In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

导入数据

In [2]:

```
f= open("机器学习考核数据集.csv")
df= pd.read_csv(f)
print (df.shape)
df.head()
```

(41188, 21)

Out[2]:

	age	job	marital	education	default	housing	loan	contact	month	day_of
0	44	blue-collar	married	basic.4y	unknown	yes	no	cellular	aug	
1	53	technician	married	unknown	no	no	no	cellular	nov	
2	28	management	single	university.degree	no	yes	no	cellular	jun	
3	39	services	married	high.school	no	no	no	cellular	apr	
4	55	retired	married	basic.4y	no	yes	no	cellular	aug	

5 rows × 21 columns

步骤一：数据概览

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
age               41188 non-null int64
job               41188 non-null object
marital           41188 non-null object
education         41188 non-null object
default           41188 non-null object
housing           41188 non-null object
loan              41188 non-null object
contact           41188 non-null object
month             41188 non-null object
day_of_week       41188 non-null object
duration          41188 non-null int64
campaign          41188 non-null int64
pdays             41188 non-null int64
previous          41188 non-null int64
poutcome          41188 non-null object
emp_var_rate      41188 non-null float64
cons_price_idx    41188 non-null float64
cons_conf_idx     41188 non-null float64
euribor3m         41188 non-null float64
nr_employed       41188 non-null float64
y                 41188 non-null int64
dtypes: float64(5), int64(6), object(10)
memory usage: 6.6+ MB
```

In [4]:

```
df.describe()
```

Out[4]:

	age	duration	campaign	pdays	previous	emp_var_rate	con
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	4
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	

查看各列值的分布

In [5]:

```
for column in df.columns:
    print("列名：%s"%df[column].name)
    print(df[column].value_counts())
    print("——"*15)
```

```
90      170
136     168
73      167
124     164
87      162
72      161
104     161
111     160
106     159
109     158
97      158
122     157
135     156
92      156
114     156
139     155
96      155
119     155
82      154
89      153
```

步骤二：缺失值处理

虽然在df.info()中看到数据都是non-null值，但在df[column].value_counts()中看到一些列有unknown值，以及“pdays”列有很多“999”的值，均表示缺失值，需要处理。

查看数据中“unknown”值个数

In [6]:

```
for column in df.columns:
    count=0
    for i in df[column]:
        if i=="unknown":
            count=count+1
    if count>0:
        print("列：%s，其unknown值有%d个"%(df[column].name,count))
```

```
列：job，其unknown值有330个
列：marital，其unknown值有80个
列：education，其unknown值有1731个
列：default，其unknown值有8597个
列：housing，其unknown值有990个
列：loan，其unknown值有990个
```

看到有六列：job、marital、education、default（是否有违约）、housing（是否有房贷）、loan（是否有个人贷款）有unknown值，需处理

“default”列有8597个缺失值，显然，将含缺失值的行删除是不现实的，需想办法填充。

查看这些含“unknown”值的列的分布

In [7]:

```
l1=['job','marital','education','default','housing','loan']
for column in l1:
    print("列名：%s"%df[column].name)
    print(df[column].value_counts())
    print("——"*15)
```

```
列名：job
admin.           10422
blue-collar       9254
technician        6743
services          3969
management        2924
retired           1720
entrepreneur      1456
self-employed     1421
housemaid         1060
unemployed        1014
student            875
unknown            330
Name: job, dtype: int64
——————————————————————————————
列名：marital
married     24928
single      11568
divorced     4612
unknown        80
Name: marital, dtype: int64
——————————————————————————————
列名：education
university.degree      12168
high.school             9515
basic.9y                6045
professional.course     5243
basic.4y                4176
basic.6y                2292
unknown                 1731
illiterate                18
Name: education, dtype: int64
——————————————————————————————
列名：default
no         32588
unknown     8597
yes            3
Name: default, dtype: int64
——————————————————————————————
列名：housing
yes        21576
no         18622
unknown      990
Name: housing, dtype: int64
——————————————————————————————
列名：loan
no         33950
yes         6248
unknown      990
Name: loan, dtype: int64
——————————————————————————————
```

为方便处理缺失值，将“unknown”全部替换为np.nan

In [8]:

```
df=df.replace("unknown",np.nan)
```

In [9]:

```
df.head()
```

Out[9]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_v
0	44	blue-collar	married	basic.4y	NaN	yes	no	cellular	aug	
1	53	technician	married	NaN	no	no	no	cellular	nov	
2	28	management	single	university.degree	no	yes	no	cellular	jun	
3	39	services	married	high.school	no	no	no	cellular	apr	
4	55	retired	married	basic.4y	no	yes	no	cellular	aug	

5 rows × 21 columns

ffill方法：用后一个非缺失值去填充该缺失值

In [10]:

```
df=df.fillna(method='bfill')
l1=['job','marital','education','default','housing','loan','pdays']
for column in l1:
    print("列名：%s"%df[column].name)
    print(df[column].value_counts())
    print("——"*15)
```

```
列名：job
admin.           10512
blue-collar       9310
technician        6814
services          4002
management        2942
retired           1732
entrepreneur      1467
self-employed     1432
housemaid         1070
unemployed        1021
student            886
Name: job, dtype: int64
——————————————————————————————
列名：marital
married     24982
single      11586
divorced     4620
Name: marital, dtype: int64
```

看到：此时已经没有“unknown”/“nan”值了。

步骤三：离散特征编码

In [11]:

```
dic1={'yes':1,"no":0}
df["weiyue"]=df['default'].map(dic1)
df["housing_map"]=df['housing'].map(dic1)
df["loan_map"]=df['loan'].map(dic1)
dic2={'cellular':1,"telephone":0}
df["contact_map"]=df['contact'].map(dic2)
dic3={'success':2,"failure":0,"nonexistent":1}
df["poutcome_map"]=df['poutcome'].map(dic3)
```

In [12]:

```
df["default"].value_counts()
```

Out[12]:

```
no     41185
yes        3
Name: default, dtype: int64
```

In [13]:

```
df["weiyue"].value_counts()
```

Out[13]:

```
0    41185
1        3
Name: weiyue, dtype: int64
```

In [14]:

```
# 去除原“default”、“housing”、“loan”、“contact”、“poutcome”列
df.drop(['default','housing','loan','contact','poutcome'],axis=1, inplace=True)
```

删除无用列

In [15]:

```
#“month”（最近一次联系的月份）、“day_of_week”（最近一次联系的星期）是不能反映有用信息的，故将其
df.drop(['month','day_of_week'],axis=1, inplace=True)
#因为“pdays”这一列含有39673个“999”值，缺失值占比达96.32%，故删除该列
df.drop('pdays',axis=1, inplace=True)
```

get_dummies离散特征编码

In [16]:

```
df1=pd.get_dummies(df,prefix=['job','marital','education'])
df1.columns
```

Out[16]:

```
Index(['age', 'duration', 'campaign', 'previous', 'emp_var_rate',
       'cons_price_idx', 'cons_conf_idx', 'euribor3m', 'nr_employed', 'y',
       'weiyue', 'housing_map', 'loan_map', 'contact_map', 'poutcome_map',
       'job_admin.', 'job_blue-collar', 'job_entrepreneur', 'job_housemaid',
       'job_management', 'job_retired', 'job_self-employed', 'job_services',
       'job_student', 'job_technician', 'job_unemployed', 'marital_divorced',
       'marital_married', 'marital_single', 'education_basic.4y',
       'education_basic.6y', 'education_basic.9y', 'education_high.school',
       'education_illiterate', 'education_professional.course',
       'education_university.degree'],
      dtype='object')
```

In [17]:

```
#np.isnan(df1).any()            #验证df1已没有缺失值
```

步骤四：连续值分组处理

4.1 “age”年龄分组

In [18]:

```
bins=[0,20,40,60,98]
labels=["20岁以下","20到40岁","40到60岁","60岁以上"]
df1["age_group"]=pd.cut(df1.age,bins,labels=labels)
```

In [19]:

```
dic10={'20岁以下':1,"20到40岁":2,"40到60岁":3,"60岁以上":4}
df1["age_map"]=df1['age_group'].map(dic10)
```

In [20]:

```
df1.age_group
```

Out[20]:

```
0        40到60岁
1        40到60岁
2        20到40岁
3        20到40岁
4        40到60岁
5        20到40岁
6        20到40岁
7        20到40岁
8        20到40岁
9        20到40岁
10       20到40岁
11       40到60岁
12       40到60岁
13       20到40岁
14       20到40岁
15       40到60岁
16       20到40岁
17       20到40岁
18       20到40岁
19       20到40岁
20       40到60岁
21       20到40岁
22       20到40岁
23       20到40岁
24       40到60岁
25       20到40岁
26       40到60岁
27       20到40岁
28       20到40岁
29       20到40岁
           ...
41158    20到40岁
41159    40到60岁
41160    40到60岁
41161    40到60岁
41162    40到60岁
41163    20到40岁
41164    20到40岁
41165    40到60岁
41166    20到40岁
41167    20到40岁
41168    20到40岁
41169    40到60岁
41170    20到40岁
41171    40到60岁
41172    20到40岁
41173    20到40岁
41174    40到60岁
41175    40到60岁
41176    20到40岁
41177    40到60岁
41178    20到40岁
41179    20到40岁
41180    40到60岁
41181    20到40岁
41182    20到40岁
```

```
41183    40到60岁
41184    20到40岁
41185    40到60岁
41186    40到60岁
41187    20到40岁
Name: age_group, Length: 41188, dtype: category
Categories (4, object): [20岁以下 < 20到40岁 < 40到60岁 < 60岁以上]
```

交叉分析：观察age_group与y的分布

In [21]:

```
df1.pivot_table(values=["age"],index=["age_group"],columns=["y"],aggfunc=[np.size])
```

Out[21]:

	size	
	age	
y	**0**	**1**
age_group		
20岁以下	83	57
20到40岁	20964	2664
40到60岁	15005	1505
60岁以上	496	414

4.2 “duration”通话持续时间分组

In [22]:

```
bins=[min(df1.duration)-1,102,180,320,max(df1.duration)+1]      #这里的102、180、320分别为df.duratio
labels=["102分钟以下","102到180分钟","180到320分钟","320分钟及以上"]
df1["duration_group"]=pd.cut(df1.duration,bins,labels=labels)
```

In [23]:

```
dic4={'102分钟以下':1,"102到180分钟":2,"180到320分钟":3,"320分钟及以上":4}
df1["duration_map"]=df1['duration_group'].map(dic4)
```

交叉分析：观察duration_group与y的分布

可大致观察到，y=1的类别里，通话分钟数越长，注册定期存款的人数越多。

In [24]:

```
df1.pivot_table(values=["duration"],index=["duration_group"],columns=["y"],aggfunc=[np.size])
```

Out[24]:

	size	
	duration	
y	0	1
duration_group		
102分钟以下	10226	87
102到180分钟	9915	477
180到320分钟	9163	1081
320分钟及以上	7244	2995

In [25]:

```
df1.drop('duration_group',axis=1, inplace=True)
df1.drop('duration',axis=1, inplace=True)
```

4.3 “campaign”联系次数分组

In [26]:

```
bins=[min(df1.campaign)-1,3,6,10,max(df1.campaign)+1]
labels=["0-2次","3-5次","6-9次","10次以上"]
df1["campaign_group"]=pd.cut(df1.campaign,bins,labels=labels,right=False)
```

In [27]:

```
dic5={"0-2次":1,"3-5次":2,"6-9次":3,"10次以上":4}
df1["campaign_map"]=df1['campaign_group'].map(dic5)
df1.drop('campaign_group',axis=1, inplace=True)
df1.drop('campaign',axis=1, inplace=True)
```

In [28]:

```
df1.head()
```

Out[28]:

	age	previous	emp_var_rate	cons_price_idx	cons_conf_idx	euribor3m	nr_employed	y	w
0	44	0	1.4	93.444	-36.1	4.963	5228.1	0	
1	53	0	-0.1	93.200	-42.0	4.021	5195.8	0	
2	28	2	-1.7	94.055	-39.8	0.729	4991.6	1	
3	39	0	-1.8	93.075	-47.1	1.405	5099.1	0	
4	55	1	-2.9	92.201	-31.4	0.869	5076.2	1	

5 rows × 38 columns

步骤五：数据标准化

In [29]:

```
X=df1[[ 'previous', 'emp_var_rate',
       'cons_price_idx', 'cons_conf_idx', 'euribor3m', 'nr_employed',
       'weiyue', 'housing_map', 'loan_map', 'contact_map', 'poutcome_map',
       'job_admin.', 'job_blue-collar', 'job_entrepreneur', 'job_housemaid',
       'job_management', 'job_retired', 'job_self-employed', 'job_services',
       'job_student', 'job_technician', 'job_unemployed', 'marital_divorced',
       'marital_married', 'marital_single', 'education_basic.4y',
       'education_basic.6y', 'education_basic.9y', 'education_high.school',
       'education_illiterate', 'education_professional.course',
       'education_university.degree']]
```

In [30]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_scaled
```

Out[30]:

```
array([[-0.34949428,  0.83906065, -0.2274652 , ..., -0.02204119,
        -0.39125376, -0.66909041],
       [-0.34949428, -0.11578127, -0.649003  , ..., -0.02204119,
        -0.39125376,  1.49456633],
       [ 3.69176641, -1.13427931,  0.82810692, ..., -0.02204119,
        -0.39125376,  1.49456633],
       ...,
       [-0.34949428,  0.64809227,  0.72272247, ..., -0.02204119,
        -0.39125376,  1.49456633],
       [-0.34949428, -2.21643348, -1.97753812, ..., -0.02204119,
         2.55588596, -0.66909041],
       [-0.34949428,  0.64809227,  0.72272247, ..., -0.02204119,
        -0.39125376, -0.66909041]])
```

步骤六：逻辑回归预测

模型训练

In [31]:

```
from sklearn.linear_model import LogisticRegression
lr1=LogisticRegression()
lr1.fit(X,df1["y"])
```

Out[31]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

模型预测（predict_proba方法）

In [32]:

```
pred=lr1.predict(X)
print(pred)
```

```
[0 0 1 ..., 0 0 0]
```

模型评判之——精度值计算

In [33]:

```
df1["pred_label"]=pred
```

In [34]:

```
match=df1["y"]==df1["pred_label"]
correct=df1[match]
accuracy=len(correct)/len(df1)
print(accuracy)
```

```
0.8989754297368165
```

模型评判之——TPR计算

In [35]:

```
TP=(df1["y"]==1)&(df1["pred_label"]==1)
TP=len(df1[TP])
print(TP)
FN=(df1["y"]==1)&(df1["pred_label"]==0)
FN=len(df1[FN])
print(FN)
TPR=TP/(TP+FN)
print(TPR)
```

```
860
3780
0.1853448275862069
```

模型评判之——TNR计算

In [36]:

```
TN=(df1["y"]==0)&(df1["pred_label"]==0)
TN=len(df1[TN])
print(TN)
FP=(df1["y"]==0)&(df1["pred_label"]==1)
FP=len(df1[FP])
print(FP)
TNR=TN/(TN+FP)
print(TNR)
```

```
36167
381
0.9895753529604903
```

ROC指标（metrics.roc_curve）

In [37]:

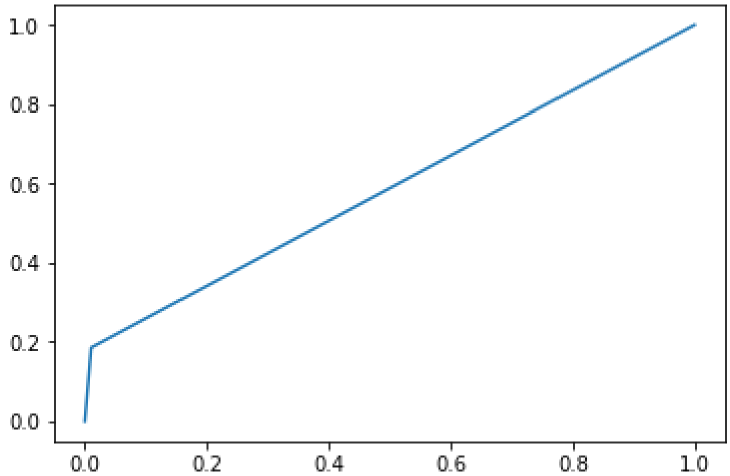
```
from sklearn import metrics

false_positive_rate,true_positive_rate,thresholds =metrics.roc_curve(df1["y"],df1["pred_label"])
print(thresholds)
plt.plot(false_positive_rate,true_positive_rate)
```

```
[2 1 0]
```

Out[37]:

```
[<matplotlib.lines.Line2D at 0xe201e10>]
```



计算AUC值（即ROC面积）（sklearn.metrics.roc_auc_score）

In [38]:

```
from sklearn.metrics import roc_auc_score

auc_score=roc_auc_score(df1["y"],df1["pred_label"])
print(auc_score)
```

```
0.587460090273
```

交叉验证（sklearn.cross_validation）

In [39]:

```
from sklearn.cross_validation import KFold
from sklearn.cross_validation import cross_val_score

lr=LogisticRegression()
kf=KFold(len(df1),5,shuffle=True)
print("每次交叉验证的准确率为：")
accuracies=cross_val_score(lr,X,df["y"],scoring="accuracy",cv=kf)
print(accuracies)
print(type(accuracies))
accuracy=accuracies.mean()
print("平均准确率为：")
print(accuracy)
```

```
每次交叉验证的准确率为：

D:\anzhuangruanjian\anaconda\lib\site-packages\sklearn\cross_validation.py:41: Depre
cationWarning: This module was deprecated in version 0.18 in favor of the model_sele
ction module into which all the refactored classes and functions are moved. Also not
e that the interface of the new CV iterators are different from that of this module.
This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)

[ 0.89900461  0.90082544  0.89839767  0.89802112  0.89328639]
<class 'numpy.ndarray'>
平均准确率为：
0.89790704801
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: