Machine Learning, Spring 2020

Project Five – KNN + Decision Tree

Python tutorial: http://learnpython.org/

TensorFlow tutorial: https://www.tensorflow.org/tutorials/

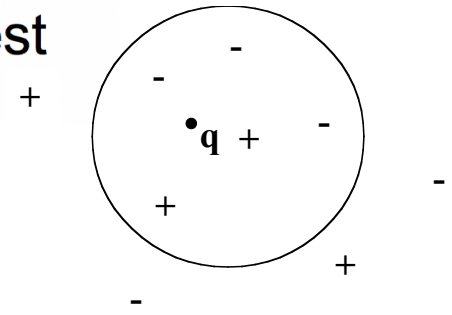
PyTorch tutorial: https://pytorch.org/tutorials/

Task1: K-Nearest Neighbor Algorithm

- For each training instance $t=(x, f(x))$
  - Add t to the set *Tr_instances*
- Given a query instance q to be classified
  - Let $x_1, \ldots, x_k$ be the k training instances in *Tr_instances* nearest to q
  - Return

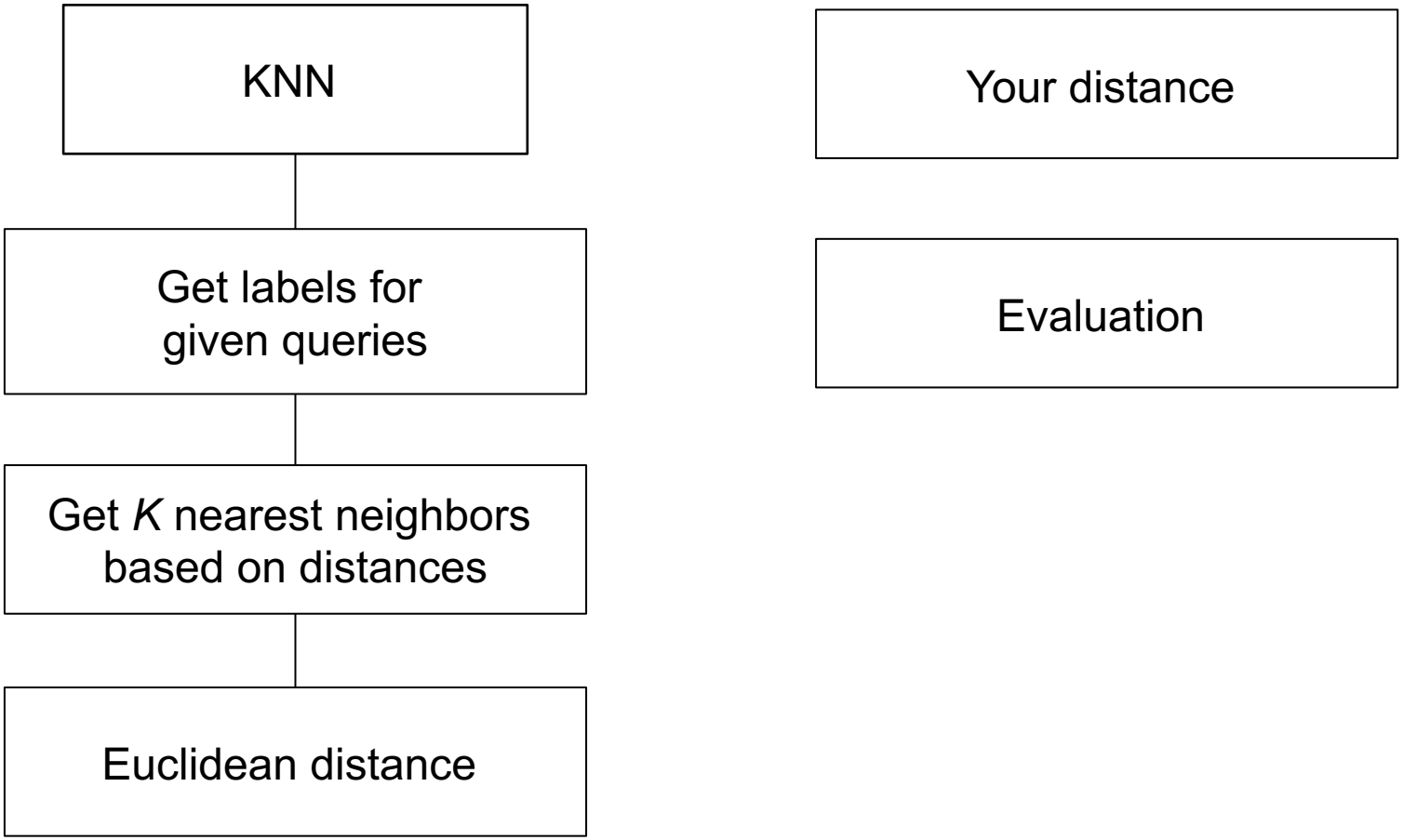
$$\hat{f}(q) = \arg\max_{v \in V} \sum_{i=1}^{k} \delta(v, f(x_i))$$

- Where V is the finite set of target class values, and $\delta(a,b)=1$ if $a=b$, and 0 otherwise (Kronecker function)
- Intuitively, the k-NN algorithm assigns to each new query instance the majority class among its k nearest neighbors



q is + under 1-NN, but – under 5-NN

Main Modules for KNN



Main Modules for KNN

Euclidean distance

- For each query, calculate the distance between the query and every training sample
- Euclidean distance:

$$D = \sqrt{\sum(x_1 - x_2)^2}$$

```
In [1]: def euclidean_distance(x1, x2):
            #suppose that x1:(1,2) x2:(N*3)

            return
```

Main Modules for KNN

Get *K* nearest neighbors based on distances

- For each query, calculate the distance between the query and every training sample
- Get the *K* nearest neighbors based on the calculated distances

[2]:
```
def get_neighbors( X, y, x_test, k, distance= euclidean_distance):
    # X in N*2, y in N*1, x_test in 2,
    # calculate all the distances
    # find the nearest K nieghtbors' indexs
    # return k nerest negibors
    return
```

Main Modules for KNN

Get labels for given queries

- For each query, calculate the distance between the query and every training sample
- Get the *K* nearest neighbors based on the calculated distances
- Calculate the majority classes from K-NN, and assign the class to the given query

In [3]:
```
def get_label(neighbors):
    # calculate and return label with the majority votes
    return
```

Main Modules for KNN

KNN

- For each query, calculate the distance between the query and every training sample
- Get the *K* nearest neighbors based on the calculated distances
- Calculate the majority classes from K-NN, and assign the class to the given query

In [4]:
```
def knn(training_data,gt,testing_data,k,distance= euclidean_distance):
    # for each testing data, using functions above to predict the class labes using knn algo

    return
```

Main Modules for KNN

Evaluation

- Given the predicted class labels using KNN and ground truth testing labels:
  - Find out the samples that are not classified correctly
  - Calculate the number of misclassified samples (N_{mc}), then calculate the accuracy :

$$A = \frac{(N - N_{mc})}{N},$$

N: total number of testing samples

```
In [ ]: def eval(y,pred):
            #find out the samples that are not classified correctly
            #calculate the accuracy

            return
```

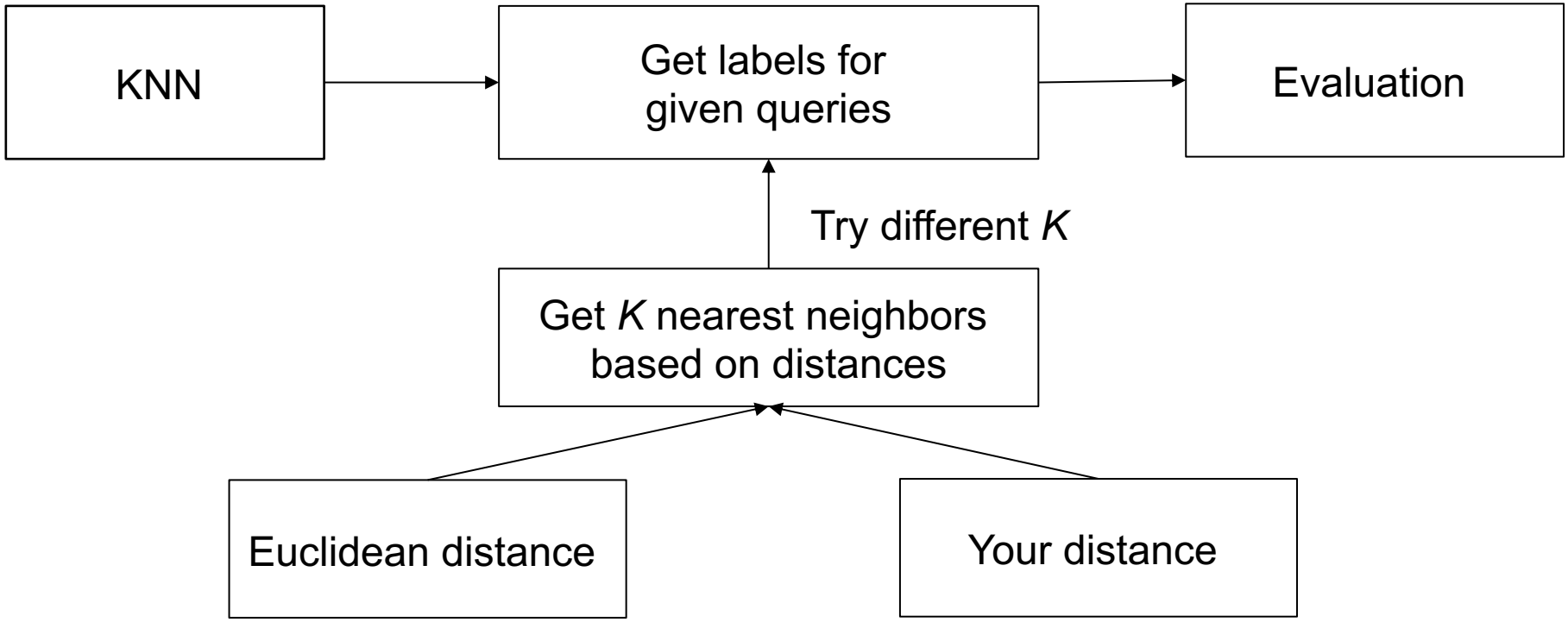
Main Modules for KNN

Your distance

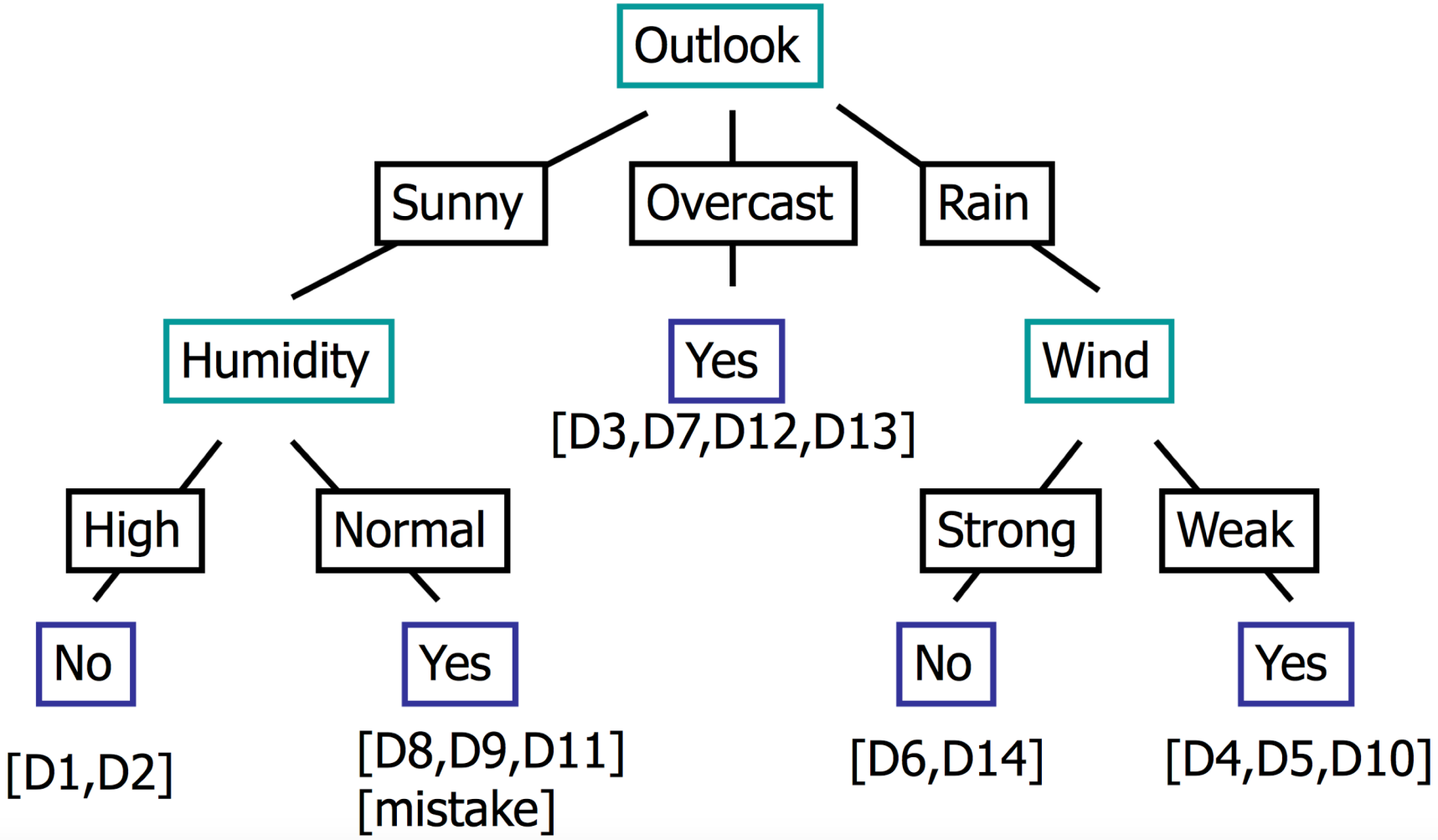
- Choose a new distance function for your k-NN algorithm. You can choose whatever distance function you like but should choose something that you think might yield higher accuracy than the Euclidean distance function.

```
In [ ]: def yourdistance(x1, x2):

            return
```

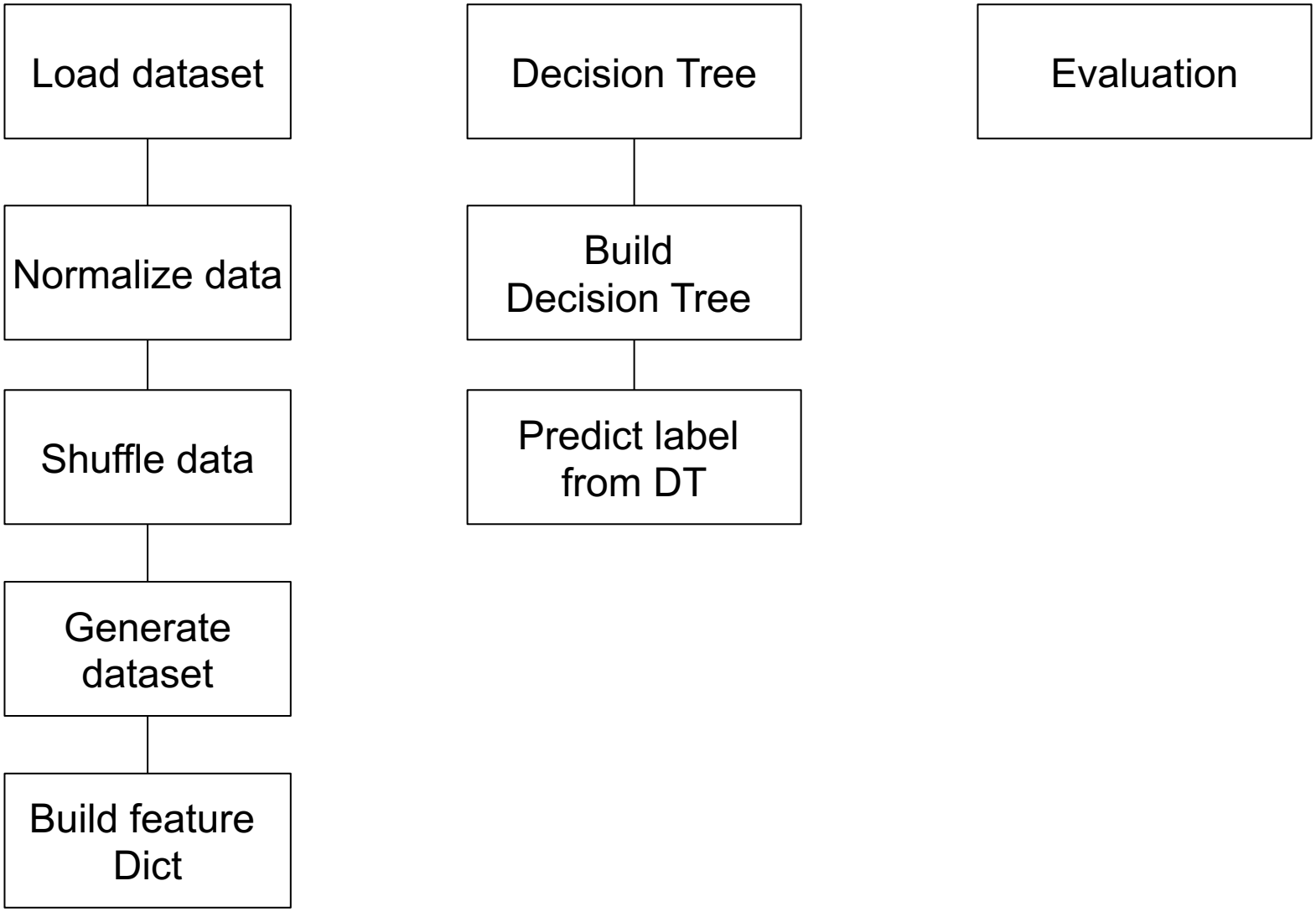
Pipeline for KNN



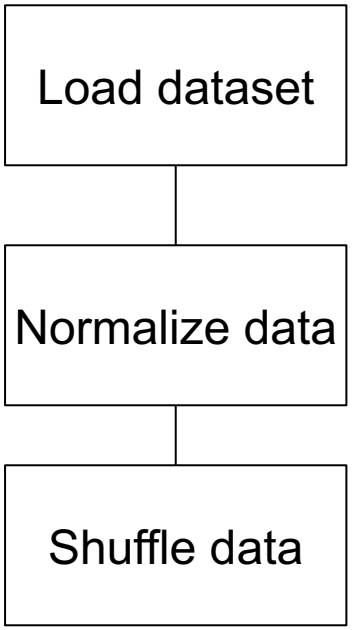
Task 2: Decision Tree



Main Modules Decision Tree



Main Modules Decision Tree



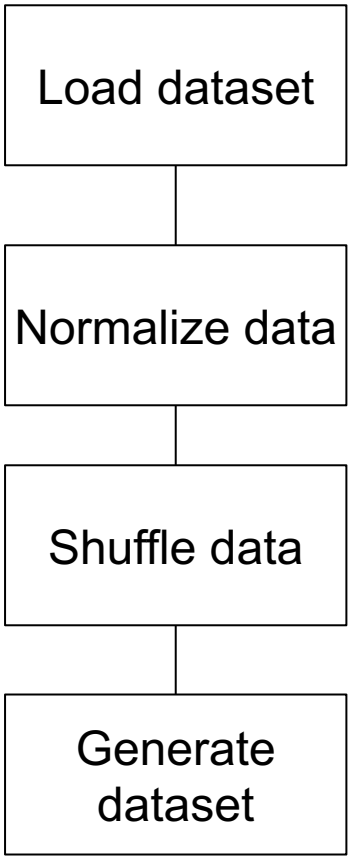
- Load the dataset from a .csv file
- Normalize dataset by $X' = \frac{(X - X_{\min})}{(X_{\max} - X_{\min})}$
- Randomly shuffle the data

```
In [21]: #normalize the entire dataset prior to learning using min-max normalization
         def normalize(matrix):
         #     transfer the data metrix to np array in float type.
             print("normalizing the entire dataset:")
             print(a)
             print("Before normalizing")
         #     apply the normalization along the 0 axis of a using the formula: (x - x_min)/(x_max - x_min)
             return
```

```
In [22]: # reading from the file using numpy genfromtxt with delimiter ','
         def load_csv(file):

             return (X)
```

```
In [23]: #method to randomly shuffle the array using the numpy.random.shuffle()
         def random_numpy_array(ar):
             return arr
```

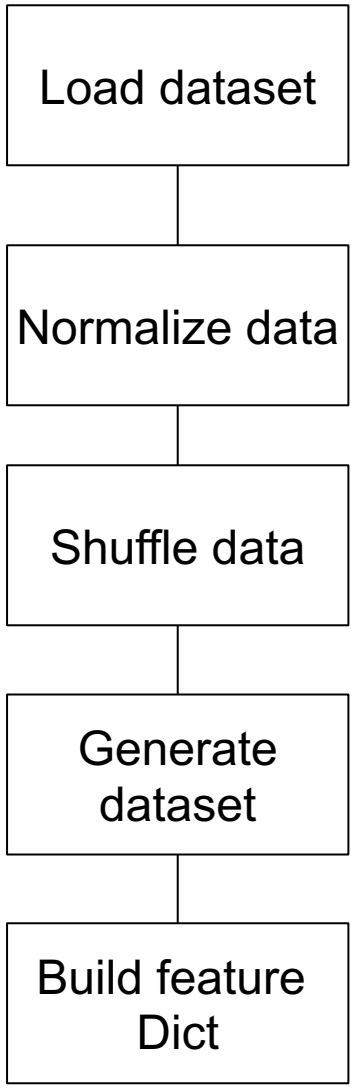
Main Modules Decision Tree



- Load the dataset from a .csv file
- Normalize dataset by $X' = \frac{(X - X_{\min})}{(X_{\max} - X_{\min})}$
- Randomly shuffle the data
- Create training and testing dataset for 10-fold cross validation

```
In [24]: #Normalize the data and generate the training labels,training features, test labels and test training
def generate_set(X):
    print(X.shape[0])
#     store the label X[:,-1] to Y

#     reshape y to (Y's length, 1)
#     store it to j

    print("J is",j)
#     create the new_X which exclude the label X[:,:-1]

#     normalize the data step
#     using our implemented function normalize()

#     add the label back to the normiazlied X
#     using np.concatenate along axis=1


#     store the size of rows of the normalized X with labels

#     use the 10% of the data to be the test set.
#     store the number of testing data

#     set the starting idex to be 0

#     set the ending index to be the number of testing data

#     create a list that store all features of the testing data

#     create a list that store all labels of the testing data

#     create a list that store all features of the training data

#     create a list that store all labels of the training data
```

Main Modules Decision Tree



- Load the dataset from a .csv file
- Normalize dataset by $X' = \frac{(X - X_{\min})}{(X_{\max} - X_{\min})}$
- Randomly shuffle the data
- Create training and testing dataset for 10-fold cross validation
- Build a dictionary where the key is the class label and values are the features which belong to that class.

In [16]:
```
#build a dictionary where the key is the class label and values are the features which belong to that class.
def build_dict_of_attributes_with_class_values(X,y):
#     init a dict for attributes

#     init feature list.

#     for each feature in the dataset
    for i in range(X.shape[1]):
#         store the featur index

#     find all the value correspond to this feature

#     init an attribute list

#     init the counter to 0

#         for each value in the "all the value correspond to this feature"

#             init a empty list that store the attribute value

#             append the this value to the list

#             append the label of this value to the list

#             append this list to the attribute list.

#             increase the counter
```

Main Modules Decision Tree

Decision Tree

Build Decision Tree

- Define a node in the tree

In [11]:
```
#Class node and explanation is self explaination
class Node(object):
#     init the node with val,lchild,rchild,thea and leaf.
    def __init__(self, val, lchild, rchild,thea,leaf):
        self.root_value = val
        self.root_left = lchild
        self.root_right = rchild
        self.theta = thea
        self.leaf = leaf

#     method to identify if the node is leaf
    def is_leaf(self):

        return

#     method to return threshold value
    def ret_thetha(self):

        return

#     method return root value
    def ret_root_value(self):

        return
```

Main Modules Decision Tree

Decision Tree

Build Decision Tree

- Define a node in the tree
- Define the entropy function

In [25]:
```
# Iterative Dichotomiser 3 entropy calculation
def entropy(y):
#     init a class frequence dict

#     init the attribute entropy to 0

#     for each label in y:
    for i in y:
#         this is label is already in the dict, we increase its feq


#          else, we set the freq to 1


#     calculate the cumulate entropy using the formula.


    return
```

Main Modules Decision Tree

Decision Tree

Build Decision Tree

- Define a node in the tree
- Define the entropy function
- Calculate the information gain to find the best threshold for each feature

```
    #method to calculate best threshold value for each feature
    def cal_best_theta_value(self,ke,attri_list):
#         init a list for data

#         init a list for class labes

#         for each attribute in the attri_list
        for i in attri_list:
#             append the data

#             append the feature value.

#         calculate the entropy of those feaure values

#         init the max info gain = 0

#         init theta=0
```

Main Modules Decision Tree

Decision Tree

Build Decision Tree

- Define a node in the tree
- Define the entropy function
- Calculate the information gain to find the best threshold for each feature → then select the best feature based on the information gain

```
    #method to select the best feature out of all the features.
    def best_feature(self,dict_rep):
#         set key value to none

#         set best info gain to -1

#         set best theta to 0

#         set best left list to empty

#         set best right list to empty

#         set best class labels after split to empty
```

Main Modules Decision Tree

Decision Tree

Build Decision Tree

- Define a node in the tree
- Define the entropy function
- Calculate the information gain to find the best threshold for each feature → then select the best feature based on the information gain → create decision tree (recursively) using the best feature

```
    #method to create decision tree
    def create_decision_tree(self, dict_of_everything,class_val,eta_min_val):
        global fea_list
        #if all the class labels are same, then we are set
        if len(set(class_val)) ==1:
            #print("Leaf node for set class is",class_val[0],len(class_val))

            return
        #if the no class vales are less than threshold, we assign the class with max values as the class label
        elif len(class_val) < eta_min_val:



            return
#         else:
        else:
#             using the best_feature to get best feature list

#             store the node name, theta,left split, right split and class labes




#             call get_remainder_dict to get left tree data

    #method to return the major class value using Counter() and .most_common()
    def cal_major_class_values(self,class_values):

        return
```

For node with instances < n_min, assign class with max instances as the class label

Main Modules Decision Tree

Decision Tree

Build Decision Tree

- Define a node in the tree
- Define the entropy function
- Calculate the information gain to find the best threshold for each feature → then select the best feature based on the information gain → create decision tree (recursively) using the best feature → get the left subtree feature (left_dict) and right subtree feature

```
    def get_remainder_dict(self,dict_of_everything,index_split):
        global fea_list
#         init a split dict

#         for each key "ke" in dict_of_everything:
        for ke in dict_of_everything.keys():
#             init a value list

#             init a modified list

#             get the corresponding values of the key"ke"

#             for each value and its corresponding index of the key"ke"

#                 if index is not in the index_split:

#                     append it to the modified list and value list


#             add this modified list to the dict

#         return the splited dict and val list
        return
```

Main Modules Decision Tree

Decision Tree

Build Decision Tree

Predict label from DT

- Assign a label for each testing sample

```
    def classify(self,row,root):
#         init the test dict

#         add row to the dict
        for k,j in enumerate(row):

#         set the current node to root

#         while the current node is not leaf:
        while not current_node.leaf:
#             implement the case whether the current shoud go to the left


#             implement the case whether the current shoud go to the right


#         return the calss of the current node
        return

    #method to the labels for the test data
    def predict(self, X, root):
#         predict using the classify()
```

Main Modules Decision Tree

- Calculate accuracy for each fold testing dataset

Evaluation

In [26]:
```
#calculating the predicited accuracy
def accuracy_for_predicted_values(test_class_names1,1):
#     init true and false count to 0

#     for each prediction,if predict is correct then, true++ else, false++
    for i in range(len(test_class_names1)):



#     return the acc
    return
```

Pipeline for Decision Tree