Practical –1 Breadth First Search & Iterative Depth First Search

Code:

```
print("VINAY PANCHAL/27/TYCSB")
from collections import deque,defaultdict
class Graph:
    def __init__(self):
        self.graph=defaultdict(list)

    def add_edge(self,u,v):
        #For undirected graph
        self.graph[u].append(v)
        self.graph[v].append(u)

    def bfs(self,start):
        visited=set()
        queue=deque([start])
        traversal=[]

        while queue:
            node=queue.popleft()
            if node not in visited:
                visited.add(node)
                traversal.append(node)
                for neighbor in self.graph[node]:
                        queue.append(neighbor)
        return traversal


    def dfs_iterative(self,start):
        visited=set()
        stack=[start]
        traversal=[]

        while stack:
            node=stack.pop()
            if node not in visited:
                visited.add(node)
                traversal.append(node)
                for neighbor in reversed(self.graph[node]):
                        stack.append(neighbor)
        return traversal


g=Graph()
edges=[
    ('A','B'),('A','C'),
    ('B','D'),('B','E'),
    ('C','F'),('E','G'),
    ('F','H')
]
#ADDing edges
for u,v in edges:
    g.add_edge(u,v)
start_node='A'
print("DFS Traversal:     ",g.dfs_iterative(start_node))
print("BFS Traversal:     ",g.bfs(start_node))
```

Output:

```
VINAY PANCHAL/27/TYCSB
DFS Traversal:  ['A', 'B', 'D', 'E', 'G', 'C', 'F', 'H']
BFS Traversal:  ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H']
```

Practical –2 A* Search and Recursive Best-First Search

Code:

```
print("VINAY PANCHAL/27/TYCSB")
import heapq
def a_star(graph,h,start,goal):
    open_list=[]
    heapq.heappush(open_list,(h[start],0,start,[start]))
    visited=set()
    while open_list:
        f,g,node,path=heapq.heappop(open_list)
        if node==goal:
            return path,g
        visited.add(node)
        for neighbor,cost in graph[node]:
            if neighbor not in visited:
                g_new=g+cost
                f_new=g_new+h[neighbor]
                heapq.heappush(open_list,(f_new,g_new,neighbor,path+[neighbor]))
    return None,float('inf')
def rbfs(graph,h,start,goal):
    def rbfs_helper(node,path,g,f_limit):
        if node==goal:
            return path,g
        successors=[]
        for neighbor,cost in graph[node]:
            if neighbor not in path:
                g_new=g+cost
                f=max(g_new+h[neighbor],f_limit)
                successors.append((f,neighbor,g_new,path+[neighbor]))
        if not successors:
            return None,float('inf')
        successors.sort()
        while successors:
            best=successors[0]
            alternative=successors[1][0] if len(successors)>1 else float('inf')
            result,f_new=rbfs_helper(best[1],best[3],best[2],min(f_limit,alternative))
            if result is not None:
                return result,f_new
            successors[0]=(f_new,best[1],best[2],best[3])
            successors.sort()
        return None,float('inf')
    return rbfs_helper(start,[start],0,float('inf'))
graph={
    'A':[('B',5),('C',10)],
    'B':[('A',5),('D',4),('E',3)],
    'C':[('A',10),('G',2)],
    'D':[('B',4),('E',6)],
    'E':[('B',3,),('D',6),('G',2)],
    'G':[('C',2),('E',2)]
}
heuristic={
    'A':7,
    'B':6,
    'C':4,
    'D':3,
    'E':2,
    'G':0
}
start='A'
goal='G'
#Run A*
a_path,a_cost=a_star(graph,heuristic,start,goal)
print("A*Path:",a_path,"Cost",a_cost)
#Run RBFS
rbfs_path,rbfs_cost=rbfs(graph,heuristic,start,goal)
print("RBFS Path:",rbfs_path,"Cost:",rbfs_cost)
```

Output:

```
VINAY PANCHAL/27/TYCSB
A* Path: ['A', 'B', 'E', 'G'] Cost: 10
RBFS Path: ['A', 'B', 'D', 'E', 'G'] Cost: 17
```

Practical – 3 Decision Tree Learning

Code:

```
from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier,plot_tree
from sklearn.metrics import accuracy_score,classification_report
import matplotlib.pyplot as plt
#load the iris dataset
iris = load_iris()
X = iris.data
y = iris.target
feature_names = iris.feature_names
target_names = iris.target_names
#split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
#craete and train the decision tree classifier
elf = DecisionTreeClassifier(criterion='entropy', random_state=42)
elf.fit(X_train,y_train)
#make predictions
y_pred = elf.predict(X_test)
#evaluate accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy",accuracy)
print("\nClassification Report",classification_report(y_test, y_pred, target_names=target_names))
#Plot the decision tree
plt.figure(figsize=(12,8))
plot_tree(elf,feature_names=feature_names,class_names=target_names,filled=True)
plt.title('Decision Tree for Classifier')
plt.show()
```

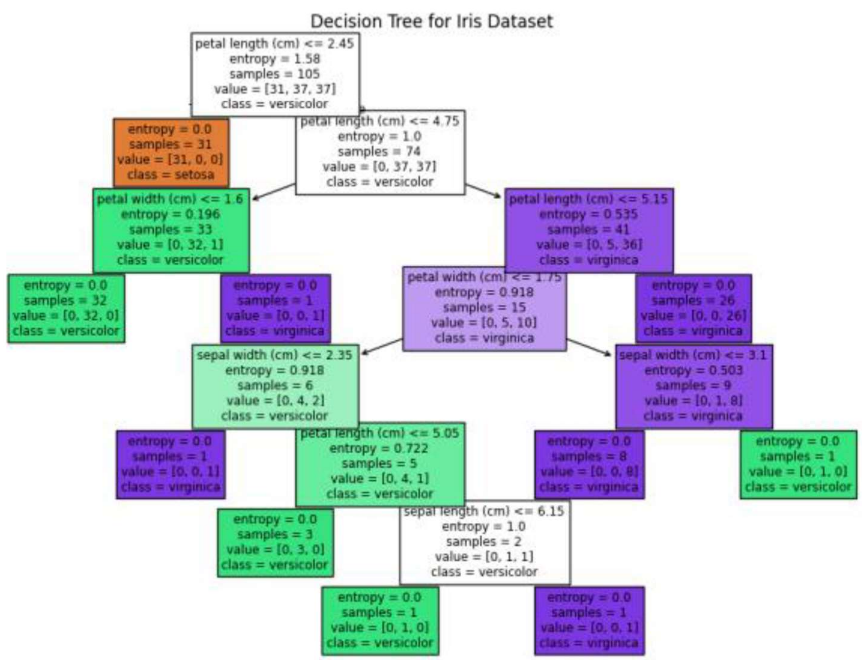
Output:

```
Accuracy: 0.9777777777777777

Classification Report:
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        19
  versicolor       0.93      1.00      0.96        13
   virginica       1.00      0.92      0.96        13

    accuracy                           0.98        45
   macro avg       0.98      0.97      0.97        45
weighted avg       0.98      0.98      0.98        45
```



Practical – 4 Support Vector Machines (SVM)

Code:

```
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report,accuracy_score,confusion_matrix

#load binary classification dataset
data=load_breast_cancer()
X=data.data
y=data.target#Labels:0=Malignant,1=Benign
#Normalized features
scalar=StandardScaler()
X_scaled=scalar.fit_transform(X)
#Split into training and testing data
X_train,X_test,y_train,y_test=train_test_split(X_scaled,y,test_size=0.2,random_state=42)
#Build SVM model
svm_model=SVC(kernel='rbf',C=1.0, gamma='scale')
svm_model.fit(X_train,y_train)
#MAke Prediction
y_pred=svm_model.predict(X_test)
#Evaluate Performance
print("Accuracy:",accuracy_score(y_test,y_pred)*100)
print("\nClassifcation Report:\n",classification_report(y_test,y_pred))
print("Confusion Matrix:\n",confusion_matrix(y_test,y_pred))
#Hyperparameter tuning using GridSearchCV
param_grid={
    'C':[0.1,1,10],
    'gamma':['scale',0.1,1],
    'kernel':['rbf']
}
grid=GridSearchCV(SVC(),param_grid,cv=5)
grid.fit(X_train,y_train)
print("\nBest Parameters:",grid.best_params_)
print("Best Cross-validation score:",grid.best_score_)
```

Output:

```
Accuracy:  97.36842105263158

Classification Report:
               precision    recall  f1-score   support

           0       0.98      0.95      0.96        43
           1       0.97      0.99      0.98        71

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114


Confusion Matrix:
 [[41  2]
 [ 1 70]]
```

Practical – 5 Adaboost Ensemble Learning

Code:

```
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score,classification_report
#Load dataset
data=load_breast_cancer()
X=data.data
y=data.target
#Train-test split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)
#weak classifier:Decision stump(1-level decision tree)
weak_classifier=DecisionTreeClassifier(max_depth=5)
#Train Adaboost model with 50 weak classifiers
adaboost_model=AdaBoostClassifier(estimator=weak_classifier,n_estimators=50,random_state=42)
adaboost_model.fit(X_train,y_train)
#Predict and evaluate
y_pred=adaboost_model.predict(X_test)
accuracy_ada=accuracy_score(y_test,y_pred)
print(f"AdaBoost Accuracy: {accuracy_ada*100:.2f}%")
print("\nClassification_report(AdaBoost):\n ",classification_report(y_test,y_pred))
#compare with a single weak classifier
weak_classifier.fit(X_train,y_train)
y_pred_weak=weak_classifier.predict(X_test)
accuracy_weak=accuracy_score(y_test,y_pred_weak)
print(f"\nSingle weak classifier Accuracy: {accuracy_weak*100:.2f}%")
```

Output:

```
AdaBoost Accuracy: 96.49%

Classification Report (Adaboost):
              precision    recall  f1-score   support

           0       0.98      0.93      0.95        43
           1       0.96      0.99      0.97        71

    accuracy                           0.96       114
   macro avg       0.97      0.96      0.96       114
weighted avg       0.97      0.96      0.96       114


Single Weak Classifier Accuracy:89.47%
```

Practical – 6 Naive Bayes ' Classifier

Code:

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
import numpy as np

#load output
data=load_iris()
X=data.data
y=data.target
class_names=data.target_names
#Split into train test
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)
#train NaiveBayes classifier
model=GaussianNB()
model.fit(X_train,y_train)
#predict
y_pred=model.predict(X_test)
#Evaluate Accuracy
accuracy=accuracy_score(y_test,y_pred)
print(f"Accuracy: {accuracy*100:.2f}%\n")
#class probabilities
probs=model.predict_proba(X_test)
print("Sample class probabilities(first 5test samples):")
print(np.round(probs[:5],3))
#detailed evaluation
print("\nClassifier Report:\n",classification_report(y_test,y_pred,target_names=class_names))
print("Confusion matrix:\n",confusion_matrix(y_test,y_pred))
```

Output:

```
Accuracy:100.00%

Sample class probabilities(first 5 test samples);
[[0.    0.996 0.004]
 [1.    0.    0.   ]
 [0.    0.    1.   ]
 [0.    0.978 0.022]
 [0.    0.87  0.13 ]]

Classification Report:
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      1.00      1.00         9
   virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Confusion Matrix:
 [[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

Practical – 7 K-Nearest Neighbors (K-NN)

Code:

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

#load dataset
data = load_iris()
X = data.data
y = data.target
class_names = data.target_names
#Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
#feature scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
#intialize KNN classifier
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)
#predict
y_pred = knn.predict(X_test)
#evaluate
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy*100:.2f}%")
print("\nClassification Report:\n", classification_report(y_test, y_pred, target_names=class_names))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

Output:

```
Accuracy: 100.00%

Classification Report:
               precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      1.00      1.00         9
   virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Confusion Matrix:
 [[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

Practical – 8 Association Rule Mining

Code:

```
import pandas as p
from mlxtend.frequent_patterns import apriori, association_rules
#sample market basket dataset
dataset=[
    ['milk','bread','butter'],
    ['bread','butter'],
    ['milk','bread'],
    ['milk','butter'],
    ['bread'],
    ['milk','bread','butter'],
    ['butter']
]

#Convert to one-hot encoded DataFrame
from mlxtend.preprocessing import TransactionEncoder
te=TransactionEncoder()
te_ary=te.fit(dataset).transform(dataset)
df = p.DataFrame(te_ary, columns=te.columns_)
#1.Find frequent itemsets wih min support of 0.3
frequent_itemsets=apriori(df,min_support=0.3,use_colnames=True)
#2.generate rule with min confidence of 0.7
rules=association_rules(frequent_itemsets,metric="confidence",min_threshold=0.7)
#display results
print("Frequency  Itemsets:\n",frequent_itemsets)
print("\nAssociation Rules:\n",rules[['antecedents','consequents','support','confidence','lift']])
```

Output:

```
Frequent Itemsets:
     support         itemsets
0  0.714286          (bread)
1  0.714286         (butter)
2  0.571429           (milk)
3  0.428571  (butter, bread)
4  0.428571    (milk, bread)
5  0.428571   (milk, butter)

Association Rules:
   antecedents consequents   support  confidence  lift
0      (milk)      (bread)  0.428571        0.75  1.05
1      (milk)     (butter)  0.428571        0.75  1.05
```