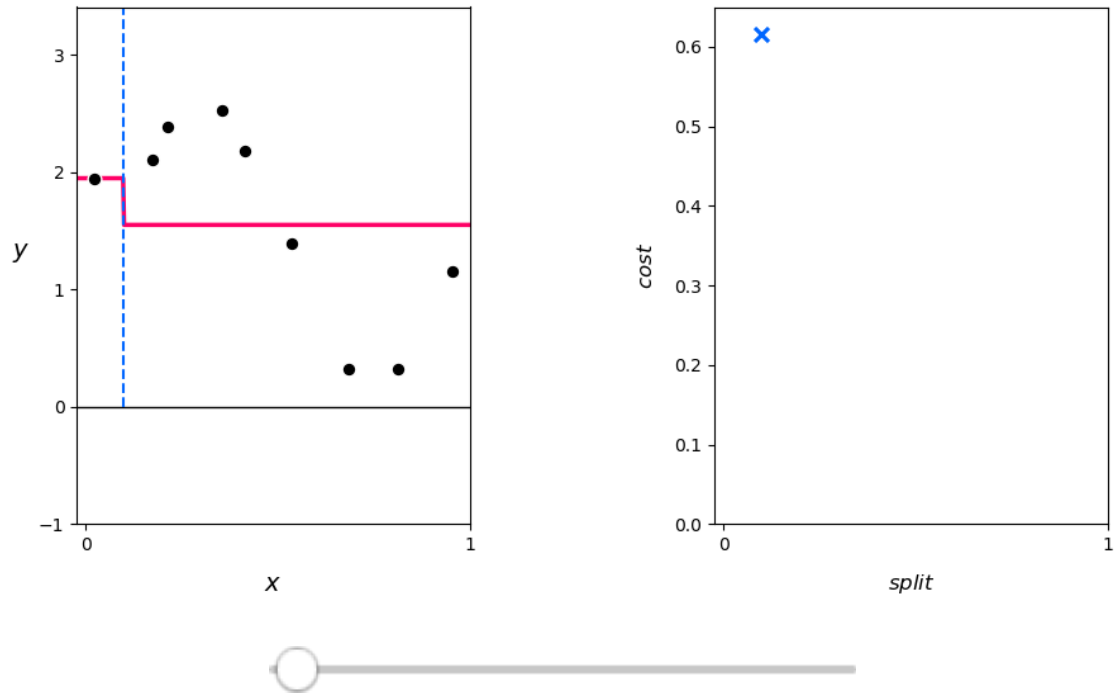
$$1 + 2 + 4 + \dots + 2^k = 2^{k+1} - 1 = 2^D - 1 \quad \Rightarrow \quad k = D - 1$$

Therefore, adding $2^D - 1$ stumps will create a tree of depth $k + 1 = D$.

Exercise 14.2. Fitting the parameters of a simple regression tree

```
In [6]: ## This code cell will not be shown in the HTML version of this notebook
# animate stump collection for a sample dataset
demo = nonlib.stump_visualizer_2d.Visualizer()
csvname = datapath + 'noisy_sin_subsample_raised_2.csv'
demo.load_data(csvname)
demo.browse_stumps()
```

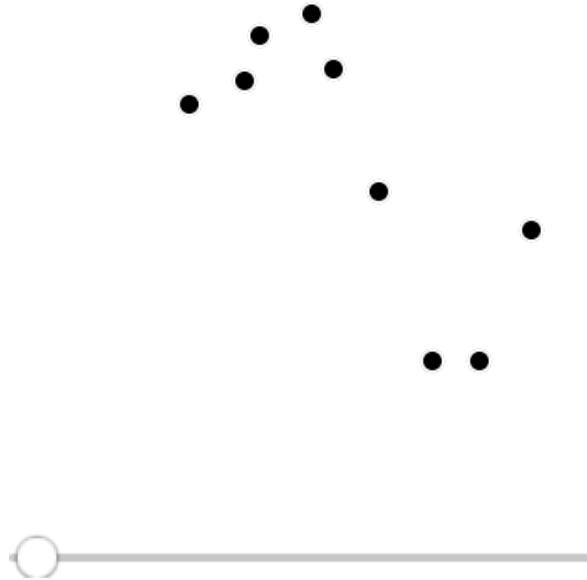
Out[6]:



Exercise 14.3. Code up a regression tree

```
In [27]: ## This code cell will not be shown in the HTML version of this notebook  
# create regression tree  
csvname = datapath + 'noisy_sin_subsample_2.csv'  
depth = 5  
tree = nonlib.recursive_tree_lib.RegressionTree.RTree(csvname,depth)  
  
# animate growth  
demo = nonlib.recursive_tree_lib.regression_animator.Visualizer(csvname)  
frames = depth  
demo.animate_trees(tree)
```

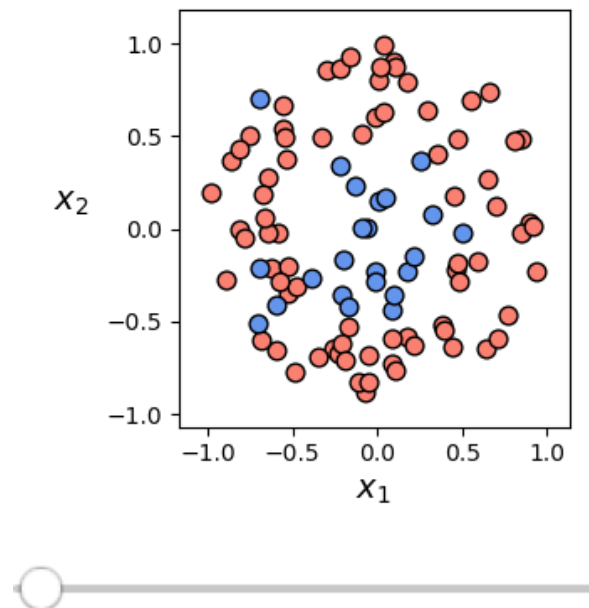
Out[27]:



Exercise 14.4. Code up a two-class classification tree

```
In [17]: ## This code cell will not be shown in the HTML version of this notebook  
# learn classification tree for input dataset  
csvname = datapath + 'new_circle_data.csv'  
depth = 7  
tree = nonlib.recursive_tree_lib.ClassificationTree.RTree(csvname,depth)  
  
# animate growth  
demo = nonlib.recursive_tree_lib.classification_animator.Visualizer(csvname)  
demo.animate_trees(tree)
```

Out[17]:



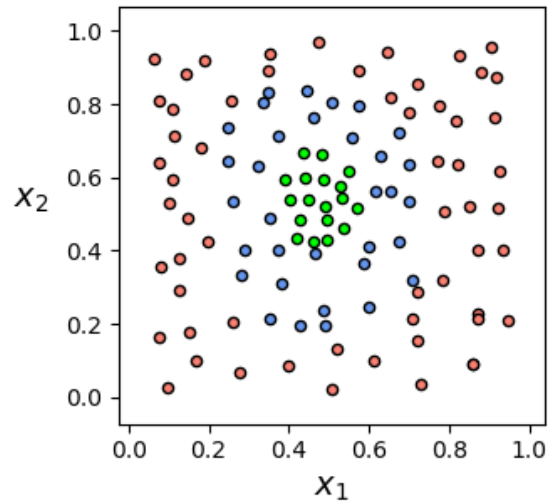
Exercise 14.5. Code up a multi-class classification tree

```
In [27]: ## This code cell will not be shown in the HTML version of this notebook
# learn classification tree for input dataset
csvname = datapath + '3_layercake_data.csv'

# learn classification tree for input dataset
depth = 7
tree = nonlib.recursive_tree_lib.ClassificationTree.RTree(csvname,depth)

# animate growth
demo = nonlib.recursive_tree_lib.classification_animator.Visualizer(csvname)
demo.animate_trees(tree,pt_size = 20)
```

Out[27]:



Exercise 14.6. Gradient boosting for regression

```
In [ ]: ## This code cell will not be shown in the HTML version of this notebook
# load in dataset
csvname = datapath + 'universal_regression_samples_0.csv'
csvname = datapath + 'noisy_sin_sample.csv'

data = np.loadtxt(csvname,delimiter = ',')
x = copy.deepcopy(data[:-1,:])
y = copy.deepcopy(data[-1,:])

# boosting procedure
num_units = 40
runs2 = []
for j in range(num_units):
    # import the vl library
    mylib2 = nonlib.boost_lib3.stump_booster.Setup(x,y)

    # choose normalizer
    mylib2.choose_normalizer(name = 'standard')

    # choose normalizer
    mylib2.make_train_valid_split(train_portion = 1)

    # choose cost|
    mylib2.choose_cost(name = 'least_squares')

    # choose optimizer
    mylib2.choose_optimizer('newtons_method',max_its=1)

    # run boosting
    mylib2.boost(1,verbose=False)
    mylib2.model = mylib2.models[-1]

    # add model to list
    runs2.append(copy.deepcopy(mylib2))

    # cut off output given model
    normalizer = mylib2.normalizer
    ind = np.argmin(mylib2.train_cost_vals[0])
    y_pred = mylib2.models[-1](mylib2.normalizer(x))
    y -= y_pred

# animate the business
frames = num_units
demo2 = nonlib.boosting_regression_animators_v3.Visualizer(csvname)
demo2.animate_boosting(runs2,frames)
```

```
In [24]: ## This code cell will not be shown in the HTML version of this notebook
# load in dataset
csvname = datapath + 'universal_regression_samples_0.csv'
csvname = datapath + 'noisy_sin_sample.csv'

data = np.loadtxt(csvname,delimiter = ',')
x = copy.deepcopy(data[:-1,:])
y = copy.deepcopy(data[-1,:])

# boosting procedure
num_units = 40
runs2 = []
for j in range(num_units):
    # import the vl library
    mylib2 = nonlib.boost_lib3.stump_booster.Setup(x,y)

    # choose normalizer
    mylib2.choose_normalizer(name = 'standard')

    # choose normalizer
    mylib2.make_train_valid_split(train_portion = 1)

    # choose cost|
    mylib2.choose_cost(name = 'least_squares')

    # choose optimizer
    mylib2.choose_optimizer('newtons_method',max_its=1)

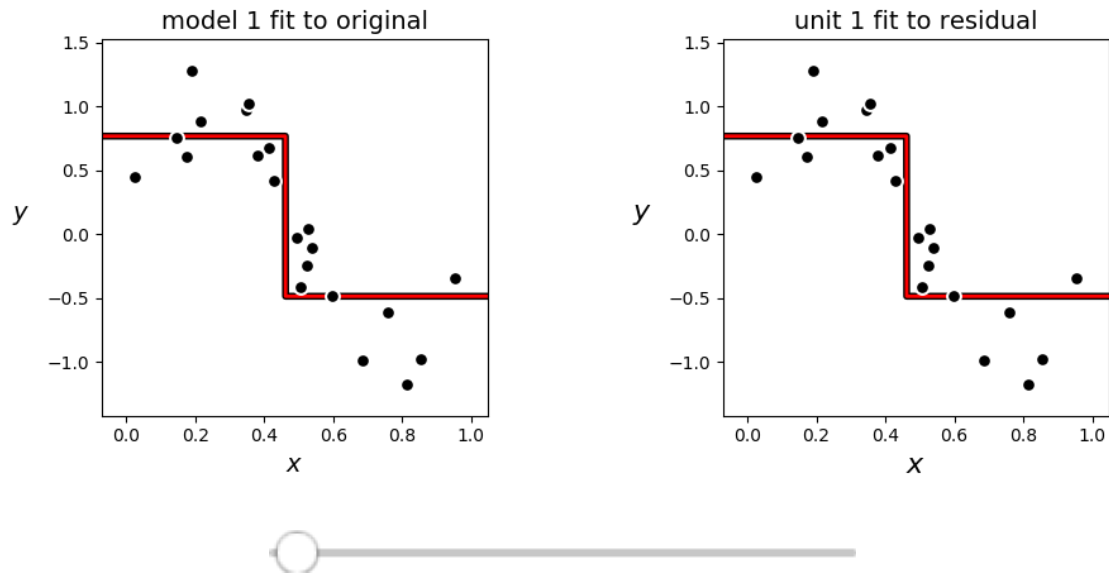
    # run boosting
    mylib2.boost(1,verbose=False)
    mylib2.model = mylib2.models[-1]

    # add model to list
    runs2.append(copy.deepcopy(mylib2))

    # cut off output given model
    normalizer = mylib2.normalizer
    ind = np.argmin(mylib2.train_cost_vals[0])
    y_pred = mylib2.models[-1](mylib2.normalizer(x))
    y -= y_pred

# animate the business
frames = num_units
demo2 = nonlib.boosting_regression_animators_v3.Visualizer(csvname)
demo2.animate_boosting(runs2,frames)
```

Out[24]:



Exercise 14.7. Gradient boosting for classification

A single step of Newton's method to minimize the cost function

$$g(v_L) = \frac{1}{|\Omega_L|} \sum_{p \in \Omega_L} \log \left(1 + e^{-y_p (\text{model}_{m-1}(\mathbf{x}_p, \Theta_{m-1}) + v_L)} \right)$$

takes the form

$$g(v_L) = v_L^0 - \frac{g'(v_L^0)}{g''(v_L^0)}$$

where v_L^0 is the starting point, and the first and second order derivative of g at this point can be computed, respectively, as

$$g'(v_L^0) = \frac{1}{|\Omega_L|} \sum_{p \in \Omega_L} \frac{-y_p e^{-y_p (\text{model}_{m-1}(\mathbf{x}_p, \Theta_{m-1}) + v_L^0)}}{1 + e^{-y_p (\text{model}_{m-1}(\mathbf{x}_p, \Theta_{m-1}) + v_L^0)}}$$

and

$$g''(v_L^0) = \frac{1}{|\Omega_L|} \sum_{p \in \Omega_L} \frac{e^{-y_p (\text{model}_{m-1}(\mathbf{x}_p, \Theta_{m-1}) + v_L^0)}}{(1 + e^{-y_p (\text{model}_{m-1}(\mathbf{x}_p, \Theta_{m-1}) + v_L^0)})^2}.$$

Exercise 14.8. Random forests

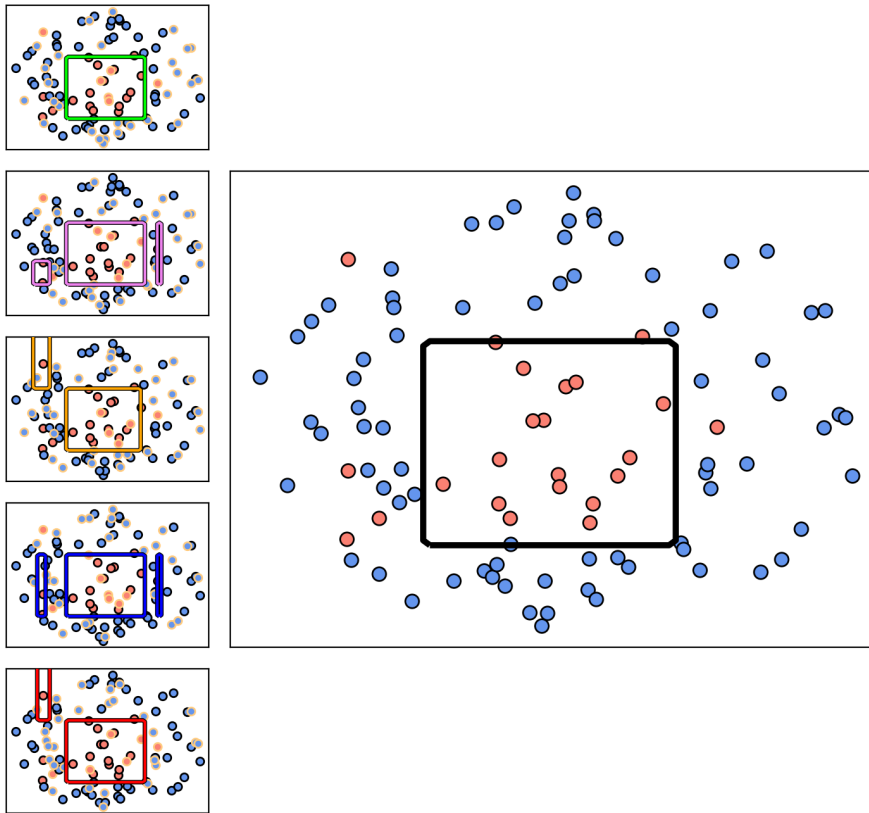

```

In [5]: ## This code cell will not be shown in the HTML version of this notebook
# path to data, container for trees
datapath = '../..mlrefined_datasets/nonlinear_superlearn_datasets/'
csvname = datapath + 'new_circle_data.csv'
trees = []
num_trees = 5
depth = 7
train_portion = 0.66

for i in range(num_trees):
    tree = nonlib.recursive_tree_lib_crossval.ClassificationTree.RTree(csvname,de
pth,train_portion=train_portion)
    trees.append(tree)

animator = nonlib.recursive_tree_lib_crossval.classification_ensemble.Visualizer
(csvname)
animator.show_runs(trees)

```



Exercise 14.9. Limitation of trees outside their training range

Any tree, or ensemble of trees, fit to such a dataset will not allow for reliable predictions to be made *outside of the input region containing the original training data*. This is because outside of where the original training data is defined the tree predicts output *using a depth 1 tree* (a leaf in the case of a single tree). In other words, all predictions made outside of the original region of input are *constant*.

With the student data our input is *time*, and so any tree (or ensemble of trees) will produce a *constant* prediction for all future time periods outside the region of our original input data.

Exercise 14.10. Naive cross-validation

```
In [22]: ## This code cell will not be shown in the HTML version of this notebook
# create root stump
csvname = datapath + 'noisy_sin_sample.csv'
depth = 7
tree = nonlib.recursive_tree_lib_crossval.RegressionTree.RTree(csvname, depth, train_portion = 0.66)

# animate
demo = nonlib.recursive_tree_lib_crossval.regression_animator.Visualizer(csvname)
demo.animate_trees(tree)
```

Out[22]:

