# Decision Trees for classifying mushrooms

Implementing a decision tree from scratch and applying it to the task of classifying whether a mushroom is edible or poisonous(based on it's physical attributes).

## steps followed by code:

- 1- Dataset --> One hot encoded dataset
- 2- Decision Tree Refresher
  - Calculate entropy
  - Split dataset
  - Calculate information gain
  - Get best split
- 3- Building the tree

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
from public_tests_tree import *
from utils_tree import *

%matplotlib inline
```

## 1- Dataset:

- There are 10 examples of mushrooms in this dataset. For each example, there are:
  - **Three features**
    - Cap Color (Brown or Red),
    - Stalk Shape (Tapering (as in \ / ) or Enlarging (as in /\ ), and
    - Solitary (Yes or No)
  - **Label**
    - Edible (1 indicating yes or 0 indicating poisonous)

### One hot encoded dataset:

| | Brown Cap | Tapering Stalk Shape | Solitary | Edible |
|---|---|---|---|---|
|  | 1 | 1 | 1 | 1 |
|  | 1 | 0 | 1 | 1 |
|  | 1 | 0 | 0 | 0 |
|  | 1 | 0 | 0 | 0 |
|  | 1 | 1 | 1 | 1 |
|  | 0 | 1 | 1 | 0 |
|  | 0 | 0 | 0 | 0 |
|  | 1 | 0 | 1 | 1 |
|  | 0 | 1 | 0 | 1 |
|  | 1 | 0 | 0 | 0 |

- **X_train** contains three features for each example
    - Brown Color (A value of **1** indicates "Brown" cap color and **0** indicates "Red" cap color)
    - Tapering Shape (A value of **1** indicates "Tapering Stalk Shape" and **0** indicates "Enlarging" stalk shape)
    - Solitary (A value of **1** indicates "Yes" and **0** indicates "No")
- **y_train** is whether the mushroom is edible
    - **y = 1** indicates edible
    - **y = 0** indicates poisonous

In [2]:
```
X_train = np.array([[1,1,1],[1,0,1],[1,0,0],[1,0,0],[1,1,1],[0,1,1],[0,0,0],[1,0,1],[0,1
y_train = np.array([1,1,0,0,1,0,0,1,1,0])
```

The code below prints the first few elements of X_train and the type of the variable:

In [3]:
```
print("First few elements of X_train:\n", X_train[:5])
print("Type of X_train:",type(X_train))
```

```
First few elements of X_train:
 [[1 1 1]
 [1 0 1]
 [1 0 0]
 [1 0 0]
 [1 1 1]]
Type of X_train: <class 'numpy.ndarray'>
```

The code below prints the first few elements of Y_train and the type of the variable:

In [4]:
```
print("First few elements of y_train:", y_train[:5])
print("Type of y_train:",type(y_train))
```

```
First few elements of y_train: [1 1 0 0 1]
Type of y_train: <class 'numpy.ndarray'>
```

### Check the dimensions of your variables:

In [5]:
```
print ('The shape of X_train is:', X_train.shape)
print ('The shape of y_train is: ', y_train.shape)
print ('Number of training examples (m):', len(X_train))
```

```
The shape of X_train is: (10, 3)
The shape of y_train is:  (10,)
Number of training examples (m): 10
```

## 2 - Decision Tree Refresher:

Building a decision tree based on the dataset provided,

- **The steps for building a decision tree are as follows:**
    - Starting with all examples at the root node
    - Calculating information gain for splitting on all possible features, and picking the one with the highest information gain
    - Splitting dataset according to the selected feature, and creating left and right branches of the tree
    - Keeping the repeating splitting process until stopping criteria is met

- The following functions will be implemented, which splitting a node into left and right branches using the feature with the highest information gain
  - Calculate the entropy at a node
  - Split the dataset at a node into left and right branches based on a given feature
  - Calculate the information gain from splitting on a given feature
  - Choose the feature that maximizes information gain

### Calculate entropy:

compute_entropy computes the entropy (measure of impurity) at a node.

- The function takes in a numpy array (y) that indicates whether the examples in that node are edible **1** or poisonous **0**
- Compute $p_1$, which is the fraction of examples that are edible
- The entropy is then calculated as

$$H(p_1) = -p_1\log_2(p_1) - (1-p_1)\log_2(1-p_1)$$

In [6]:
```
def compute_entropy(y):
    """
    Computes the entropy for

    Args:
       y (ndarray): Numpy array indicating whether each example at a node is
           edible (`1`) or poisonous (`0`)

    Returns:
        entropy (float): Entropy at that node

    """

    entropy = 0.

    if len(y) != 0 :
        p1 = len(y[y==1]) / len(y)

        if p1!=0 and p1!=1:
            entropy = -p1 * np.log2(p1) - (1-p1)* np.log2(1-p1)
        else:
            entropy = 0


    return entropy
```

In [7]:
```
# Compute entropy at the root node
# Since there are 5 edible and 5 non-edible mushrooms, the entropy should be 1"

print("Entropy at root node: ", compute_entropy(y_train))

# UNIT TESTS
compute_entropy_test(compute_entropy)
```

```
Entropy at root node:  1.0
 All tests passed.
```

### Split dataset:

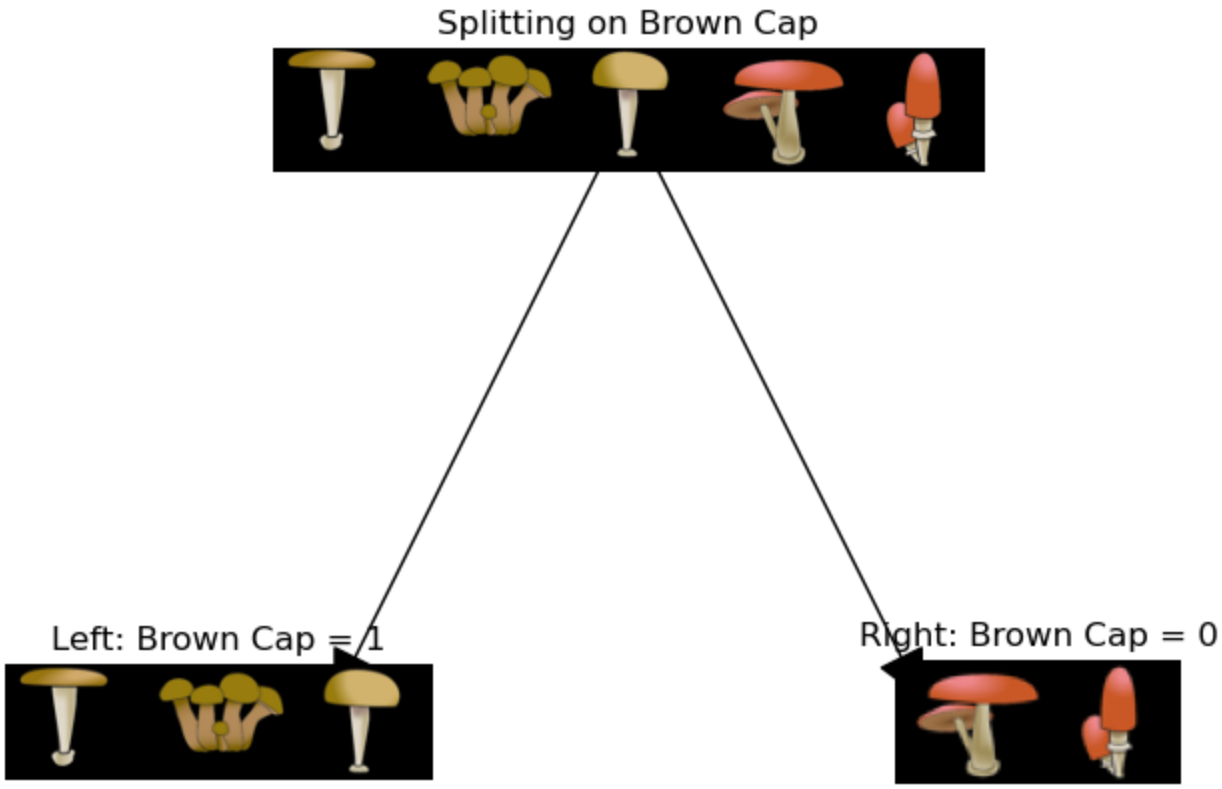
- For each index in **node_indices**

- If the value of X at that index for that feature is **1**, add the index to **left_indices**
- If the value of X at that index for that feature is **0**, add the index to **right_indices**

In [8]:
```
def split_dataset(X, node_indices, feature):
    """
    Splits the data at the given node into
    left and right branches

    Args:
        X (ndarray):             Data matrix of shape(n_samples, n_features)
        node_indices (list):     List containing the active indices. I.e, the samples be
        feature (int):           Index of feature to split on

    Returns:
        left_indices (list):     Indices with feature value == 1
        right_indices (list):    Indices with feature value == 0
    """

    left_indices = []
    right_indices = []

    for i in node_indices:
        if X[i][feature] == 1:
            left_indices.append(i)
        else:
            right_indices.append(i)


    return left_indices, right_indices
```

In [10]:
```
# Case 1

root_indices = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]

# The dataset only has three features, so this value can be 0 (Brown Cap), 1 (Tapering S
feature = 0

left_indices, right_indices = split_dataset(X_train, root_indices, feature)

print("CASE 1:")
print("Left indices: ", left_indices)
print("Right indices: ", right_indices)


# Case 2

root_indices_subset = [0, 2, 4, 6, 8]
left_indices, right_indices = split_dataset(X_train, root_indices_subset, feature)

print("CASE 2:")
print("Left indices: ", left_indices)
print("Right indices: ", right_indices)

# Visualize the split
generate_split_viz(root_indices_subset, left_indices, right_indices, feature)

# UNIT TESTS
split_dataset_test(split_dataset)
```

```
CASE 1:
Left indices:  [0, 1, 2, 3, 4, 7, 9]
Right indices:  [5, 6, 8]
CASE 2:
Left indices:  [0, 2, 4]
Right indices:  [6, 8]
```




```
All tests passed.
```

## Calculate information gain:

information_gain function takes in the training data, the indices at a node and a feature to split on and returns the information gain from the split.

$$\text{Information Gain} = H(p_1^{\text{node}}) - (w^{\text{left}} H(p_1^{\text{left}}) + w^{\text{right}} H(p_1^{\text{right}}))$$

where

- $H(p_1^{\text{node}})$ is entropy at the node
- $H(p_1^{\text{left}})$ and $H(p_1^{\text{right}})$ are the entropies at the left and the right branches resulting from the split
- $w^{\text{left}}$ and $w^{\text{right}}$ are the proportion of examples at the left and right branch, respectively

- compute_entropy() function -> to calculate the entropy
- split_dataset() function --> to split the dataset

In [11]:
```
def compute_information_gain(X, y, node_indices, feature):

    """
    Compute the information of splitting the node on a given feature

    Args:
        X (ndarray):            Data matrix of shape(n_samples, n_features)
        y (array like):         list or ndarray with n_samples containing the target var
        node_indices (ndarray): List containing the active indices. I.e, the samples bei
```

```
        cost (float):        Cost computed

    """
    # Splitting dataset
    left_indices, right_indices = split_dataset(X, node_indices, feature)

    X_node, y_node = X[node_indices], y[node_indices]
    X_left, y_left = X[left_indices], y[left_indices]
    X_right, y_right = X[right_indices], y[right_indices]


    information_gain = 0


    node_entropy = compute_entropy(y_node)
    left_entropy = compute_entropy(y_left)
    right_entropy = compute_entropy(y_right)

    w_left = len(X_left) / len(X_node)
    w_right = len(X_right) / len(X_node)

    weighted_entropy = w_left * left_entropy + w_right * right_entropy
    information_gain = node_entropy - weighted_entropy



    return information_gain
```

In [12]:
```
info_gain0 = compute_information_gain(X_train, y_train, root_indices, feature=0)
print("Information Gain from splitting the root on brown cap: ", info_gain0)

info_gain1 = compute_information_gain(X_train, y_train, root_indices, feature=1)
print("Information Gain from splitting the root on tapering stalk shape: ", info_gain1)

info_gain2 = compute_information_gain(X_train, y_train, root_indices, feature=2)
print("Information Gain from splitting the root on solitary: ", info_gain2)

# UNIT TESTS
compute_information_gain_test(compute_information_gain)
```

```
Information Gain from splitting the root on brown cap:  0.034851554559677034
Information Gain from splitting the root on tapering stalk shape:  0.12451124978365313
Information Gain from splitting the root on solitary:  0.2780719051126377
 All tests passed.
```

## Get best split:

get_best_split() function gets the best feature to split on by computing the information gain from each featuren and returning the feature that gives the maximum information gain.

- The function takes in the training data, along with the indices of datapoint at that node
- The output of the function is the feature that gives the maximum information gain
  - using compute_information_gain() function to iterate through the features and calculate the information for each feature

In [13]:
```
def get_best_split(X, y, node_indices):
    """
    Returns the optimal feature and threshold value
    to split the node data

    Args:
        X (ndarray):            Data matrix of shape(n_samples, n_features)
```

```
        y (array like):         list or ndarray with n_samples containing the target var
        node_indices (ndarray): List containing the active indices. I.e, the samples bei

    Returns:
        best_feature (int):     The index of the best feature to split
    """

    num_features = X.shape[1]

    best_feature = -1

    max_info_gain = 0

    for feature in range(num_features):
        info_gain = compute_information_gain(X, y, node_indices, feature)

        if info_gain > max_info_gain:
            max_info_gain = info_gain
            best_feature = feature


    return best_feature
```

In [14]:
```
best_feature = get_best_split(X_train, y_train, root_indices)
print("Best feature to split on: %d" % best_feature)

# UNIT TESTS
get_best_split_test(get_best_split)
```

```
Best feature to split on: 2
 All tests passed.
```

So, due to results of codes were written above, the function returns that **the best feature to split on at the root node is feature 2 ("Solitary")**

## 3 - Building the tree:

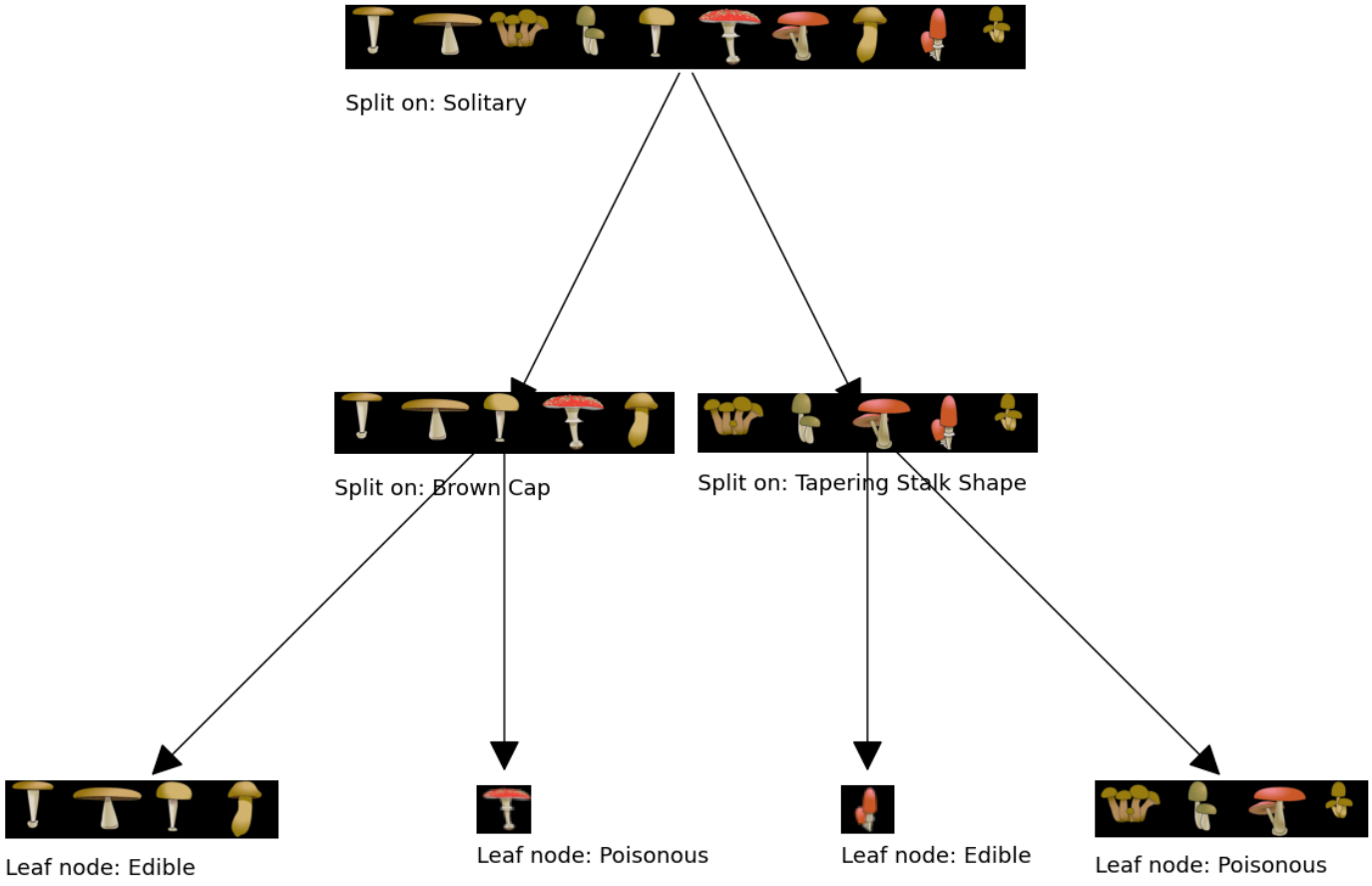
Generating a decision tree by successively picking the best feature to split on until reaching the stopping criteria (maximum depth is 2).

In [15]:
```
tree = []

def build_tree_recursive(X, y, node_indices, branch_name, max_depth, current_depth):
    """
    Build a tree using the recursive algorithm that split the dataset into 2 subgroups a
    This function just prints the tree.

    Args:
        X (ndarray):            Data matrix of shape(n_samples, n_features)
        y (array like):         list or ndarray with n_samples containing the target var
        node_indices (ndarray): List containing the active indices. I.e, the samples bei
        branch_name (string):   Name of the branch. ['Root', 'Left', 'Right']
        max_depth (int):        Max depth of the resulting tree.
        current_depth (int):    Current depth. Parameter used during recursive call.

    """

    # Maximum depth reached - stop splitting
    if current_depth == max_depth:
        formatting = " "*current_depth + "-"*current_depth
        print(formatting, "%s leaf node with indices" % branch_name, node_indices)
```

```
    # Otherwise, get best split and split the data
    # Getting the best feature and threshold at this node
    best_feature = get_best_split(X, y, node_indices)

    formatting = "-"*current_depth
    print("%s Depth %d, %s: Split on feature: %d" % (formatting, current_depth, branch_n

    # Split the dataset at the best feature
    left_indices, right_indices = split_dataset(X, node_indices, best_feature)
    tree.append((left_indices, right_indices, best_feature))

    # continue splitting the left and the right child.
    build_tree_recursive(X, y, left_indices, "Left", max_depth, current_depth+1)
    build_tree_recursive(X, y, right_indices, "Right", max_depth, current_depth+1)
```

In [16]:
```
build_tree_recursive(X_train, y_train, root_indices, "Root", max_depth=2, current_depth=
generate_tree_viz(root_indices, y_train, tree)
```

```
 Depth 0, Root: Split on feature: 2
- Depth 1, Left: Split on feature: 0
  -- Left leaf node with indices [0, 1, 4, 7]
  -- Right leaf node with indices [5]
- Depth 1, Right: Split on feature: 1
  -- Left leaf node with indices [8]
  -- Right leaf node with indices [2, 3, 6, 9]
```




In [ ]:
```

```