How To Implement The Decision Tree Algorithm From Scratch In Python

by **Jason Brownlee** on November 9, 2016 in **Algorithms From Scratch**

Decision trees are a powerful prediction method and extremely popular.

They are popular because the final model is so easy to understand by practitioners and domain experts alike. The final decision tree can explain exactly why a specific prediction was made, making it very attractive for operational use.

Decision trees also provide the foundation for more advanced ensemble methods such as bagging, random forests and gradient boosting.

In this tutorial, you will discover how to implement the Classification And Regression Tree algorithm from scratch with Python.

After completing this tutorial, you will know:

- How to calculate and evaluate candidate split points in a data.
- How to arrange splits into a decision tree structure.
- How to apply the classification and regression tree algorithm to a real problem.

Let's get started.

- **Update Jan/2017**: Changed the calculation of fold_size in cross_validation_split() to always be an integer. Fixes issues with Python 3.
- **Update Feb/2017**: Fixed a bug in build_tree.

How To Implement The Decision Tree Algorithm From Scratch In Python
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Descriptions

This section provides a brief introduction to the Classification and Regression Tree algorithm and the Banknote dataset used in this tutorial.

Classification and Regression Trees

Classification and Regression Trees or CART for short is an acronym introduced by Leo Breiman to refer to Decision Tree algorithms that can be used for classification or regression predictive modeling problems.

We will focus on using CART for classification in this tutorial.

The representation of the CART model is a binary tree. This is the same binary tree from algorithms and data structures, nothing too fancy (each node can have zero, one or two child nodes).

A node represents a single input variable (X) and a split point on that variable, assuming the variable is numeric. The leaf nodes (also called terminal nodes) of the tree contain an output variable (y) which is used to make a prediction.

Once created, a tree can be navigated with a new row of data following each branch with the splits until a final prediction is made.

Creating a binary decision tree is actually a process of dividing up the input space. A greedy approach is used to divide the space called recursive binary splitting. This is a numerical procedure where all the values are lined up and different split points are tried and tested using a cost function.

The split with the best cost (lowest cost because we minimize cost) is selected. All input variables and all possible split points are evaluated and chosen in a greedy manner based on the cost function.

- **Regression**: The cost function that is minimized to choose split points is the sum squared error across all training samples that fall within the rectangle.
- **Classification**: The Gini cost function is used which provides an indication of how pure the nodes are, where node purity refers to how mixed the training data assigned to each node is.

Splitting continues until nodes contain a minimum number of training examples or a maximum tree depth is reached.

Banknote Dataset

The banknote dataset involves predicting whether a given banknote is authentic given a number of measures taken from a photograph.

The dataset contains 1,372 with 5 numeric variables. It is a classification problem with two classes (binary classification).

Below provides a list of the five variables in the dataset.

1. variance of Wavelet Transformed image (continuous).
2. skewness of Wavelet Transformed image (continuous).
3. kurtosis of Wavelet Transformed image (continuous).
4. entropy of image (continuous).
5. class (integer).

Below is a sample of the first 5 rows of the dataset

```
3.6216,8.6661,-2.8073,-0.44699,0
4.5459,8.1674,-2.4586,-1.4621,0
3.866,-2.6383,1.9242,0.10645,0
3.4566,9.5228,-4.0112,-3.5944,0
0.32924,-4.4552,4.5718,-0.9888,0
4.3684,9.6718,-3.9606,-3.1625,0
```

Using the Zero Rule Algorithm to predict the most common class value, the baseline accuracy on the problem is about 50%.

You can learn more and download the dataset from the UCI Machine Learning Repository.

Download the dataset and place it in your current working directory with the filename **data_**

Tutorial

This tutorial is broken down into 5 parts:

1. Gini Index.
2. Create Split.
3. Build a Tree.
4. Make a Prediction.

5. Banknote Case Study.

These steps will give you the foundation that you need to implement the CART algorithm from scratch and apply it to your own predictive modeling problems.

1. Gini Index

The Gini index is the name of the cost function used to evaluate splits in the dataset.

A split in the dataset involves one input attribute and one value for that attribute. It can be used to divide training patterns into two groups of rows.

A Gini score gives an idea of how good a split is by how mixed the classes are in the two groups created by the split. A perfect separation results in a Gini score of 0, whereas the worst case split that results in 50/50 classes in each group results in a Gini score of 1.0 (for a 2 class problem).

Calculating Gini is best demonstrated with an example.

We have two groups of data with 2 rows in each group. The rows in the first group all belong to class 0 and the rows in the second group belong to class 1, so it's a perfect split.

We first need to calculate the proportion of classes in each group.

```
proportion = count(class_value) / count(rows)
```

The proportions for this example would be:

```
group_1_class_0 = 2 / 2 = 1
group_1_class_1 = 0 / 2 = 0
group_2_class_0 = 0 / 2 = 0
group_2_class_1 = 2 / 2 = 1
```

Gini is then calculated as follows:

```
gini_index = sum(proportion * (1.0 - proportion))
```

Across all of the proportions calculated for each group and each class value. In our case, this would be calculated as:

```
gini_index =    (group_1_class_0 * (1.0 - group_1_class_0)) +
        (group_1_class_1 * (1.0 - group_1_class_1)) +
        (group_2_class_0 * (1.0 - group_2_class_0)) +
        (group_2_class_1 * (1.0 - group_2_class_1))
```

Or:

```
gini_index = 0 + 0 + 0 + 0 = 0
```

Below is a function named **gini_index()** the calculates the Gini index for a list of groups and a list of known class values.

You can see that there are some safety checks in there to avoid a divide by zero for an empty group.

```
# Calculate the Gini index for a split dataset
def gini_index(groups, class_values):
    gini = 0.0
    for class_value in class_values:
        for group in groups:
            size = len(group)
            if size == 0:
                continue
            proportion = [row[-1] for row in group].count(class_value) / float(size)
            gini += (proportion * (1.0 - proportion))
    return gini
```

We can test this function with our worked example above. We can also test it for the worst case of a 50/50 split in each group. The complete example is listed below.

```
# Calculate the Gini index for a split dataset
def gini_index(groups, class_values):
    gini = 0.0
    for class_value in class_values:
        for group in groups:
            size = len(group)
            if size == 0:
                continue
            proportion = [row[-1] for row in group].count(class_value) / float(
            gini += (proportion * (1.0 - proportion))
    return gini

# test Gini values
print(gini_index([[[1, 1], [1, 0]], [[1, 1], [1, 0]]], [0, 1]))
print(gini_index([[[1, 0], [1, 0]], [[1, 1], [1, 1]]], [0, 1]))
```

Running the example prints the two Gini scores, first the score for the worst case at 1.0 followed by the score for the best case at 0.0.

```
1.0
0.0
```

Now that we know how to evaluate the results of a split, let's look at creating splits.

2. Create Split

A split is comprised of an attribute in the dataset and a value.

We can summarize this as the index of an attribute to split and the value by which to split rows on that attribute. This is just a useful shorthand for indexing into rows of data.

Creating a split involves three parts, the first we have already looked at which is calculating the Gini score. The remaining two parts are:

1. Splitting a Dataset.
2. Evaluating All Splits.

Let's take a look at each.

2.1. Splitting a Dataset

Splitting a dataset means separating a dataset into two lists of rows given the index of an attribute and a split value for that attribute.

Once we have the two groups, we can then use our Gini score above to evaluate the cost of the split.

Splitting a dataset involves iterating over each row, checking if the attribute value is below or above the split value and assigning it to the left or right group respectively.

Below is a function named **test_split()** that implements this procedure.

```
# Split a dataset based on an attribute and an attribute value
def test_split(index, value, dataset):
    left, right = list(), list()
    for row in dataset:
        if row[index] < value:
            left.append(row)
        else:
            right.append(row)
    return left, right
```

Not much to it.

Note that the right group contains all rows with a value at the index above or equal to the split value.

2.2. Evaluating All Splits

With the Gini function above and the test split function we now have everything we need to evaluate splits.

Given a dataset, we must check every value on each attribute as a candidate split, evaluate the cost of the split and find the best possible split we could make.

Once the best split is found, we can use it as a node in our decision tree.

This is an exhaustive and greedy algorithm.

We will use a dictionary to represent a node in the decision tree as we can store data by name. When selecting the best split and using it as a new node for the tree we will store the index of the chosen attribute, the value of that attribute by which to split and the two groups of data split by the chosen split point.

Each group of data is its own small dataset of just those rows assigned to the left or right g ... w we might split each group again, recursively as we build out our decision tree.

Below is a function named **get_split()** that implements this procedure. You can see that it i ...) and then each value for that attribute, splitting and evaluating splits as it goes.

The best split is recorded and then returned after all checks are complete.

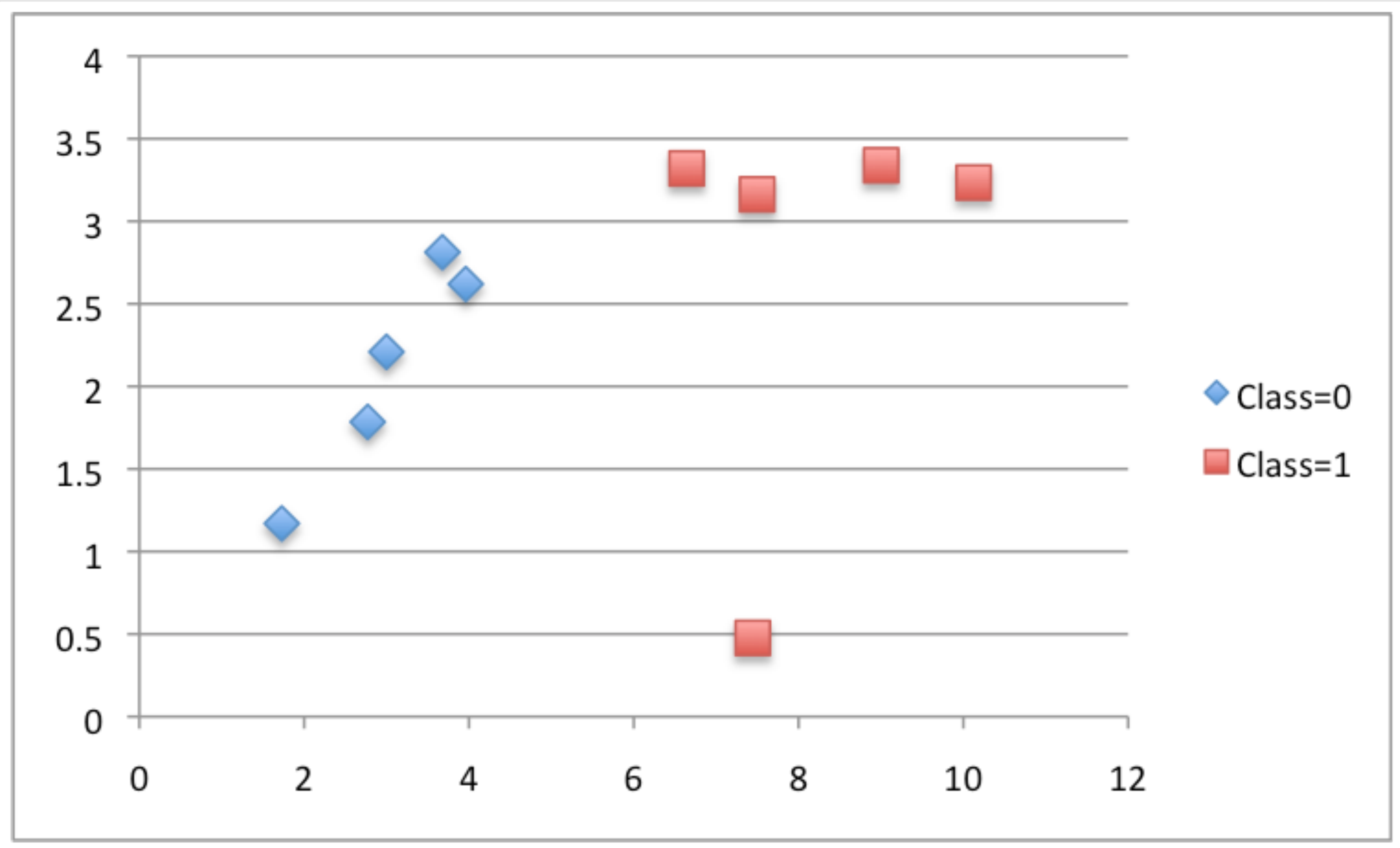

```
# Select the best split point for a dataset
def get_split(dataset):
    class_values = list(set(row[-1] for row in dataset))
    b_index, b_value, b_score, b_groups = 999, 999, 999, None
    for index in range(len(dataset[0])-1):
        for row in dataset:
            groups = test_split(index, row[index], dataset)
            gini = gini_index(groups, class_values)
```

```
            if gini < b_score:
                b_index, b_value, b_score, b_groups = index, row[index], gini, groups
    return {'index':b_index, 'value':b_value, 'groups':b_groups}
```

We can contrive a small dataset to test out this function and our whole dataset splitting process.

```
X1           X2           Y
2.771244718     1.784783929     0
1.728571309     1.169761413     0
3.678319846     2.81281357      0
3.961043357     2.61995032      0
2.999208922     2.209014212     0
7.497545867     3.162953546     1
9.00220326      3.339047188     1
7.444542326     0.476683375     1
10.12493903     3.234550982     1
6.642287351     3.319983761     1
```

We can plot this dataset using separate colors for each class. You can see that it would not be difficult to manually pick a value of X1 (x-axis on the plot) to split this dataset.



CART Contrived Dataset

The example below puts all of this together.

```
# Split a dataset based on an attribute and an attribute value
def test_split(index, value, dataset):
    left, right = list(), list()
    for row in dataset:
        if row[index] < value:
            left.append(row)
        else:
            right.append(row)
    return left, right

# Calculate the Gini index for a split dataset
def gini_index(groups, class_values):
    gini = 0.0
    for class_value in class_values:
        for group in groups:
            size = len(group)
            if size == 0:
                continue
            proportion = [row[-1] for row in group].count(class_value) / float(
            gini += (proportion * (1.0 - proportion))
    return gini

# Select the best split point for a dataset
def get_split(dataset):
    class_values = list(set(row[-1] for row in dataset))
    b_index, b_value, b_score, b_groups = 999, 999, 999, None
    for index in range(len(dataset[0])-1):
        for row in dataset:
            groups = test_split(index, row[index], dataset)
            gini = gini_index(groups, class_values)
            print('X%d < %.3f Gini=%.3f' % ((index+1), row[index], gini))
            if gini < b_score:
                b_index, b_value, b_score, b_groups = index, row[index], gini,
    return {'index':b_index, 'value':b_value, 'groups':b_groups}

dataset = [[2.771244718,1.784783929,0],
    [1.728571309,1.169761413,0],
```

```
    [3.678319846,2.81281357,0],
    [3.961043357,2.61995032,0],
    [2.999208922,2.209014212,0],
    [7.497545867,3.162953546,1],
    [9.00220326,3.339047188,1],
    [7.444542326,0.476683375,1],
    [10.12493903,3.234550982,1],
    [6.642287351,3.319983761,1]]
split = get_split(dataset)
print('Split: [X%d < %.3f]' % ((split['index']+1), split['value']))
```

The **get_split()** function was modified to print out each split point and it's Gini index as it was evaluated.

Running the example prints all of the Gini scores and then prints the score of best split in the dataset of X1 < 6.642 with a Gini Index of 0.0 or a perfect split.

```
X1 < 2.771 Gini=0.494
X1 < 1.729 Gini=0.500
X1 < 3.678 Gini=0.408
X1 < 3.961 Gini=0.278
X1 < 2.999 Gini=0.469
X1 < 7.498 Gini=0.408
X1 < 9.002 Gini=0.469
X1 < 7.445 Gini=0.278
X1 < 10.125 Gini=0.494
X1 < 6.642 Gini=0.000
X2 < 1.785 Gini=1.000
X2 < 1.170 Gini=0.494
X2 < 2.813 Gini=0.640
X2 < 2.620 Gini=0.819
X2 < 2.209 Gini=0.934
X2 < 3.163 Gini=0.278
X2 < 3.339 Gini=0.494
X2 < 0.477 Gini=0.500
X2 < 3.235 Gini=0.408
X2 < 3.320 Gini=0.469
Split: [X1 < 6.642]
```

Now that we know how to find the best split points in a dataset or list of rows, let's see how we can use it to build out a decision tree.

3. Build a Tree

Creating the root node of the tree is easy.

We call the above **get_split()** function using the entire dataset.

Adding more nodes to our tree is more interesting.

Building a tree may be divided into 3 main parts:

1. Terminal Nodes.
2. Recursive Splitting.
3. Building a Tree.

3.1. Terminal Nodes

We need to decide when to stop growing a tree.

We can do that using the depth and the number of rows that the node is responsible for in the training dataset.

- **Maximum Tree Depth**. This is the maximum number of nodes from the root node of the tree. Once a maximum depth of the tree is met, we must stop splitting adding new nodes. Deeper trees are more complex and are more likely to overfit the training data.
- **Minimum Node Records**. This is the minimum number of training patterns that a given node is responsible for. Once at or below this minimum, we must stop splitting and adding new nodes. Nodes that account for too few training patterns are expected to be too specific and are likely to overfit the training data.

These two approaches will be user-specified arguments to our tree building procedure.

There is one more condition. It is possible to choose a split in which all rows belong to one
splitting and adding child nodes as we will have no records to split on one side or another.

Now we have some ideas of when to stop growing the tree. When we do stop growing at a … nd
is used to make a final prediction.

This is done by taking the group of rows assigned to that node and selecting the most com
make predictions.

Below is a function named **to_terminal()** that will select a class value for a group of rows. I … f
rows.

```
# Create a terminal node value
def to_terminal(group):
    outcomes = [row[-1] for row in group]
    return max(set(outcomes), key=outcomes.count)
```

3.2. Recursive Splitting

We know how and when to create terminal nodes, now we can build our tree.

Building a decision tree involves calling the above developed **get_split()** function over and over again on the groups created for each node.

New nodes added to an existing node are called child nodes. A node may have zero children (a terminal node), one child (one side makes a prediction directly) or two child nodes. We will refer to the child nodes as left and right in the dictionary representation of a given node.

Once a node is created, we can create child nodes recursively on each group of data from the split by calling the same function again.

Below is a function that implements this recursive procedure. It takes a node as an argument as well as the maximum depth, minimum number of patterns in a node and the current depth of a node.

You can imagine how this might be first called passing in the root node and the depth of 1. This function is best explained in steps:

1. Firstly, the two groups of data split by the node are extracted for use and deleted from the node. As we work on these groups the node no longer requires access to these data.
2. Next, we check if either left or right group of rows is empty and if so we create a terminal node using what records we do have.
3. We then check if we have reached our maximum depth and if so we create a terminal node.
4. We then process the left child, creating a terminal node if the group of rows is too small, otherwise creating and adding the left node in a depth first fashion until the bottom of the tree is reached on this branch.
5. The right side is then processed in the same manner, as we rise back up the constructed tree to the root.

```
# Create child splits for a node or make terminal
def split(node, max_depth, min_size, depth):
    left, right = node['groups']
    del(node['groups'])
    # check for a no split
    if not left or not right:
        node['left'] = node['right'] = to_terminal(left + right)
        return
    # check for max depth
    if depth >= max_depth:
        node['left'], node['right'] = to_terminal(left), to_terminal(right)
        return
    # process left child
    if len(left) <= min_size:
        node['left'] = to_terminal(left)
    else:
        node['left'] = get_split(left)
        split(node['left'], max_depth, min_size, depth+1)
    # process right child
    if len(right) <= min_size:
        node['right'] = to_terminal(right)
    else:
        node['right'] = get_split(right)
        split(node['right'], max_depth, min_size, depth+1)
```

3.3. Building a Tree

We can now put all of the pieces together.

Building the tree involves creating the root node and calling the **split()** function that then calls itself recursively to build out the whole tree.

Below is the small **build_tree()** function that implements this procedure.

```
# Build a decision tree
def build_tree(train, max_depth, min_size):
    root = get_split(train)
    split(root, max_depth, min_size, 1)
    return root
```

We can test out this whole procedure using the small dataset we contrived above.

Below is the complete example.

Also included is a small **print_tree()** function that recursively prints out nodes of the decisi
striking as a real decision tree diagram, it gives an idea of the tree structure and decisions

```
# Split a dataset based on an attribute and an attribute value
def test_split(index, value, dataset):
    left, right = list(), list()
    for row in dataset:
        if row[index] < value:
            left.append(row)
```

```
        else:
            right.append(row)
    return left, right

# Calculate the Gini index for a split dataset
def gini_index(groups, class_values):
    gini = 0.0
    for class_value in class_values:
        for group in groups:
            size = len(group)
            if size == 0:
                continue
            proportion = [row[-1] for row in group].count(class_value) / float(size)
            gini += (proportion * (1.0 - proportion))
    return gini

# Select the best split point for a dataset
def get_split(dataset):
    class_values = list(set(row[-1] for row in dataset))
    b_index, b_value, b_score, b_groups = 999, 999, 999, None
    for index in range(len(dataset[0])-1):
        for row in dataset:
            groups = test_split(index, row[index], dataset)
            gini = gini_index(groups, class_values)
            if gini < b_score:
                b_index, b_value, b_score, b_groups = index, row[index], gini, groups
    return {'index':b_index, 'value':b_value, 'groups':b_groups}

# Create a terminal node value
def to_terminal(group):
    outcomes = [row[-1] for row in group]
    return max(set(outcomes), key=outcomes.count)

# Create child splits for a node or make terminal
def split(node, max_depth, min_size, depth):
    left, right = node['groups']
    del(node['groups'])
    # check for a no split
    if not left or not right:
        node['left'] = node['right'] = to_terminal(left + right)
        return
    # check for max depth
    if depth >= max_depth:
        node['left'], node['right'] = to_terminal(left), to_terminal(right)
        return
    # process left child
    if len(left) <= min_size:
        node['left'] = to_terminal(left)
    else:
        node['left'] = get_split(left)
        split(node['left'], max_depth, min_size, depth+1)
    # process right child
    if len(right) <= min_size:
        node['right'] = to_terminal(right)
    else:
        node['right'] = get_split(right)
        split(node['right'], max_depth, min_size, depth+1)

# Build a decision tree
def build_tree(train, max_depth, min_size):
    root = get_split(train)
    split(root, max_depth, min_size, 1)
    return root

# Print a decision tree
def print_tree(node, depth=0):
    if isinstance(node, dict):
        print('%s[X%d < %.3f]' % ((depth*' ', (node['index']+1), node['value'])))
        print_tree(node['left'], depth+1)
        print_tree(node['right'], depth+1)
    else:
        print('%s[%s]' % ((depth*' ', node)))

dataset = [[2.771244718,1.784783929,0],
    [1.728571309,1.169761413,0],
    [3.678319846,2.81281357,0],
    [3.961043357,2.61995032,0],
    [2.999208922,2.209014212,0],
    [7.497545867,3.162953546,1],
    [9.00220326,3.339047188,1],
    [7.444542326,0.476683375,1],
    [10.12493903,3.234550982,1],
    [6.642287351,3.319983761,1]]
tree = build_tree(dataset, 1, 1)
print_tree(tree)
```

We can vary the maximum depth argument as we run this example and see the effect on t

With a maximum depth of 1 (the second parameter in the call to the **build_tree()** function), discovered in the previous section. This is a tree with one node, also called a decision stur

```
[X1 < 6.642]
 [0]
 [1]
```

Increasing the maximum depth to 2, we are forcing the tree to make splits even when none are required. The **X1** attribute is then used again by both the left and right children of the root node to split up the already perfect mix of classes.

```
[X1 < 6.642]
 [X1 < 2.771]
  [0]
  [0]
 [X1 < 7.498]
  [1]
  [1]
```

Finally, and perversely, we can force one more level of splits with a maximum depth of 3.

```
[X1 < 6.642]
 [X1 < 2.771]
  [0]
  [X1 < 2.771]
   [0]
   [0]
 [X1 < 7.498]
  [X1 < 7.445]
   [1]
   [1]
  [X1 < 7.498]
   [1]
   [1]
```

These tests show that there is great opportunity to refine the implementation to avoid unnecessary splits. This is left as an extension.

Now that we can create a decision tree, let's see how we can use it to make predictions on new data.

4. Make a Prediction

Making predictions with a decision tree involves navigating the tree with the specifically provided row of data.

Again, we can implement this using a recursive function, where the same prediction routine is called again with the left or the right child nodes, depending on how the split affects the provided data.

We must check if a child node is either a terminal value to be returned as the prediction, or if it is a dictionary node containing another level of the tree to be considered.

Below is the **predict()** function that implements this procedure. You can see how the index and value in a given node

You can see how the index and value in a given node is used to evaluate whether the row of provided data falls on the left or the right of the split.

```python
# Make a prediction with a decision tree
def predict(node, row):
    if row[node['index']] < node['value']:
        if isinstance(node['left'], dict):
            return predict(node['left'], row)
        else:
            return node['left']
    else:
        if isinstance(node['right'], dict):
            return predict(node['right'], row)
        else:
            return node['right']
```

We can use our contrived dataset to test this function. Below is an example that uses a hard-coded decision tree with a single node that best splits the data (a decision stump).

The example makes a prediction for each row in the dataset.

```python
# Make a prediction with a decision tree
def predict(node, row):
    if row[node['index']] < node['value']:
        if isinstance(node['left'], dict):
            return predict(node['left'], row)
        else:
            return node['left']
    else:
        if isinstance(node['right'], dict):
            return predict(node['right'], row)
        else:
            return node['right']

dataset = [[2.771244718,1.784783929,0],
    [1.728571309,1.169761413,0],
    [3.678319846,2.81281357,0],
    [3.961043357,2.61995032,0],
    [2.999208922,2.209014212,0],
    [7.497545867,3.162953546,1],
    [9.00220326,3.339047188,1],
    [7.444542326,0.476683375,1],
```

```
    [10.12493903,3.234550982,1],
    [6.642287351,3.319983761,1]]

#  predict with a stump
stump = {'index': 0, 'right': 1, 'value': 6.642287351, 'left': 0}
for row in dataset:
    prediction = predict(stump, row)
    print('Expected=%d, Got=%d' % (row[-1], prediction))
```

Running the example prints the correct prediction for each row, as expected.

```
Expected=0, Got=0
Expected=0, Got=0
Expected=0, Got=0
Expected=0, Got=0
Expected=0, Got=0
Expected=1, Got=1
Expected=1, Got=1
Expected=1, Got=1
Expected=1, Got=1
Expected=1, Got=1
```

We now know how to create a decision tree and use it to make predictions. Now, let's apply it to a real dataset.

5. Banknote Case Study

This section applies the CART algorithm to the Bank Note dataset.

The first step is to load the dataset and convert the loaded data to numbers that we can use to calculate split points. For this we will use the helper function **load_csv()** to load the file and **str_column_to_float()** to convert string numbers to floats.

We will evaluate the algorithm using k-fold cross-validation with 5 folds. This means that 1372/5=274.4 or just over 270 records will be used in each fold. We will use the helper functions **evaluate_algorithm()** to evaluate the algorithm with cross-validation and **accuracy_metric()** to calculate the accuracy of predictions.

A new function named **decision_tree()** was developed to manage the application of the CART algorithm, first creating the tree from the training dataset, then using the tree to make predictions on a test dataset.

The complete example is listed below.

```
# CART on the Bank Note dataset
from random import seed
from random import randrange
from csv import reader

# Load a CSV file
def load_csv(filename):
    file = open(filename, "rb")
    lines = reader(file)
    dataset = list(lines)
    return dataset

# Convert string column to float
def str_column_to_float(dataset, column):
    for row in dataset:
        row[column] = float(row[column].strip())

# Split a dataset into k folds
def cross_validation_split(dataset, n_folds):
    dataset_split = list()
    dataset_copy = list(dataset)
    fold_size = int(len(dataset) / n_folds)
    for i in range(n_folds):
        fold = list()
        while len(fold) < fold_size:
            index = randrange(len(dataset_copy))
            fold.append(dataset_copy.pop(index))
        dataset_split.append(fold)
    return dataset_split

# Calculate accuracy percentage
def accuracy_metric(actual, predicted):
    correct = 0
    for i in range(len(actual)):
        if actual[i] == predicted[i]:
            correct += 1
    return correct / float(len(actual)) * 100.0

# Evaluate an algorithm using a cross validation split
def evaluate_algorithm(dataset, algorithm, n_folds, *args):
    folds = cross_validation_split(dataset, n_folds)
    scores = list()
    for fold in folds:
        train_set = list(folds)
        train_set.remove(fold)
        train_set = sum(train_set, [])
        test_set = list()
        for row in fold:
            row_copy = list(row)
```

```
            test_set.append(row_copy)
            row_copy[-1] = None
        predicted = algorithm(train_set, test_set, *args)
        actual = [row[-1] for row in fold]
        accuracy = accuracy_metric(actual, predicted)
        scores.append(accuracy)
    return scores

# Split a dataset based on an attribute and an attribute value
def test_split(index, value, dataset):
    left, right = list(), list()
    for row in dataset:
        if row[index] < value:
            left.append(row)
        else:
            right.append(row)
    return left, right

# Calculate the Gini index for a split dataset
def gini_index(groups, class_values):
    gini = 0.0
    for class_value in class_values:
        for group in groups:
            size = len(group)
            if size == 0:
                continue
            proportion = [row[-1] for row in group].count(class_value) / float(size)
            gini += (proportion * (1.0 - proportion))
    return gini

# Select the best split point for a dataset
def get_split(dataset):
    class_values = list(set(row[-1] for row in dataset))
    b_index, b_value, b_score, b_groups = 999, 999, 999, None
    for index in range(len(dataset[0])-1):
        for row in dataset:
            groups = test_split(index, row[index], dataset)
            gini = gini_index(groups, class_values)
            if gini < b_score:
                b_index, b_value, b_score, b_groups = index, row[index], gini, groups
    return {'index':b_index, 'value':b_value, 'groups':b_groups}

# Create a terminal node value
def to_terminal(group):
    outcomes = [row[-1] for row in group]
    return max(set(outcomes), key=outcomes.count)

# Create child splits for a node or make terminal
def split(node, max_depth, min_size, depth):
    left, right = node['groups']
    del(node['groups'])
    # check for a no split
    if not left or not right:
        node['left'] = node['right'] = to_terminal(left + right)
        return
    # check for max depth
    if depth >= max_depth:
        node['left'], node['right'] = to_terminal(left), to_terminal(right)
        return
    # process left child
    if len(left) <= min_size:
        node['left'] = to_terminal(left)
    else:
        node['left'] = get_split(left)
        split(node['left'], max_depth, min_size, depth+1)
    # process right child
    if len(right) <= min_size:
        node['right'] = to_terminal(right)
    else:
        node['right'] = get_split(right)
        split(node['right'], max_depth, min_size, depth+1)

# Build a decision tree
def build_tree(train, max_depth, min_size):
    root = get_split(train)
    split(root, max_depth, min_size, 1)
    return root

# Make a prediction with a decision tree
def predict(node, row):
    if row[node['index']] < node['value']:
        if isinstance(node['left'], dict):
            return predict(node['left'], row)
        else:
            return node['left']
    else:
        if isinstance(node['right'], dict):
            return predict(node['right'], row)
        else:
            return node['right']

# Classification and Regression Tree Algorithm
def decision_tree(train, test, max_depth, min_size):
    tree = build_tree(train, max_depth, min_size)
    predictions = list()
    for row in test:
```

```
        prediction = predict(tree, row)
        predictions.append(prediction)
    return(predictions)

# Test CART on Bank Note dataset
seed(1)
# load and prepare data
filename = 'data_banknote_authentication.csv'
dataset = load_csv(filename)
# convert string attributes to integers
for i in range(len(dataset[0])):
    str_column_to_float(dataset, i)
# evaluate algorithm
n_folds = 5
max_depth = 5
min_size = 10
scores = evaluate_algorithm(dataset, decision_tree, n_folds, max_depth, min_size)
print('Scores: %s' % scores)
print('Mean Accuracy: %.3f%%' % (sum(scores)/float(len(scores))))
```

The example uses the max tree depth of 5 layers and the minimum number of rows per node to 10. These parameters to CART were chosen with a little experimentation, but are by no means are they optimal.

Running the example prints the average classification accuracy on each fold as well as the average performance across all folds.

You can see that CART and the chosen configuration achieved a mean classification accuracy of about 83% which is dramatically better than the Zero Rule algorithm that achieved 50% accuracy.

```
Scores: [83.57664233576642, 82.84671532846716, 86.86131386861314, 79.92700729927007, 82.11678832116789]
Mean Accuracy: 83.066%
```

Extensions

This section lists extensions to this tutorial that you may wish to explore.

- **Algorithm Tuning**. The application of CART to the Bank Note dataset was not tuned. Experiment with different parameter values and see if you can achieve better performance.
- **Cross Entropy**. Another cost function for evaluating splits is cross entropy (logloss). You could implement and experiment with this alternative cost function.
- **Tree Pruning**. An important technique for reducing overfitting of the training dataset is to prune the trees. Investigate and implement tree pruning methods.
- **Categorical Dataset**. The example was designed for input data with numerical or ordinal input attributes, experiment with categorical input data and splits that may use equality instead of ranking.
- **Regression**. Adapt the tree for regression using a different cost function and method for creating terminal nodes.
- **More Datasets**. Apply the algorithm to more datasets on the UCI Machine Learning Repository.

Did you explore any of these extensions?
Share your experiences in the comments below.

Review

In this tutorial, you discovered how to implement the decision tree algorithm from scratch with Python.

Specifically, you learned:

- How to select and evaluate split points in a training dataset.
- How to recursively build a decision tree from multiple splits.
- How to apply the CART algorithm to a real world classification predictive modeling problem.

Do you have any questions?
Ask your questions in the comments below and I will do my

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About Jason Brownlee

Dr. Jason Brownlee is a husband, proud father, academic researcher, author, professional developer and a machine learning practitioner. He is dedicated to helping developers get started and get good at applied machine learning. Learn more.
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60 Responses to *How To Implement The Decision Tree Algorithm From Scratch In Python*

steve November 23, 2016 at 4:02 am # REPLY

Super good .. Thanks a lot for sharing

Jason Brownlee November 23, 2016 at 9:01 am # REPLY

I'm glad you found it useful steve.

jonathan November 27, 2016 at 9:22 am # REPLY

can this code be used for a multinomial Decision tree dataset?

Jason Brownlee November 27, 2016 at 10:22 am # REPLY

It can with some modification.

STORM RICK November 29, 2016 at 1:02 am # REPLY

What modifications would you recommend?

Jason Brownlee November 29, 2016 at 8:53 am # REPLY

Specifically the handling of evaluating and selecting nominal values at split points.

Mike December 24, 2016 at 2:48 pm #

Thanks for detailed description and code.

I tried to run and got 'ValueError: empty range for randrange()' in line 26:

index = randrange(len(dataset_copy))

if replace dataset_copy to list(dataset) and run this line manually it works.

Jason Brownlee December 26, 2016 at 7:39 am # REPLY

Sounds like a Python 3 issue Mike.

Replace

```
fold_size = len(dataset) / n_folds
```

With:

```
fold_size = int(len(dataset) / n_folds)
```

Jason Brownlee January 3, 2017 at 9:53 am # REPLY

I have updated the cross_validation_split() function in the above example to address issues with Python 3.

Mohendra Roy January 4, 2017 at 12:32 am # REPLY

How about to use of euclidian distance instead of calculating for each element in the dataset?

Jason Brownlee January 4, 2017 at 8:55 am # REPLY

What do you mean exactly? Are you able to elaborate?

Selva Rani B January 12, 2017 at 4:43 pm # REPLY

Thank you very much

Jason Brownlee January 13, 2017 at 9:09 am # REPLY

You're welcome.

Sokrates January 21, 2017 at 4:10 am # REPLY

Hi Jason,

Great tutorial on CART!

The results of decision trees are quite dependent on the training vs test data. With this in mind, how do I set the amount of training vs test data in the code right now to changes in the result? From what I can see, it looks like they are being set in the evaluate_algorithm method.

//Kind regards
Sokrates

Jason Brownlee January 21, 2017 at 10:37 am # REPLY

That is correct Sokrates.

The example uses k-fold cross validation to evaluate the performance of the algorithm on the dataset.

You can change the number of folds by setting the "n_folds" variable.

You can use a different resampling method, like train/test splits, see this post:
http://machinelearningmastery.com/implement-resampling-methods-scratch-python/

Adeshina Alani January 27, 2017 at 3:52 am # REPLY

Nice Post. I will like to ask if i this implementation can be used for time series data wi

Jason Brownlee January 27, 2017 at 12:13 pm # REPLY

Yes it could, but the time series data would have to be re-framed as a supervised learning problem.

See this post for more information:
http://machinelearningmastery.com/time-series-forecasting-supervised-learning/

vishal January 30, 2017 at 5:06 am # REPLY

Really helpful. Thanks a lot for sharing.

Jason Brownlee February 1, 2017 at 10:18 am # REPLY

I'm glad you found the post useful vishal.

elberiver February 3, 2017 at 6:02 pm # REPLY

Hi Jason,

there is a minor point in your code. Specifically, in the follwing procedure:

——

# Build a decision tree
def build_tree(train, max_depth, min_size):
root = get_split(dataset)
split(root, max_depth, min_size, 1)
return root

——

I think it should be root = get_split(train), eventhough your code is still running correctly since dataset is the global variable.

Thank you for your nice posts.
I like your blog very much.

Jason Brownlee February 4, 2017 at 9:59 am # REPLY

I think you're right, nice catch!

I'll investigate and fix up the example.

from Thailand March 8, 2017 at 2:35 pm # REPLY

Thanks a lot Jason, really helpful

Jason Brownlee March 9, 2017 at 9:52 am # REPLY

I'm glad to hear that.

Amit Moondra April 2, 2017 at 6:31 am # REPLY

I'm slowly going through your code and I'm confused about a line in your get_split fu

groups = test_split(index, row[index], dataset)

Doesn't this only return the left group? It seems we need both groups to calculate the gini_ind

Thank you.

Jason Brownlee April 2, 2017 at 6:34 am # REPLY

Hi Amit,

The get_split() function evaluates all possible split points and returns a dict of the best found split point, gini score, split data.

Amit Moondra April 2, 2017 at 12:15 pm # REPLY

After playing around with the code for a bit, I realized that function returns both groups (left and right) under one variable.

Amit Moondra April 2, 2017 at 9:59 am # REPLY

In the function split

if not left or not right:
node['left'] = node['right'] = to_terminal(left + right)
return

Why do you add (left + right)? Are you adding the two groups together into one group?

Thank you.

Jason Brownlee April 4, 2017 at 9:05 am # REPLY

Yes.

Amit Moondra April 2, 2017 at 12:30 pm # REPLY

Another question (line 132)

if isinstance(node['left'], dict):
return predict(node['left'], row)

isinstance is just checking if we have already created such a dictionary instance?

Thank you.

Jason Brownlee April 4, 2017 at 9:05 am # REPLY

It is checking if the type of the variable is a dict.

Ann April 3, 2017 at 9:25 am # REPLY

Hello,

I've been trying some stuff out with this code and I thought I was understanding what was going on but when I tried it on a dataset with binary values it doesn't seem to work and I can't figure out why. Could you help me out please?

Thanks.

Jason Brownlee April 4, 2017 at 9:11 am #

The example assumes real-valued inputs, binary or categorical inputs should be

I don't have an example at hand, sorry.

Dimple April 17, 2017 at 1:37 am # REPLY

Hi

Could you tell me how decision trees are used for predicting an unknown function when a sample dataset is given. What i mean how it is used for regression?

Jason Brownlee April 17, 2017 at 5:15 am # REPLY

Good question, sorry, I don't have an example of decision trees for regression from scratch.

Dimple April 17, 2017 at 10:18 am # REPLY

How can we use weka for regression using decision trees?

Jason Brownlee April 18, 2017 at 8:28 am # REPLY

Consider using the search function of this blog.

See this post:
http://machinelearningmastery.com/use-regression-machine-learning-algorithms-weka/

Joe April 18, 2017 at 1:31 am # REPLY

Great article, this is exactly what I was looking for!

Jason Brownlee April 18, 2017 at 8:33 am # REPLY

I'm really glad to hear that Joe!

ansar April 19, 2017 at 3:13 am # REPLY

I am new to machine learning … successfully ran the code with the given data set

Now I want to run it for my own data set … will the algo always treat the last column as the column to classify?

thanks

Jason Brownlee April 19, 2017 at 7:54 am # REPLY

Yes, that is how it was coded.

Ansar April 20, 2017 at 2:53 am # REPLY

Thank you! It works beautifully

Jason Brownlee April 20, 2017 at 9:32 am #

Well done!

Ansar April 21, 2017 at 10:22 pm # REPLY

Apologies if I am taking too much time but I tried to run this algo on the below scenar

#
#https://www.youtube.com/watch?v=eKD5gxPPeY0&list=PLBv09BD7ez_4temBw7vLA19p3td
#

#outlook
#
#1 = sunny
#2 = overcast
#3 = rain
#
#humidity
#
#1 = high
#2 = normal
#
#wind
#
#1 = weak
#2 = strong
#
#play
#
#0 = no
#1 = yes

The tree generated does not cater to x2, x3 variables (for some reason), just generates for x1 (what am I doing wrong?) … the accuracy has dropped to 60%

[X1 < 1.000]
[1.0]
[1.0]
[X1 < 1.000]
[1.0]
[1.0]
[X1 < 1.000]
[1.0]
[1.0]
[X1 < 1.000]
[1.0]
[1.0]
[X1 < 3.000]
[X1 < 1.000]
[1.0]
[1.0]
[0.0]
[X1 < 1.000]
[1.0]
[1.0]
[X1 < 1.000]
[1.0]
[1.0]
[X1 < 1.000]
[1.0]
[1.0]
[X1 < 1.000]
[1.0]
[1.0]
[X1 < 1.000]
[1.0]
[1.0]
Scores: [100.0, 100.0, 0.0, 100.0, 0.0, 100.0, 0.0, 0.0, 100.0, 100.0]
Mean Accuracy: 60.000%

Jason Brownlee April 22, 2017 at 9:26 am #

Ensure that you have loaded your data correctly.

Ansar April 25, 2017 at 3:01 am #

Yes, working fine now □

REPLY

Would love to get my hands on a script that would print the tree in a more graphical (readable) format. The current format helps but does get confusing at times.

Thanks a lot!

Greg May 6, 2017 at 10:15 am # REPLY

This will generate a graphviz dot file that you can use to generate a .pnj, jpeg etc.

e.g:

dot -Tpng graph1.dot > graph.png

Note it generates a new file each time it is called – graph1.dot … graphN.dot

code begin

```
def graph_node(f, node):
if isinstance(node, dict):
f.write(' %d [label=\"[X%d %d;\n' % ((id(node), id(node['left']))))
f.write(' %d -> %d;\n' % ((id(node), id(node['right']))))
graph_node(f, node['left'])
graph_node(f, node['right'])
else:
f.write(' %d [label=\"[%s]\"];\n' % ((id(node), node)))

def graph_tree(node):
if not hasattr(graph_tree, 'n'): graph_tree.n = 0
graph_tree.n += 1
fn = 'graph' + str(graph_tree.n) + '.dot'
f = open(fn, 'w')
f.write('digraph {\n')
f.write(' node[shape=box];\n')
graph_node(f, node)
f.write('}\n')
```

katana April 28, 2017 at 1:27 am # REPLY

Thanks a lot for this, Dr. Brownlee!

Jason Brownlee April 28, 2017 at 7:47 am # REPLY

I'm glad you found it useful.

godavari May 4, 2017 at 11:08 pm # REPLY

excellent explanation

Jason Brownlee May 5, 2017 at 7:31 am # REPLY

I'm glad you found it useful.

King Deng May 14, 2017 at 7:15 am #

I'm implementing AdaBoost from scratch now, and I have a tough time understanding iteration to build the decision tree? I guess I should modify the gini index in this regard, but I'm some light? Thanks!

Jason Brownlee May 14, 2017 at 7:35 am # REPLY

I offer a step-by-step example in this book:
https://machinelearningmastery.com/master-machine-learning-algorithms/

I would also recommend this book for a great explanation:
http://www-bcf.usc.edu/~gareth/ISL/

Pavithra May 19, 2017 at 7:10 pm # REPLY

Part of the code: predicted = algorithm(train_set, test_set, *args)

TypeError: 'int' object is not callable

Issue: I'm getting error like this. Please help me

Jason Brownlee May 20, 2017 at 5:36 am # REPLY

I'm sorry to hear that.

Ensure that you have copied all of the code without any extra white space.

Luis llabaca May 25, 2017 at 9:23 am # REPLY

hey jason

honestly dude stuff like this is no joke man.

I did BA in math and one year of MA in math
then MA in Statistical Computing and Data Mining
and then sas certifications and a lot of R and man let me tell you,
when I read your work and see how you have such a strong understanding of the unifications of all the different fields needed to be successful at applying machine learning.

you my friend, are a killer.

Jason Brownlee June 2, 2017 at 11:40 am # REPLY

Thanks.

Saurabh May 25, 2017 at 7:16 pm # REPLY

Hello Sir!!
First of all Thank You for such a great tutorial.

I would like to make a suggestion for function get_split()-
In this function instead of calculating gini index considering every value of that attribute in data set , we can just use the mean of that attribute as the split_value for test_split function.

This is just my idea please do correct me if this approach is wrong.

Thank You!!

Jason Brownlee June 2, 2017 at 11:43 am #

Try it and see.

Habiba June 4, 2017 at 6:36 am #

REPLY

Hello Sir,
I am a student and i need to develop an algorithm for both Decision Tree and Ensemble(Preferably,Random Forest) both using python and R. i really need the book that contains everything that is,the super bundle.

Thank you so very much for the post and the tutorials. They have been really helpful.

Jason Brownlee June 4, 2017 at 7:55 am #

REPLY

You can grab the super bundle here:
https://machinelearningmastery.com/super-bundle/

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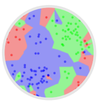
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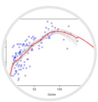
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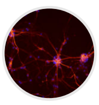
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