天津大学

机器学习实验---决策树

树状算法进化路线：

决策树 DT，随机森林 RF，梯度提升树 GBDT，比赛大师 XGBoost，微软算法 LightGBM

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学院名称 智能与计算

专　　业 人工智能

学　　号 好好好你这么玩是吧

时　　间 **2023/4/13**

机器学习实验---决策树

一、实验目的

1. 理解 C4.5 算法原理，能实现 C4.5 算法；
2. 掌握信息增益的计算方式；
3. 掌握决策树的构建和利用决策树进行推断；
4. 理解决策树的优缺点。

二、实验内容

1. 利用 WDBC 数据集，设计一个基于 C4.5 的决策树。以 2/3 的数据为训练集，1/3 为测试集。（可以参考样例，需补充标 XXX 的部分）
   Index of /ml/machine-learning-databases/breast-cancer-wisconsin (uci.edu)

- breast-cancer-wisconsin.data
- breast-cancer-wisconsin.names

2*. 针对数据缺失问题，设计权重划分的决策树。

三、实验报告要求

1. 按实验内容撰写实验过程；
2. 报告中涉及到的代码，每一个模块需要有详细的注释；

四、实验代码

```
import matplotlib.pyplot as plt
import cv2
import time
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from math import log


class Tree(object):
    def __init__(self, node_type, Class=None, attribute=None):
        self.node_type = node_type    # 节点类型（internal 或 leaf）
        self.dict = {}    # dict 的键表示属性 Ag 的可能值 ai，值表示根据 ai 得
到的子树
        self.Class = Class    # 叶节点表示的类，若是内部节点则为 none
        self.attribute = attribute    # 表示当前的树即将由第 attribute 个属性划
分（即第 attribute 属性是使得当前树中信息增益最大的属性）

    def add_tree(self, key, tree):
        self.dict[key] = tree
```

```
    def predict(self, attributes):
        # print('attribute', self.attribute)
        if self.node_type == 'leaf' or (attributes[self.attribute] not in self.dict):
            # print('self.Class', self.Class)
            return self.Class
        tree = self.dict.get(attributes[self.attribute])
        return tree.predict(attributes)


# 计算数据集 x 的经验熵 H(x)
# 划分前的信息熵 Ent(D)
def calc_ent(x):
    all_nums = len(x)
    labels = {}
    calc_ent = 0.0
    for label in x:
        if label not in labels.keys():
            labels[label] = 0
        labels[label] += 1
    for key in labels:
        prob = float(labels[key]) / all_nums
        calc_ent -= prob * log(prob, 2)
    return calc_ent


# 计算条件熵 H(y/x)
# 划分后的信息熵 sum(D^/D)*Ent(D^)
def calc_condition_ent(x, y):
    all_nums = len(x)
    labels_2 = {}
    labels_4 = {}
    labels = {}
    for i in range(all_nums):
        label = x[i]
        y_n = y[i]
        if label not in labels.keys():
            labels[label] = 0
        labels[label] += 1
        if y_n == 2:
            if label not in labels_2.keys():
                labels_2[label] = 0
            labels_2[label] += 1
        if y_n == 4:
            if label not in labels_4.keys():
```

```
                labels_4[label] = 0
            labels_4[label] += 1
    calc_condition_ent = 0.0
    for key in labels:
        prob = float(labels[key]) / all_nums
        if key in labels_2.keys() and key in labels_4.keys():
            prob0 = float(labels_2[key]) / float(labels[key])
            prob1 = float(labels_4[key]) / float(labels[key])
            prob2 = -(prob0 * log(prob0, 2) + prob1 * log(prob1, 2))
        else:
            prob2 = 0
        calc_condition_ent += prob * prob2
    return calc_condition_ent


# 计算信息增益 Gain(D,attribute)
def calc_ent_gain(x, y):
    return calc_ent(x) - calc_condition_ent(x, y)


# C4.5 算法
def recurse_train(train_set, train_label, attributes):
    LEAF = 'leaf'
    INTERNAL = 'internal'

    # 步骤 1——如果训练集 train_set 中的所有实例都属于同一类 C，则将该类表示为新的叶子节点
    label_set = set(train_label)   # 一般情况下这个集合有两种数字

    # print(label_set)
    # print(len(label_set))
    if len(label_set) == 1:   # 如果现在只有一种数字了，就意味着这个子树的样本是同一类别的
        return Tree(LEAF, Class=label_set.pop())   # 那么这个子树就是叶节点

    # 步骤 2——如果属性集为空，表示不能再分了，将剩余样本中样本数最多的一类赋给叶子节点
    # 如果 function 是 None ，则会假设它是一个身份函数，即 iterable 中所有返回假的元素会被移除。
    # 即 train_label 中所有 x == i 返回假的元素会被移除。
    class_len = [(i, len(list(filter(lambda x: x == i, train_label)))) for i in label_set]   # 计算每一个类出现的个数
    # print(class_len)
```

```
    # 以元组第二个值，即出现次数，为比较键
    (max_class, max_len) = max(class_len, key=lambda x: x[1])   # 出现个数最多的类

    # 属性列表为空，即没有属性可供决策了，决策树需要模糊定位一个类，于是选择为当前出现次数最多的类
    if len(attributes) == 0:
        return Tree(LEAF, Class=max_class)

    # 步骤 3——计算信息增益率,并选择信息增益率最大的属性
    max_attribute = 0   # 最大信息增益的属性
    max_gain_r = 0   # 信息增益率
    D = train_label   # 类别的集合 D
    for attribute in attributes:   # 对属性集中的所有属性
        # print(type(train_set))
        A = np.array(train_set[:, attribute].flat)   # 选择训练集中的第 attribute 列（即第 attribute 个属性）
        # 信息熵(entropy)ent
        # 信息增益(gain)ent_gain
        # 算出每一个属性的信息增益值
        gain = calc_ent_gain(A, D)
        if calc_ent(A) != 0:   # 计算信息增益率，这是与 ID3 算法唯一的不同
            gain_r = gain / calc_ent(A)   # 确保除数非零
        if gain_r > max_gain_r:   # 更新最大信息增益
            max_gain_r, max_attribute = gain_r, attribute

    # 步骤 4——如果最大的信息增益率小于阈值,说明所有属性的增益都非常小，那么取样本中最多的类为叶子节点
    if max_gain_r < epsilon:
        return Tree(LEAF, Class=max_class)

    # 步骤 5——依据样本在最大增益率属性的取值，划分非空子集，进而构建树或子树
    # lambda 表达式，刨除最大增益率属性的子属性集
    sub_attributes = list(filter(lambda x: x != max_attribute, attributes))
    # print(sub_attributes)
    tree = Tree(INTERNAL, attribute=max_attribute)
    print("[INFO]: create a internal node，feature is %sth" % max_attribute)
    # 获得最大增益率的通道的所有通道取值
    max_attribute_values = set(train_set[:, max_attribute])
    # print(train_set[:, max_attribute])
    # print(max_attribute_values)
    # 对每一种可能的取值
    for value in max_attribute_values:
```

```
            indexes = train_set[:, max_attribute] == value    # 获得当前 value 的
情况列表
            # print("indexes:", indexes, len(indexes))
            # 抛去所有 false 的样本，把 true 的样本作为下一部分决策树，并规
定 value 为当前分类所基于的属性名称
            sub_data = train_set[indexes]
            # print("sub_Data:", sub_data, len(sub_data))
            sub_label = train_label[indexes]
            # print("sub_label:", sub_label, len(sub_label))
            sub_tree = recurse_train(sub_data, sub_label, sub_attributes)
            tree.add_tree(value, sub_tree)
      return tree


def train(train_set, train_label, attributes):
      return recurse_train(train_set, train_label, attributes)


def predict(test_set, tree):
      result = []
      for attributes in test_set:
            tmp_predict = tree.predict(attributes)
            result.append(tmp_predict)
      return np.array(result)


decision_node = dict(boxstyle="sawtooth", fc="0.8")
leaf_node = dict(boxstyle="round4", fc="0.8")
arrow_args = dict(arrowstyle="<-")


def create_plot(tree):
      fig = plt.figure(1, facecolor='white')
      fig.clf()
      axprops = dict(xticks=[], yticks=[])
      create_plot.ax1 = plt.subplot(111, frameon=False, **axprops)
      print(create_plot.ax1)
      plot_tree.totalW = float(get_leafnum(tree))    # 此处调用 def
get_leafnum(mytree):
      plot_tree.totalD = float(get_treedepth(tree))    # 此处调用 def
get_treedepth(mytree):
      plot_tree.xOff = -0.5 / plot_tree.totalW
      plot_tree.yOff = 1.0
      # print(plot_tree)
```

```
    plot_tree(tree, (0.5, 1.0), '')
    plt.show()


def plot_tree(mytree, parent_pt, node_text):
    # 此处调用 def get_leafnum(mytree):
    num_leafs = get_leafnum(mytree)
    # 此处调用 def get_treedepth(mytree):
    depth = get_treedepth(mytree)
    # ? ? ? ? ? ? ? ?
    cntr_pt = (plot_tree.xOff + (1.0 + float(num_leafs)) / 2.0 / plot_tree.totalW,
plot_tree.yOff)
    # 此处调用 def plot_mid_text(cntr_pt, parent_pt, txt):
    plot_mid_text(cntr_pt, parent_pt, node_text)
    # 此处调用 def plot_node(node_txt, center_pt, parent_pt, node_type):
    plot_node(mytree.attribute, cntr_pt, parent_pt, decision_node)

    tree_dict = mytree.dict
    plot_tree.yOff = plot_tree.yOff - 1.0 / plot_tree.totalD
    for key in tree_dict.keys():
        if tree_dict[key].node_type == "internal":
            plot_tree(tree_dict[key], cntr_pt, str(key))
        else:
            plot_tree.xOff = plot_tree.xOff + 1.0 / plot_tree.totalW
            plot_node(tree_dict[key].Class, (plot_tree.xOff, plot_tree.yOff),
cntr_pt, leaf_node)
            plot_mid_text((plot_tree.xOff, plot_tree.yOff), cntr_pt, str(key))
    plot_tree.yOff = plot_tree.yOff + 1.0 / plot_tree.totalD


def plot_node(node_txt, center_pt, parent_pt, node_type):
    create_plot.ax1.annotate(node_txt, xy=parent_pt,
                             xycoords='axes fraction', xytext=center_pt,
                             textcoords='axes fraction', va="center",
ha="center",
                             bbox=node_type, arrowprops=arrow_args)


def plot_mid_text(cntr_pt, parent_pt, txt):
    xMid = (parent_pt[0] - cntr_pt[0]) / 2.0 + cntr_pt[0]
    yMid = (parent_pt[1] - cntr_pt[1]) / 2.0 + cntr_pt[1]
    create_plot.ax1.text(xMid, yMid, txt)
```

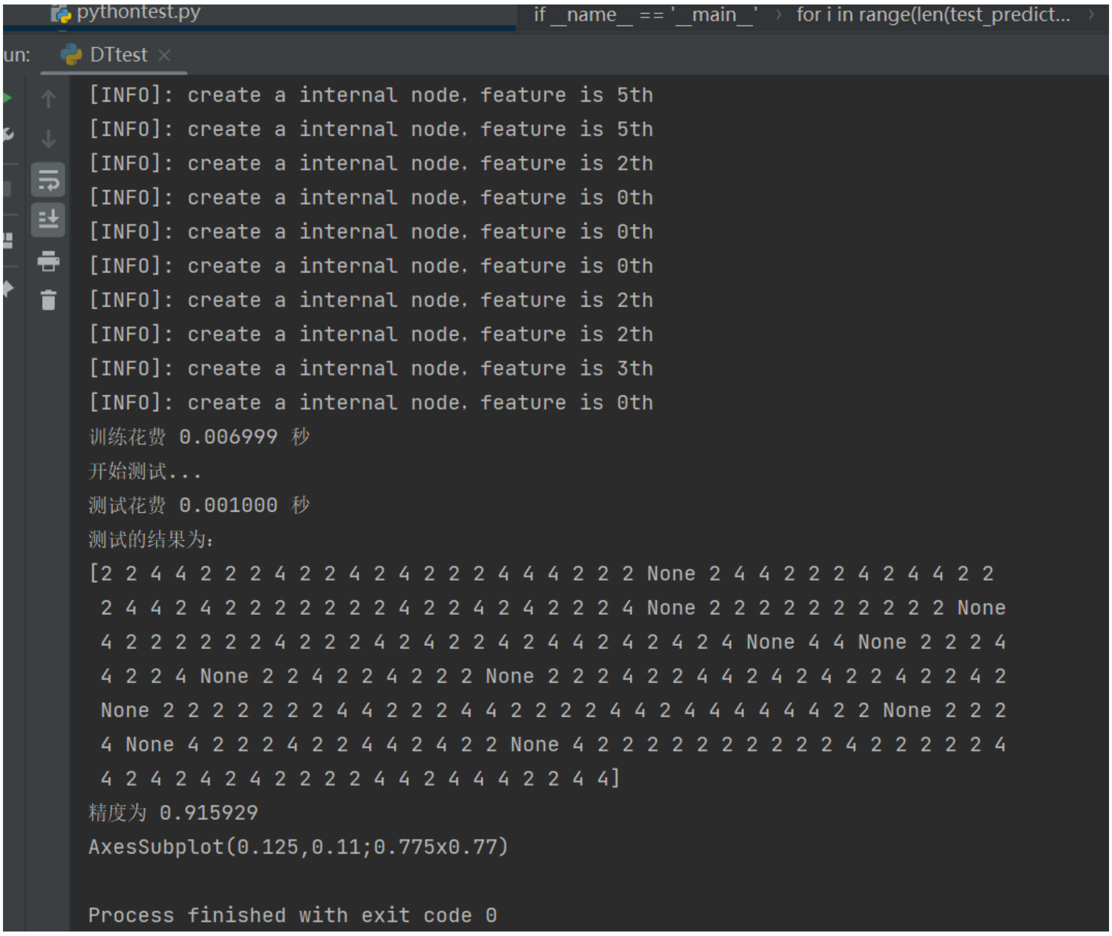
```
def get_leafnum(mytree):
    num_leafs = 0
    tree_dict = mytree.dict
    for key in tree_dict.keys():
        if tree_dict[key].node_type == "internal":
            num_leafs += get_leafnum(tree_dict[key])
        else:
            num_leafs += 1
    return num_leafs


def get_treedepth(mytree):
    max_depth = 0
    tree_dict = mytree.dict
    for key in tree_dict.keys():
        if tree_dict[key].node_type == "internal":
            depth = 1 + get_treedepth(tree_dict[key])
        else:
            depth = 1
        if depth > max_depth:
            max_depth = depth
    return max_depth


if __name__ == '__main__':
    class_num = 2   # wdbc 数据集有 10 种 labels，分别是“2,4”
    attribute_len = 9   # wdbc 数据集每个样本有 9 个属性
    epsilon = 0.001   # 设定阈值

    print("开始读取数据...")
    # 数据处理开始
    time_1 = time.time()
    raw_data = pd.read_csv('breast-cancer-wisconsin.data', header='infer')
# 读取 csv 数据
    data = raw_data.values
    # print(time_1)
    # print(raw_data)
    # print(data)

    # 去掉第一列和最后一列
    features = data[:, 1:-1]
    # print(features.shape)

    # 删除缺失值
```

```
    index0 = np.where(features[:, 5] != '?')
    # print(index0)
    features = features[index0].astype('int32')
    labels = data[:, -1][index0]   # 分类标签
    # print(labels)

    # 避免过拟合，采用交叉验证，随机选取 33%数据作为测试集，剩余为训
练集
    train_attributes, test_attributes, train_labels, test_labels =
train_test_split(features, labels, test_size=0.33,

random_state=0)
    # 数据处理结束
    time_2 = time.time()
    print('读取数据花费 %f 秒' % (time_2 - time_1))

    # 通过 C4.5 算法生成决策树
    print('开始训练...')
    # print(list(range(attribute_len)))
    # 训练集，标签集，训练集通道索引
    tree = train(train_attributes, train_labels, list(range(attribute_len)))
    # 训练结束
    time_3 = time.time()
    print('训练花费 %f 秒' % (time_3 - time_2))

    print('开始测试...')
    test_predict = predict(test_attributes, tree)
    time_4 = time.time()
    print('测试花费 %f 秒' % (time_4 - time_3))

    print("测试的结果为：")
    print(test_predict)
    for i in range(len(test_predict)):
        if test_predict[i] is None:
            test_predict[i] = epsilon
    score = accuracy_score(test_labels.astype('int32'),
test_predict.astype('int32'))
    print("精度为 %f" % score)

    # 手动进行函数声明
    # def create_plot(tree):
    create_plot(tree)
    # def plot_tree(mytree, parent_pt, node_text):
    # def plot_node(node_txt, center_pt, parent_pt, node_type):
```

def get_leafnum(mytree):
def get_treedepth(mytree):
def plot_mid_text(cntr_pt, parent_pt, txt):

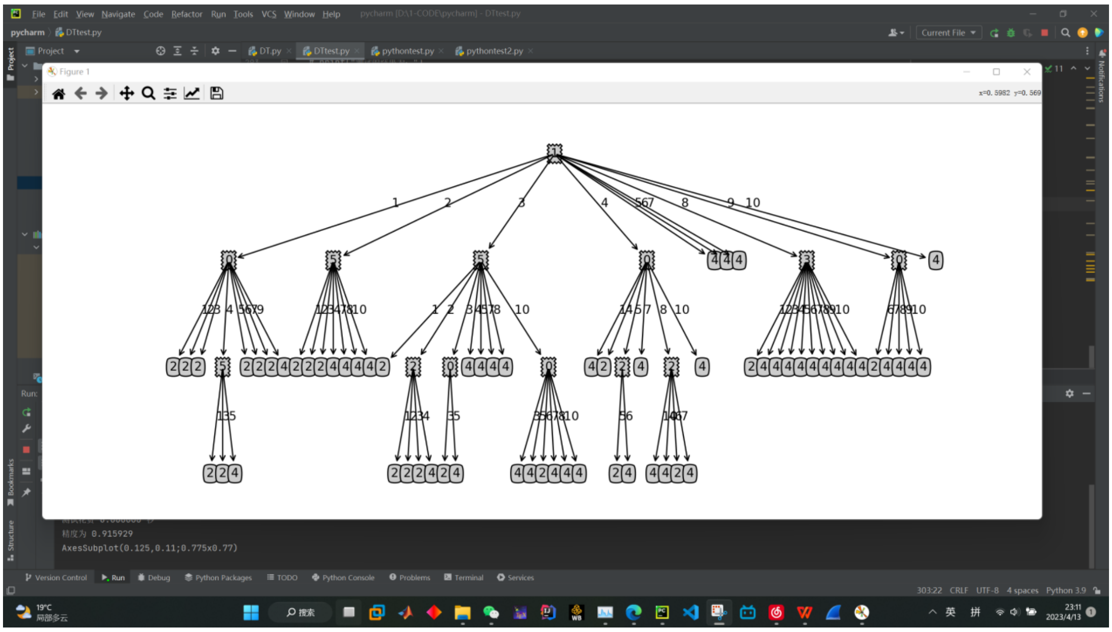
五、运行结果

1. 预测测试集上的结果，并输出精度



```
pythontest.py    if __name__ == '__main__'  ›  for i in range(len(test_predict...
un:  DTtest
[INFO]: create a internal node. feature is 5th
[INFO]: create a internal node. feature is 5th
[INFO]: create a internal node. feature is 2th
[INFO]: create a internal node. feature is 0th
[INFO]: create a internal node. feature is 0th
[INFO]: create a internal node. feature is 0th
[INFO]: create a internal node. feature is 2th
[INFO]: create a internal node. feature is 2th
[INFO]: create a internal node. feature is 3th
[INFO]: create a internal node. feature is 0th
训练花费 0.006999 秒
开始测试...
测试花费 0.001000 秒
测试的结果为:
[2 2 4 4 2 2 2 4 2 2 4 2 4 2 2 2 4 4 4 2 2 2 None 2 4 4 2 2 2 4 2 4 4 2 2
 2 4 4 2 4 2 2 2 2 2 2 2 4 2 2 4 2 4 2 2 2 4 None 2 2 2 2 2 2 2 2 2 2 None
 4 2 2 2 2 2 2 4 2 2 2 4 2 4 2 2 4 2 4 4 2 4 2 4 2 4 None 4 4 None 2 2 2 4
 4 2 2 4 None 2 2 4 2 2 4 2 2 2 None 2 2 2 4 2 2 4 4 2 4 2 4 2 2 4 2 2 4 2
 None 2 2 2 2 2 2 2 4 4 2 2 2 4 4 2 2 2 2 4 4 2 4 4 4 4 4 4 2 2 None 2 2 2
 4 None 4 2 2 2 4 2 2 4 4 2 4 2 2 None 4 2 2 2 2 2 2 2 2 2 2 4 2 2 2 2 2 4
 4 2 4 2 4 2 4 2 2 2 2 4 4 2 4 4 4 2 2 4 4]
精度为 0.915929
AxesSubplot(0.125,0.11;0.775x0.77)

Process finished with exit code 0
```

2*. 绘制出决策树的图



六、实验小结

本次实验是理解 C4.5 算法的原理并实现。理解信息增益在决策树中的意义。构建决策树的过程中，需要利用到递归的思想，每一个内部节点嵌套着一个子树。