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BE-ETRX **UID:**2019110039 **Sub-Minor ML**

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Exp 3

Aim: Implementing KNN algorithm on the given dataset.

Code:

```
import numpy as np
from numpy import linalg as lin
from cs771 import genSyntheticData as gsd
from cs771 import plotData as pd
from matplotlib import pyplot as plt
import time as t
class Node:
    # A node stores its own depth (root = depth 0), its decision stump,
its parent and child information
    # Leaf nodes also store a constant label that is assigned to every
data point that reaches that leaf
    def __init__( self, depth = 0, stump = (0,0), parent = None ):
        self.depth = depth
        self.stump = stump
        self.parent = parent
        self.left = None
        self.right = None
        self.isLeaf = True
        self.label = 0

    def predict( self, data ):
        # If I am a leaf I can predict rightaway
        # May change this constant leaf action to something more
interesting and powerful
        if self.isLeaf:
```

```
            return self.label
        # Else I have to ask one of my children to do the job
        else:
            if data[self.stump[0]] > self.stump[1]:
                return self.right.predict( data )
            else:
                return self.left.predict( data )

    # Get the Gini coefficient of a node with nPos positive points and
nNeg negative points
    def getGini( self, nPos, nNeg ):
        nTot = nPos + nNeg
        # Find the proportion of the positives and negatives in that node
        pPos = nPos/nTot
        pNeg = nNeg/nTot
        # The gini index is always a real number between 0 and 0.5
        # A perfectly pure node has gini index = 0
        # The smaller the gini index the purer the node
        gini = 1 - (pPos**2 + pNeg**2)
        return gini
        def getStump( self, X, y ):
        # How many data points do I have at this node?
        n = y.size
        bestObjective = float('inf')

        # For each of the features in the data
        for i in range( X.shape[1] ):
            # Do not use the same feature as used by the parent node
            if self.parent is not None and i == self.parent.stump[0]:
                continue
            # Find out all values at which we can threshold that feature
            candidateThresholds = np.sort( X[:, i] )
            idx = np.argsort( X[:, i] )
            # The cumulative sum trick used here will work only if labels
are binary
            ySorted = y[idx]
            yCum = np.cumsum( ySorted )
            yCumRev = np.cumsum( ySorted[::-1] )[::-1]
            # For each possible threshold (except the ones at the extreme)
            for j in range( 1, candidateThresholds.size-1 ):
```

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                # Give 0.5 weight to balance and 1 weight to purity of the
two nodes
                candidateObjective = 0.0 * 0.0 \
                                    + 1.0 * self.getGini( (yCum[j] +
j+1)/2, (j+1 - yCum[j])/2 ) \
                                    + 1.0 * self.getGini( (yCumRev[j+1] +
n-j-1)/2, (n-j-1 - yCumRev[j+1])/2 )
                if candidateObjective < bestObjective:
                    bestObjective = candidateObjective
                    bestFeat = i
                    bestThresh = candidateThresholds[j]

        # Can try LwP decision stump as well
        bestThresh = (np.mean(X[y > 0, bestFeat]) + np.mean(X[y < 0,
bestFeat]))/2
        return (bestFeat, bestThresh)
         def train( self, X, y, maxLeafSize, maxDepth ):
        # If too few data points are present, or else if this node is too
deep in the tree, make this a leaf
        if y.size < maxLeafSize or self.depth >= maxDepth:
            self.isLeaf = True
            self.label = np.mean( y )
        else:
            # This node will be split and hence it is not a leaf
            self.isLeaf = False
            # Get the best possible decision stump
            self.stump = self.getStump( X, y )
            self.left = Node( depth = self.depth + 1, parent = self )
            self.right = Node( depth = self.depth + 1, parent = self )
            # Find which points go to my left child and which go to my
right child
            discriminant = X[:, self.stump[0]] - self.stump[1]
            # Train my two children recursively
            self.left.train( X[discriminant <= 0, :], y[discriminant <=
0], maxLeafSize, maxDepth )
            self.right.train( X[discriminant > 0, :], y[discriminant > 0],
maxLeafSize, maxDepth )
d = 2
n = 50
r = 2
```

```
tmp1 = gsd.genSphericalData( d, n, [-5, -7], r )
tmp2 = gsd.genSphericalData( d, n, [5, 0], r )
tmp3 = gsd.genSphericalData( d, n, [-5, 7], r )
XPos = np.vstack( (tmp1, tmp2, tmp3) )
yPos = np.ones( (3*n,) )

tmp1 = gsd.genSphericalData( d, n, [5, -7], r )
tmp2 = gsd.genSphericalData( d, n, [-5, 0], r )
tmp3 = gsd.genSphericalData( d, n, [5, 7], r )
XNeg = np.vstack( (tmp1, tmp2, tmp3) )
yNeg = -np.ones( (3*n,) )

X = np.vstack( (XPos, XNeg) )
y = np.concatenate( (yPos, yNeg) )

DT = Tree( maxLeafSize = 5, maxDepth = 4 )
DT.train( X, y )

def drawTreeSplits( node, fig, xlim, ylim ):
    if not node.isLeaf:
        plt.figure( fig.number )
        # Is this a vertical split or a horizontal one?
        if node.stump[0] == 0:
            plt.plot( [node.stump[1], node.stump[1]], ylim, color = 'c',
linestyle = '--' )
            drawTreeSplits( node.left, fig, [xlim[0], node.stump[1]], ylim
)
            drawTreeSplits( node.right, fig, [node.stump[1], xlim[1]],
ylim )
        elif node.stump[0] == 1:
            plt.plot( xlim, [node.stump[1], node.stump[1]], color = 'c',
linestyle = '--' )
            drawTreeSplits( node.left, fig, xlim, [ylim[0], node.stump[1]]
)
            drawTreeSplits( node.right, fig, xlim, [node.stump[1],
ylim[1]] )

def kNNClass( xt, yt ):
    diff = X - np.array( [xt, yt] )
```

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    dist = lin.norm( diff, axis = 1 )
    idx = np.argsort( dist )
    yhat = 0
    wsum = 0
    for i in range( k ):
        yhat = yhat + y[idx[i]]
    return yhat/k

fig = pd.getFigure()
tic = t.process_time()
pd.shade2D( DT.predict, fig, mode = 'point', xlim = 10, ylim = 10, nBins =
500 )
toc = t.process_time()
print( "It took " + str(toc - tic) + " seconds to complete the shading
with a DT")
drawTreeSplits(DT.root, fig, xlim = [-10, 10],  ylim = [-10, 10])
pd.plot2D( XNeg, fig, color = 'r', marker = '+' )
pd.plot2D( XPos, fig, color = 'g', marker = 'x' )

k = 1
fig2 = pd.getFigure()
tic = t.process_time()
pd.shade2D( kNNClass, fig2, mode = 'point', xlim = 10, ylim = 10, nBins =
500 )
toc = t.process_time()
print( "It took " + str(toc - tic) + " seconds to complete the shading
with kNN")
pd.plot2D( XNeg, fig2, color = 'r', marker = '+' )
pd.plot2D( XPos, fig2, color = 'g', marker = 'x' )
print( "DTs get faster compared to kNN as number of training points
increases - set n = 500 and see" )
```
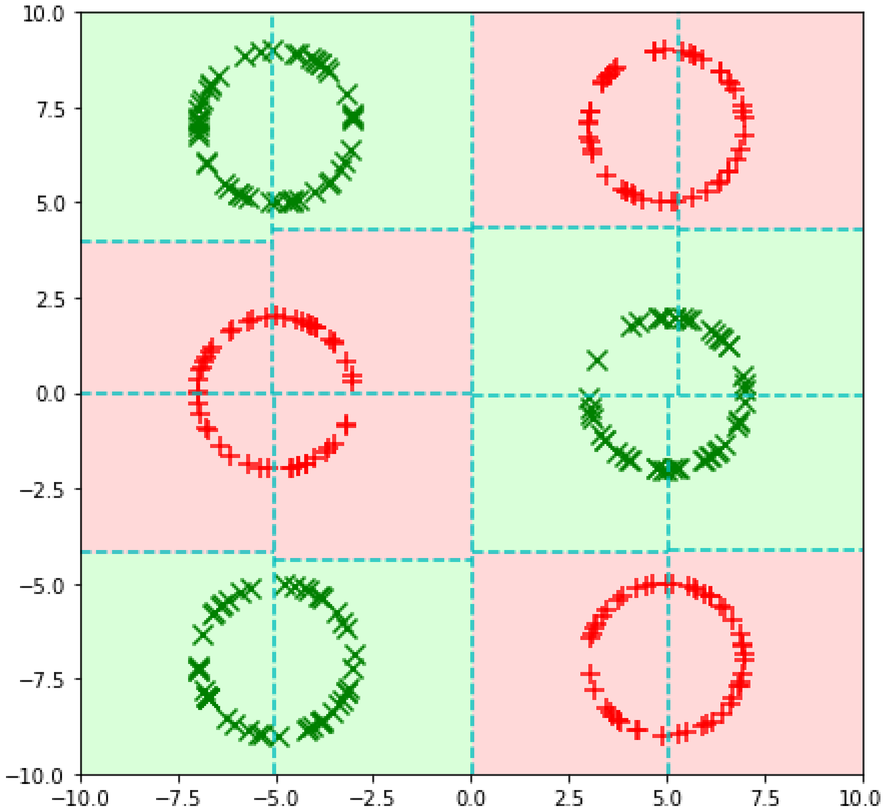
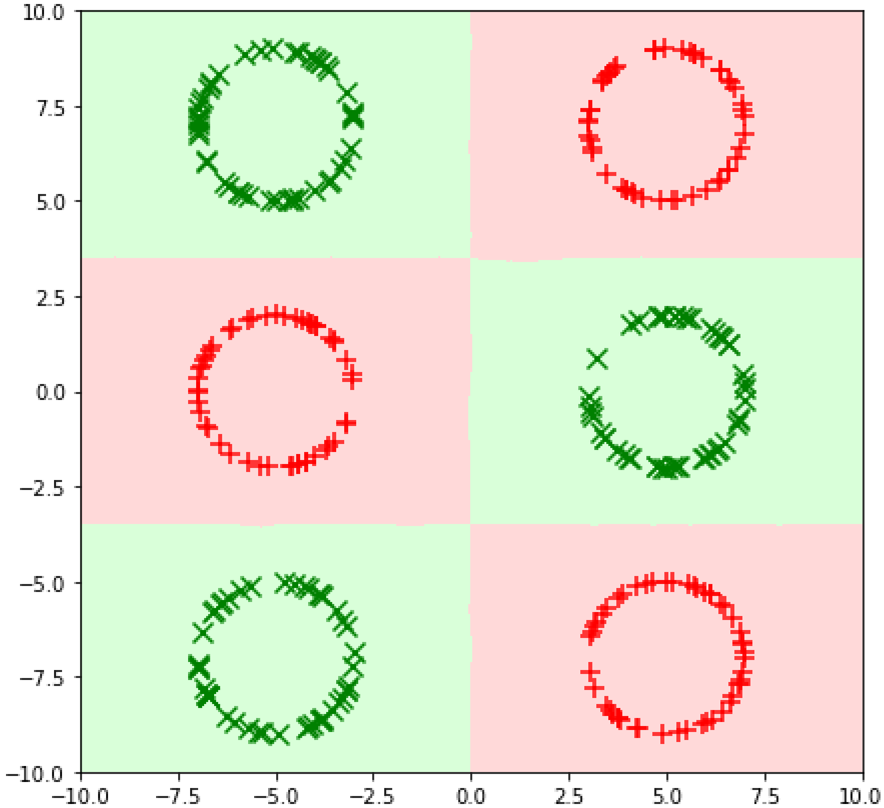

Output:

It took 0.8856712210000026 seconds to complete the shading with a DT

It took 8.132892257000002 seconds to complete the shading with kNN

DTs get faster compared to kNN as number of training points increases - set n = 500 and see





Can you change the DT to use information gain instead of Gini impurity for the criterion split?

- The Gini Impurity favors bigger partitions (distributions) and is simple to implement, whereas information gains favor smaller partitions (distributions) with a variety of diverse values, necessitating a data and splitting criterion experiment.
- Gini index favors larger partitions (distributions) and is very easy to implement whereas information gain supports smaller partitions (distributions) with various distinct values, i.e there is a need to perform an experiment with data and splitting criterion.

What is KNN?

- K-Nearest Neighbour is one of the simplest Machine Learning algorithms based on Supervised Learning technique.
- K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories.

- K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.
- K-NN algorithm can be used for Regression as well as for Classification but mostly it is used for the Classification problems.
- K-NN is a non-parametric algorithm, which means it does not make any assumption on underlying data.
- It is also called a lazy learner algorithm because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset.
- KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data.