8.3.4 决策树的应用 2

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决策树的应用——电话营销数据集

数据集信息:
该数据与葡萄牙银行机构的直接营销活动有关。营销活动是基于电话。通常，需要多个与同一客户的联系，以了解产品 (银行定期存款) 是否已认购 (“yes”) 或未认购 (“no”)。数据集位置：“数据/bank-marketing.csv”

数据包含有 41188 条数据样本，20 个变量大致分为三组：

银行客户信息：年龄、职业、婚姻状况、教育程度、违约、余额、房贷、个人贷本次营销最后一次通话记录：联系方式、日期（日）、月份、通话时长其他特征：活动次数、联系间隔时常、之前联系次数、之前营销结果预测值：是否购买定存（y）

数据来源：https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

本节例子基于某银行的营销活动数据，目标是建立模型预测客户是否会响应电话营销，订阅该银行的定期存款产品，包含 3,000 个样本，每个样本包含 21 个属性，如下表所示

属性	定义
age	年龄
job	职业
marital	婚姻状况
education	学历
default	是否有过违约
housing	是否有房贷
loan	是否有现金贷
contact	电话类型（手机或固定电话）
month	上次联络月份
day_of_week	上次联络是一星期中的那一天
duration	上次联络通话时长（以秒计算）

属性	定义
campaign	本次营销活动联络次数
pdays	以前营销活动联络距离现在的时间（以天计算）
previous	以前营销活动联络次数
poutcome	以前营销活动响应情况
emp.var.rate	就业变化率
cons.price.idx	消费者价格指数
cons.conf.idx	消费者信心指数
euribor3m	欧元银行同业拆借利率
nr.employed	员工数
y	是否转化

数据集：电话营销数据集

1. 读取数据

[1]:
```
import pandas as pd
df = pd.read_csv("datasets/电话营销数据集.csv", delimiter=";")
df.head()
```

[1]:

	age	job	marital	education	default	housing	loan	contact	\
0	56	housemaid	married	basic.4y	no	no	no	telephone	
1	57	services	married	high.school	unknown	no	no	telephone	
2	37	services	married	high.school	no	yes	no	telephone	
3	40	admin.	married	basic.6y	no	no	no	telephone	
4	56	services	married	high.school	no	no	yes	telephone	

	month	day_of_week	…	campaign	pdays	previous	poutcome	emp.var.rate	\
0	may	mon	…	1	999	0	nonexistent	1.1	
1	may	mon	…	1	999	0	nonexistent	1.1	
2	may	mon	…	1	999	0	nonexistent	1.1	
3	may	mon	…	1	999	0	nonexistent	1.1	
4	may	mon	…	1	999	0	nonexistent	1.1	

	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	y
0	93.994	-36.4	4.857	5191.0	no

```
1          93.994          -36.4      4.857       5191.0  no
2          93.994          -36.4      4.857       5191.0  no
3          93.994          -36.4      4.857       5191.0  no
4          93.994          -36.4      4.857       5191.0  no

[5 rows x 21 columns]
```

[2]:
```
df.describe()
```

[2]:

	age	duration	campaign	pdays	previous	\
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	
mean	40.02406	258.285010	2.567593	962.475454	0.172963	
std	10.42125	259.279249	2.770014	186.910907	0.494901	
min	17.00000	0.000000	1.000000	0.000000	0.000000	
25%	32.00000	102.000000	1.000000	999.000000	0.000000	
50%	38.00000	180.000000	2.000000	999.000000	0.000000	
75%	47.00000	319.000000	3.000000	999.000000	0.000000	
max	98.00000	4918.000000	56.000000	999.000000	7.000000	

	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
count	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000
mean	0.081886	93.575664	-40.502600	3.621291	5167.035911
std	1.570960	0.578840	4.628198	1.734447	72.251528
min	-3.400000	92.201000	-50.800000	0.634000	4963.600000
25%	-1.800000	93.075000	-42.700000	1.344000	5099.100000
50%	1.100000	93.749000	-41.800000	4.857000	5191.000000
75%	1.400000	93.994000	-36.400000	4.961000	5228.100000
max	1.400000	94.767000	-26.900000	5.045000	5228.100000

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
```

```
 1   job             41188 non-null  object
 2   marital         41188 non-null  object
 3   education       41188 non-null  object
 4   default         41188 non-null  object
 5   housing         41188 non-null  object
 6   loan            41188 non-null  object
 7   contact         41188 non-null  object
 8   month           41188 non-null  object
 9   day_of_week     41188 non-null  object
 10  duration        41188 non-null  int64
 11  campaign        41188 non-null  int64
 12  pdays           41188 non-null  int64
 13  previous        41188 non-null  int64
 14  poutcome        41188 non-null  object
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

类别变量编码

类别变量（categorical variable）：只有有限个值得变量，如性别就是一个类别变量，如男或女。或者如本数据集里‘job’这一列，其包含多个字符，无法直接输入到模型中进行数值计算，所以我们将其转换成**数值型变量**。

[4]:
```
df["job"]
```

[4]:
```
0          housemaid
1           services
2           services
3              admin.
4           services
           …
```

```
41183        retired
41184    blue-collar
41185        retired
41186     technician
41187        retired
Name: job, Length: 41188, dtype: object
```

序数编码

一种最简单的方式是进行序数编码（整数编码），就是将其各个类别对应不同的整数。

[5]:
```
def encode_function(array):
    encode_result = {}
    integer = 1
    for i in array:
        if i not in encode_result:
            encode_result[i] = integer
            integer += 1
        else:
            continue
    return encode_result
```

[6]:
```
encode_function(df["job"])
```

[6]:
```
{'housemaid': 1,
 'services': 2,
 'admin.': 3,
 'blue-collar': 4,
 'technician': 5,
 'retired': 6,
 'management': 7,
 'unemployed': 8,
 'self-employed': 9,
 'unknown': 10,
 'entrepreneur': 11,
 'student': 12}
```

[7]:
```
df = df.copy()
for i in ['job', 'marital', 'education', 'default', 'housing', 'loan',
          'contact', 'month', 'day_of_week',  'poutcome', 'y']:
    df[i] = df[i].map(encode_function(df[i]))
```

[8]:
```
df.head()
```

[8]:

	age	job	marital	education	default	housing	loan	contact	month	\
0	56	1	1	1	1	1	1	1	1	
1	57	2	1	2	2	1	1	1	1	
2	37	2	1	2	1	2	1	1	1	
3	40	3	1	3	1	1	1	1	1	
4	56	2	1	2	1	1	2	1	1	

	day_of_week	…	campaign	pdays	previous	poutcome	emp.var.rate	\
0	1	…	1	999	0	1	1.1	
1	1	…	1	999	0	1	1.1	
2	1	…	1	999	0	1	1.1	
3	1	…	1	999	0	1	1.1	
4	1	…	1	999	0	1	1.1	

	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	y
0	93.994	-36.4	4.857	5191.0	1
1	93.994	-36.4	4.857	5191.0	1
2	93.994	-36.4	4.857	5191.0	1
3	93.994	-36.4	4.857	5191.0	1
4	93.994	-36.4	4.857	5191.0	1

[5 rows x 21 columns]

2 标准化处理

观察上面的箱形图，你会发现各个变量的取值范围差异较大，有没有什么办法将变量的取值范围统一呢？常用的标准化处理方法有最小最大值标准化处理、均值标准差标准化处理、小数标度标准化处理等。下面我们采用均值标准差标准化处理：

[9]:
```
from sklearn.model_selection import train_test_split
X = df[['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed']]
y = df['y']
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size = 0.2,␣
 ↪random_state = 123)
```

[10]:
```
#X = (X - X.mean())/X.std()
```

[11]:
```
#X.boxplot(figsize=(20,4))
```

3. 决策树模型

样本内训练

[12]:
```
from sklearn import tree
clf = tree.DecisionTreeClassifier(max_depth=3)
clf = clf.fit(train_X,train_y)
```

[13]:
```
train_predicted_y = clf.predict(train_X)
```

[14]:
```
print('样本内的精度: %.2f' %clf.score(train_X, train_y))
```

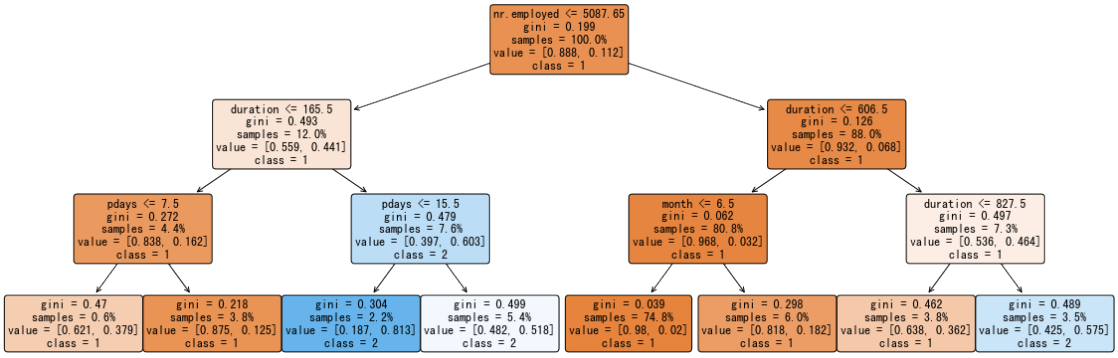
```
样本内的精度: 0.91
```

[15]:
```
from sklearn import metrics
precision = metrics.precision_score(train_y, train_predicted_y)
recall = metrics.recall_score(train_y, train_predicted_y)
f1_score = metrics.f1_score(train_y,train_predicted_y)
print('样本内的查准率:%.2f' %precision)
print('样本内的查全率:%.2f' %recall)
print('样本内的 f1 值:%.2f' %f1_score)
```

```
样本内的查准率:0.95
样本内的查全率:0.95
样本内的 f1 值:0.95
```

[16]:
```
import matplotlib.pyplot as plt
plt.rcParams['font.sans-serif'] = 'SimHei'  # 设置字体为 SimHei
plt.rcParams['axes.unicode_minus'] = False  # 解决负号“-”显示异常

from sklearn.tree import plot_tree
plt.figure(figsize = (20,7))
plot_tree(clf,
          max_depth=4,
          feature_names=X.columns.values,
          class_names=clf.classes_.astype(str),
          filled=True,
          rounded=True,
          proportion=True,
          fontsize=12)
plt.title("", fontsize=12)
plt.show()
```



样本外检验

[17]:
```
test_predicted_y = clf.predict(test_X)
```

[18]:
```
clf.score(test_X, test_y)
```

[18]: 0.9083515416363195

[19]:
```
print('样本外的精度: %.2f' %clf.score(test_X, test_y))
```

样本外的精度: 0.91

[20]:
```
from sklearn import metrics
precision = metrics.precision_score(test_y, test_predicted_y)
recall = metrics.recall_score(test_y, test_predicted_y)
f1_score = metrics.f1_score(test_y, test_predicted_y)
print('样本外的查准率:%.2f' %precision)
print('样本外的查全率:%.2f' %recall)
print('样本外的 f1 值:%.2f' %f1_score)
```

样本外的查准率:0.95
样本外的查全率:0.95
样本外的 f1 值:0.95

对比样本内和样本外的各个指标，模型表现优秀。