信用评分卡建模

本文将针对 Kaggle 数据 Give me some credit构建一个信用评分卡模型。本文主要分为载入数据、数据的探索与分析、数据预处理、特征工程、定义评价指标、模型构建、制作评分卡等部分。(由于所给测试集SeriousDlqin2yrs字段全为空，所以无法做模型评估)

1. 加载库并读入数据

1.1 加载库

```
# -*- coding: utf-8 -*-
#!/usr/bin/env python

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import itertools
import xgboost as xgb
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import precision_score, recall_score, confusion_matrix, classification_report
from sklearn.metrics import roc_curve, precision_recall_curve
from __future__ import division
import warnings

# 忽略告警
warnings.filterwarnings('ignore')
```

1.2 读入数据

```
data_train = pd.read_csv('./data/cs-training.csv')
```

2. 数据探索与分析

2.1 变量分布和描述

```
data_train.describe()
```

	Unnamed: 0	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	NumberOfTime30-59DaysPastDueNotWorse	DebtRat
count	150000.000000	150000.000000	150000.000000	150000.000000	150000.000000	150000.0
mean	75000.500000	0.066840	6.048438	52.295207	0.421033	353.0050
std	43301.414527	0.249746	249.755371	14.771866	4.192781	2037.818
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	37500.750000	0.000000	0.029867	41.000000	0.000000	0.175074
50%	75000.500000	0.000000	0.154181	52.000000	0.000000	0.366508
75%	112500.250000	0.000000	0.559046	63.000000	0.000000	0.868254
max	150000.000000	1.000000	50708.000000	109.000000	98.000000	329664.0

了解各列名的含义：

- SeriousDlqin2yrs：超过90天或更糟的逾期拖欠
- RevolvingUtilizationOfUnsecuredLines：除了房贷车贷之外的信用卡账面金额（即贷款金额）/信用卡总额度
- age：贷款人年龄
- NumberOfTime30-59DaysPastDueNotWorse：35-59天逾期但不糟糕次数
- DebtRatio：负债比率
- MonthlyIncome：月收入
- NumberOfOpenCreditLinesAndLoans：开放式信贷和贷款数量，开放式贷款（分期付款如汽车贷款或抵押贷款）和信贷（如信用卡）的数量
- NumberOfTimes90DaysLate：借款者有90天或更高逾期的次数
- NumberRealEstateLoansOrLines：不动产贷款或额度数量
- NumberOfTime60-89DaysPastDueNotWorse：60-89天逾期但不糟糕次数
- NumberOfDependents：不包括本人在内的家属数量

```
data_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150000 entries, 0 to 149999
Data columns (total 12 columns):
Unnamed: 0                            150000 non-null int64
SeriousDlqin2yrs                      150000 non-null int64
RevolvingUtilizationOfUnsecuredLines  150000 non-null float64
age                                   150000 non-null int64
NumberOfTime30-59DaysPastDueNotWorse  150000 non-null int64
DebtRatio                             150000 non-null float64
MonthlyIncome                         120269 non-null float64
NumberOfOpenCreditLinesAndLoans       150000 non-null int64
NumberOfTimes90DaysLate               150000 non-null int64
NumberRealEstateLoansOrLines          150000 non-null int64
NumberOfTime60-89DaysPastDueNotWorse  150000 non-null int64
NumberOfDependents                    146076 non-null float64
dtypes: float64(4), int64(8)
memory usage: 13.7 MB
```

从以上信息可以看出：

- RevolvingUtilizationOfUnsecuredLines的正常取值应在0-1之间，而其最大值为50708，很有可能含有异常值
- age最小值为0，最大值为109，也很可能含有异常值
- MonthlyIncome只有120269条记录，NumberOfDependents只有146076条记录，说明有缺失值

2.2 初步清洗

```
#选择子集
data_train.drop('Unnamed: 0',axis=1,inplace=True)
data_train.head()
```

	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	NumberOfTime30-59DaysPastDueNotWorse	DebtRatio	MonthlyIncome	Numbe
0	1	0.766127	45	2	0.802982	9120.0	13
1	0	0.957151	40	0	0.121876	2600.0	4
2	0	0.658180	38	1	0.085113	3042.0	2
3	0	0.233810	30	0	0.036050	3300.0	5
4	0	0.907239	49	1	0.024926	63588.0	7

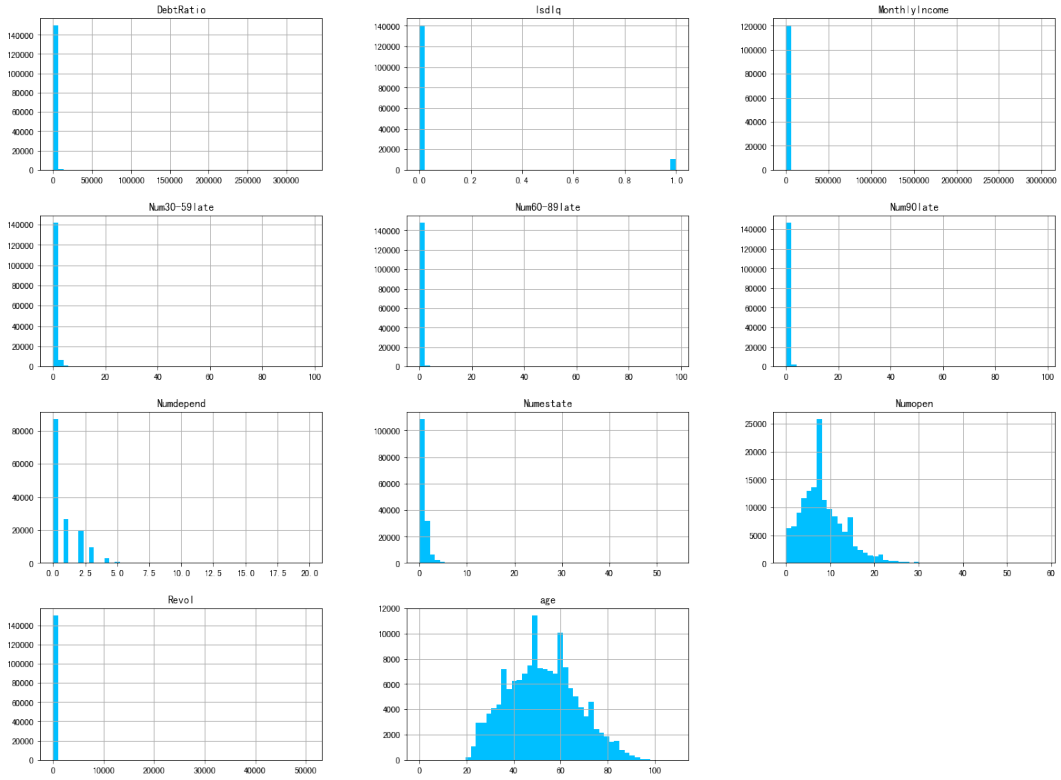
```
#列名重命名
colnames={'SeriousDlqin2yrs':'Isdlq',
          'RevolvingUtilizationOfUnsecuredLines':'Revol',
          'NumberOfTime30-59DaysPastDueNotWorse':'Num30-59late',
          'NumberOfOpenCreditLinesAndLoans':'Numopen',
          'NumberOfTimes90DaysLate':'Num90late',
          'NumberRealEstateLoansOrLines':'Numestate',
          'NumberOfTime60-89DaysPastDueNotWorse':'Num60-89late',
          'NumberOfDependents':'Numdepend'}
data_train.rename(columns=colnames,inplace=True)
data_train.head()
```

	Isdlq	Revol	age	Num30-59late	DebtRatio	MonthlyIncome	Numopen	Num90late	Numestate	Num60-89late	Numdepen
0	1	0.766127	45	2	0.802982	9120.0	13	0	6	0	2.0
1	0	0.957151	40	0	0.121876	2600.0	4	0	0	0	1.0
2	0	0.658180	38	1	0.085113	3042.0	2	1	0	0	0.0
3	0	0.233810	30	0	0.036050	3300.0	5	0	0	0	0.0
4	0	0.907239	49	1	0.024926	63588.0	7	0	1	0	0.0

2.3 各变量分析

先看总体情况，然后对各变量逐一分析：

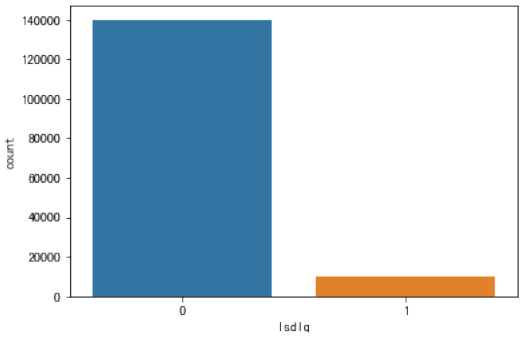
```
data_train.hist (bins=50, figsize=(20,15), color = 'deepskyblue')

plt.show()
```



- **Isdlq**

```
sns.countplot('Isdlq',data=data_train)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x11405e710>
```




```
badNum=data_train.loc[data_train['Isdlq']==1,:].shape[0]
goodNum=data_train.loc[data_train['Isdlq']==0,:].shape[0]
print('The rate of SeriousDlqin2yrs=1: {0}%'.format(round(badNum*100/(goodNum+badNum),2)))
```

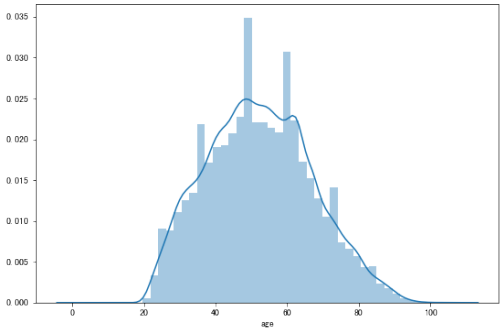
```
The rate of SeriousDlqin2yrs=1: 6.0%
```

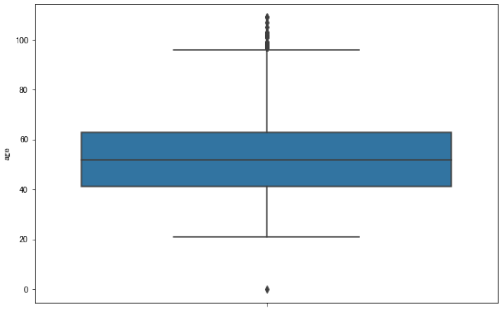
数据不平衡，逾期拖欠发生数量占总数的6.0%，后期需处理。

- **Age**

```
#Age数据分布情况
fig,[ax1,ax2]=plt.subplots(1,2,figsize=(20,6))
sns.distplot(data_train['age'],ax=ax1)
sns.boxplot(y='age',data=data_train,ax=ax2)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x112729f50>
```





可看出年龄分布基本符合正太分布，但存在异常值。用3倍标准差来筛选异常值。

```
#异常值情况
age_mean=data_train['age'].mean()
age_std=data_train['age'].std()
age_lowlimit=age_mean-3*age_std
age_uplimit=age_mean+3*age_std
print('age_lowlimit:',age_lowlimit,'age_uplimit:',age_uplimit)
```

```
('age_lowlimit:', 7.979609077365616, 'age_uplimit:', 96.61080425596771)
```

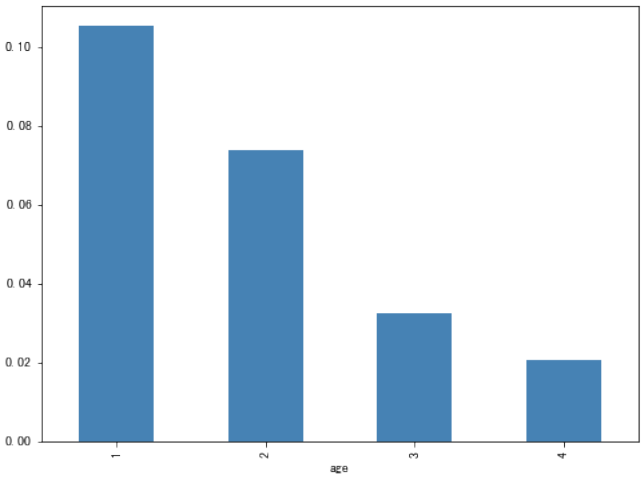
```
#筛选异常值
age_lowlimitd=data_train.loc[data_train['age']<age_lowlimit,:]
age_uplimitd=data_train.loc[data_train['age']>age_uplimit,:]
print('The rate of age_lowlimit: {0}%'.format(age_lowlimitd.shape[0]*100/data_train.shape[0]),
      'The rate of age_uplimit: {0}%'.format(age_uplimitd.shape[0]*100/data_train.shape[0]))
```

```
('The rate of age_lowlimit: 0.0006666666666667%', 'The rate of age_uplimit: 0.03%')
```

年龄为0的应删除，超过96岁的可判断为噪声。再看下各年龄段违约率情况：

```
data_age=data_train.loc[data_train['age']>0,['age','Isdlq']]
data_age.loc[(data_age['age']>18)&(data_age['age']<40),'age'] = 1
data_age.loc[(data_age['age']>=40)&(data_age['age']<60),'age'] = 2
data_age.loc[(data_age['age']>=60)&(data_age['age']<80),'age'] = 3
data_age.loc[(data_age['age']>=80),'age'] = 4
age_Isdlq=data_age.groupby('age')['Isdlq'].sum()
age_total=data_age.groupby('age')['Isdlq'].count()
age_Isratio=age_Isdlq/age_total
age_Isratio.plot(kind='bar',figsize=(8,6),color='#4682B4')
```

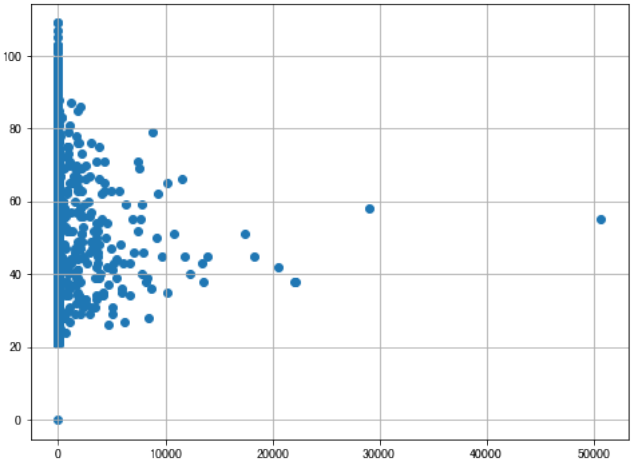
```
<matplotlib.axes._subplots.AxesSubplot at 0x112533890>
```



可看出18-40岁违约率最高，随年岁增长，违约率降低。

- **Revol**

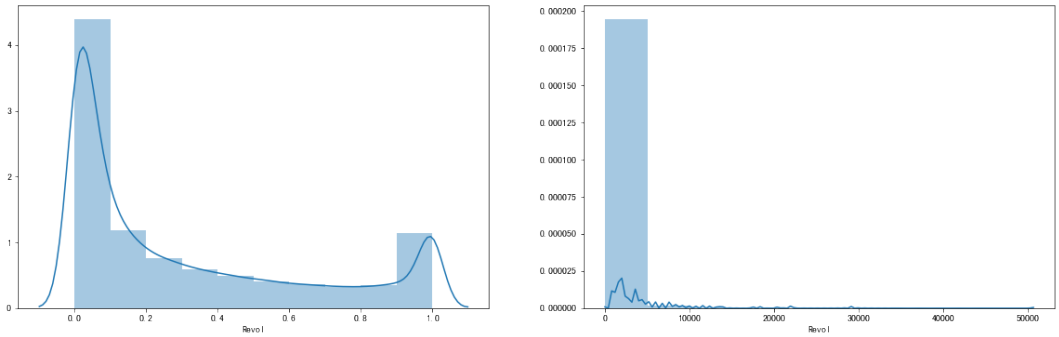
```
#Revol数据分布
figure=plt.figure(figsize=(8,6))
plt.scatter(data_train['Revol'],data_train['age'])
plt.grid()
```



Revol的正常取值在0-1之间，超出1的为透支，但有些超过10000的数据应为异常值。把数据分为两部分，小于1的部分和大于1的部分，看看这两部分的数据分布情况。

```
#将数据分为两部分，小于1和大于1的部分
data1=data_train.loc[data_train['Revol']<1,:]
data2=data_train.loc[data_train['Revol']>=1,:]
#看一下两部分数据分布情况
fig=plt.figure(figsize=(20,6))
ax1=fig.add_subplot(1,2,1)
ax2=fig.add_subplot(1,2,2)
sns.distplot(data1['Revol'],ax=ax1,bins=10)
sns.distplot(data2['Revol'],ax=ax2,bins=10)
```

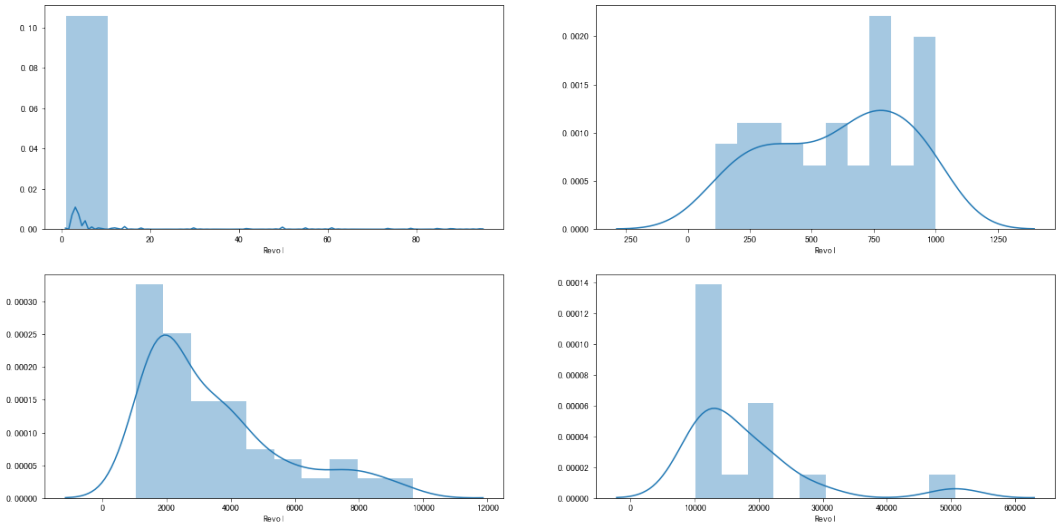
```
<matplotlib.axes._subplots.AxesSubplot at 0x11265aed0>
```



由第二个图可看出大于1的数据大部分在0-10000之间。把区间0-10000进一步细分为[1，100, [100，1000), [1000，10000), 10000以上，分别查看数据的分布情况。

```
fig,[[ax1,ax2],[ax3,ax4]]=plt.subplots(2,2,figsize=(20,10))
sns.distplot(data_train.loc[(data_train['Revol']>=1)&(data_train['Revol']<100),'Revol'],bins=10,ax=ax1)
sns.distplot(data_train.loc[(data_train['Revol']>=100)&(data_train['Revol']
<1000),'Revol'],bins=10,ax=ax2)
sns.distplot(data_train.loc[(data_train['Revol']>=1000)&(data_train['Revol']
<10000),'Revol'],bins=10,ax=ax3)
sns.distplot(data_train.loc[data_train['Revol']>=10000,'Revol'],bins=10,ax=ax4)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x11234cb50>
```



可见大于1的数据绝大多数数据集中在1-20之间，我们的目的是找到异常值的阈值，我们分区间，分别看一下违约率情况。

```
#将区间分为（0-1），(1-10)，(10-20)， (20-100)， (100,1000)， (1000-10000)， (10000,51000) 看一下违约率情况
data_1=data_train.loc[(data_train['Revol']>=0)&(data_train['Revol']<1),:]
Is_1=data_1.loc[data_1['Isdlq']==1,:].shape[0]*100/data_1.shape[0]

data_2=data_train.loc[(data_train['Revol']>=1)&(data_train['Revol']<10),:]
Is_2=data_2.loc[data_2['Isdlq']==1,:].shape[0]*100/data_2.shape[0]

data_3=data_train.loc[(data_train['Revol']>=10)&(data_train['Revol']<20),:]
Is_3=data_3.loc[data_3['Isdlq']==1,:].shape[0]*100/data_3.shape[0]

data_4=data_train.loc[(data_train['Revol']>=20)&(data_train['Revol']<100),:]
Is_4=data_4.loc[data_4['Isdlq']==1,:].shape[0]*100/data_4.shape[0]

data_5=data_train.loc[(data_train['Revol']>=100)&(data_train['Revol']<1000),:]
Is_5=data_5.loc[data_5['Isdlq']==1,:].shape[0]*100/data_5.shape[0]

data_6=data_train.loc[(data_train['Revol']>=1000)&(data_train['Revol']<10000),:]
Is_6=data_6.loc[data_6['Isdlq']==1,:].shape[0]*100/data_6.shape[0]

data_7=data_train.loc[(data_train['Revol']>=10000)&(data_train['Revol']<51000),:]
Is_7=data_7.loc[data_7['Isdlq']==1,:].shape[0]*100/data_7.shape[0]

print('0-1: {0}%'.format(Is_1),
      '1-10: {0}%'.format(Is_2),
      '10-20: {0}%'.format(Is_3),
      '20-100: {0}%'.format(Is_4),
      '100-1000: {0}%'.format(Is_5),
      '1000-10000: {0}%'.format(Is_6),
      '10000-51000: {0}%'.format(Is_7))
```

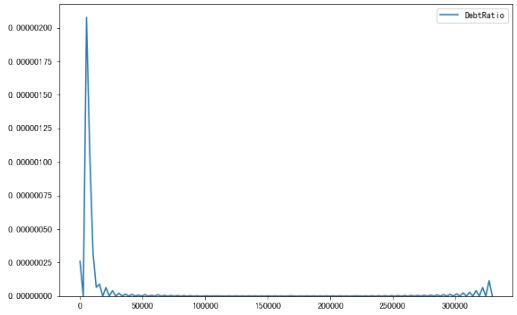
```
('0-1: 5.98996331701%', '1-10: 39.5221181789%', '10-20: 57.1428571429%', '20-100: 18.1818181818%',
'100-1000: 1.96078431373%', '1000-10000: 6.41025641026%', '10000-51000: 0.0%')
```

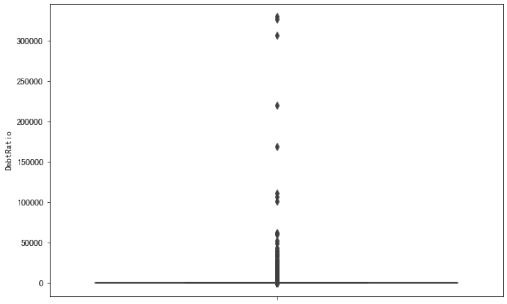
可以看出在Revol大于1时，违约率开始上升，10-20之间违约率达到高峰，超过20后开始下降，超过1000后开始恢复正常。说明20左右的值可能为异常值上限的阈值。可将超过20的值都定义为异常值。

- **DebtRatio**

```
#DebtRatio数据的分布情况
fig,[ax1,ax2]=plt.subplots(1,2,figsize=(20,6))
sns.kdeplot(data_train['DebtRatio'],ax=ax1)
sns.boxplot(y=data_train['DebtRatio'],ax=ax2)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x113de5dd0>
```

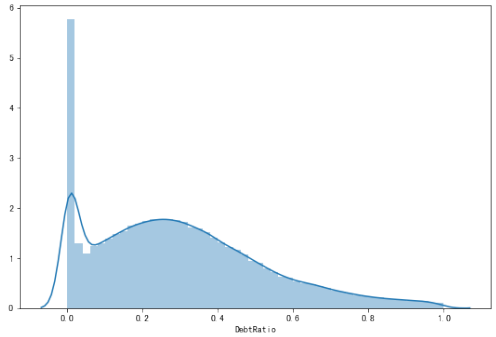


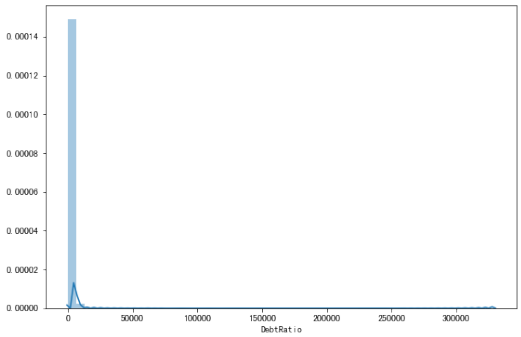


数据分布跨度较大，先分组查看数据的分布情况：

```
Debt1=data_train.loc[data_train['DebtRatio']<1,:]
Debt2=data_train.loc[data_train['DebtRatio']>=1,:]
fig,[ax1,ax2]=plt.subplots(1,2,figsize=(20,6))
sns.distplot(Debt1['DebtRatio'],ax=ax1)
sns.distplot(Debt2['DebtRatio'],ax=ax2)
```

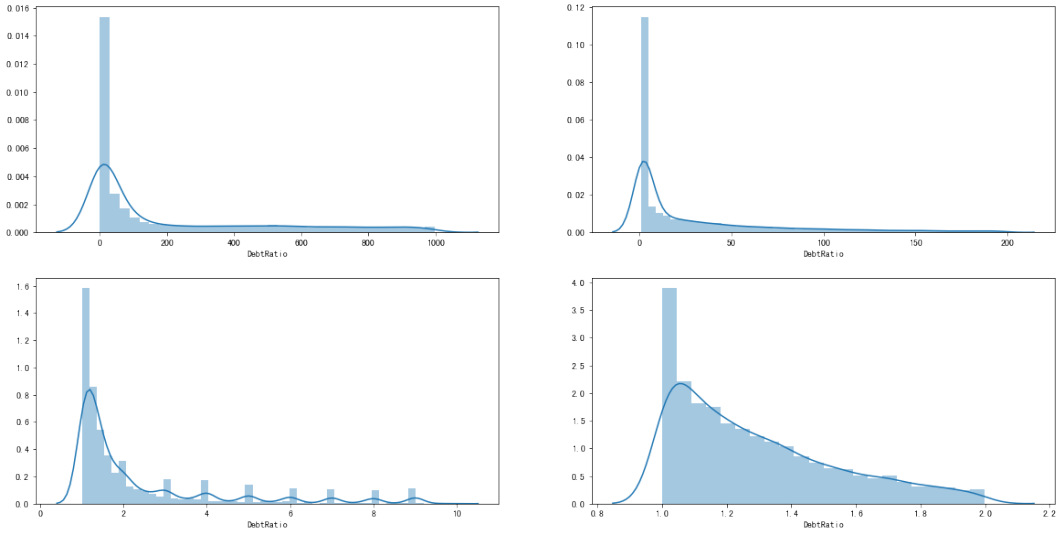
```
<matplotlib.axes._subplots.AxesSubplot at 0x1120fdcd0>
```






```
#尝试多次细分
Debt3=data_train.loc[(data_train['DebtRatio']>=1)&(data_train['DebtRatio']<1000),:]
Debt4=data_train.loc[(data_train['DebtRatio']>=1)&(data_train['DebtRatio']<200),:]
Debt5=data_train.loc[(data_train['DebtRatio']>=1)&(data_train['DebtRatio']<10),:]
Debt6=data_train.loc[(data_train['DebtRatio']>=1)&(data_train['DebtRatio']<2),:]

fig,[[ax1,ax2],[ax3,ax4]]=plt.subplots(2,2,figsize=(20,10))
sns.distplot(Debt3['DebtRatio'],ax=ax1)
sns.distplot(Debt4['DebtRatio'],ax=ax2)
sns.distplot(Debt5['DebtRatio'],ax=ax3)
sns.distplot(Debt6['DebtRatio'],ax=ax4)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1127d2050>
```



查看各区间的违约情况：

```
#各区间的违约率(0,1),(1-2),(2-10),(10-50),(50-200),(200,1000),1000以上
Debt_1=data_train.loc[(data_train['DebtRatio']>=0)&(data_train['DebtRatio']<1),:]
DebIs_1=Debt_1.loc[Debt_1['Isdlq']==1,:].shape[0]*100/Debt_1.shape[0]

Debt_2=data_train.loc[(data_train['DebtRatio']>=1)&(data_train['DebtRatio']<2),:]
DebIs_2=Debt_2.loc[Debt_2['Isdlq']==1,:].shape[0]*100/Debt_2.shape[0]

Debt_3=data_train.loc[(data_train['DebtRatio']>=2)&(data_train['DebtRatio']<10),:]
DebIs_3=Debt_3.loc[Debt_3['Isdlq']==1,:].shape[0]*100/Debt_3.shape[0]

Debt_4=data_train.loc[(data_train['DebtRatio']>=10)&(data_train['DebtRatio']<50),:]
DebIs_4=Debt_4.loc[Debt_4['Isdlq']==1,:].shape[0]*100/Debt_4.shape[0]

Debt_5=data_train.loc[(data_train['DebtRatio']>=50)&(data_train['DebtRatio']<200),:]
DebIs_5=Debt_5.loc[Debt_5['Isdlq']==1,:].shape[0]*100/Debt_5.shape[0]

Debt_6=data_train.loc[(data_train['DebtRatio']>=200)&(data_train['DebtRatio']<1000),:]
DebIs_6=Debt_6.loc[Debt_6['Isdlq']==1,:].shape[0]*100/Debt_6.shape[0]

Debt_7=data_train.loc[data_train['DebtRatio']>=1000,:]
DebIs_7=Debt_7.loc[Debt_7['Isdlq']==1,:].shape[0]*100/Debt_7.shape[0]

print('0-1: {0}%'.format(DebIs_1),
      '1-2: {0}%'.format(DebIs_2),
      '2-10: {0}%'.format(DebIs_3),
      '10-50: {0}%'.format(DebIs_4),
      '50-200: {0}%'.format(DebIs_5),
      '200-1000: {0}%'.format(DebIs_6),
      '1000: {0}%'.format(DebIs_7))
```

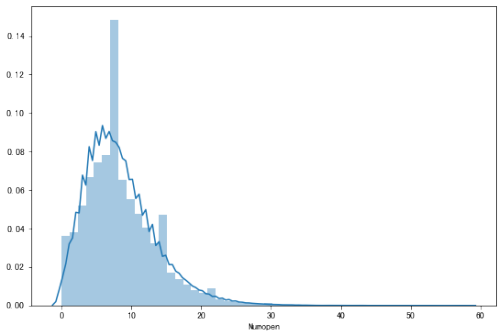
```
('0-1: 6.74494478078%', '1-2: 13.0089135148%', '2-10: 6.25844214318%', '10-50: 4.34638354346%', '50-200: 5.6269538034%', '200-1000: 7.95033059184%', '1000: 4.90532544379%')
```

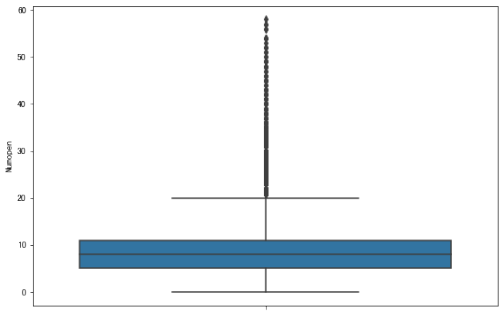
可看到1-2的违约率达到最高，超过2以后违约率开始稳定。这里把2作为异常值上限的阈值。并把大于2的数据和0-1的数据进行合并。

- **Numopen**

```
#数据分布
fig,[ax1,ax2]=plt.subplots(1,2,figsize=(20,6))
sns.distplot(data_train['Numopen'],ax=ax1)
sns.boxplot(y=data_train['Numopen'],ax=ax2)
```

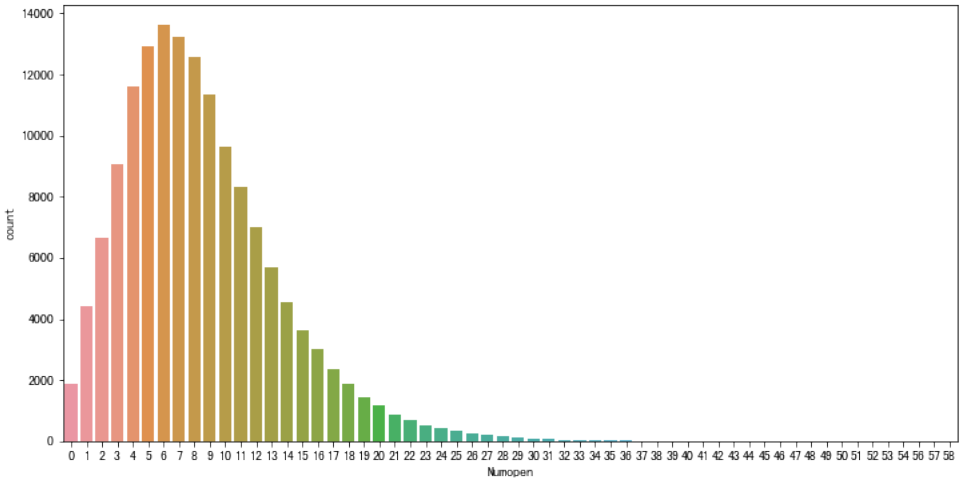
```
<matplotlib.axes._subplots.AxesSubplot at 0x114c50090>
```






```
#查看数据点分布
figure=plt.figure(figsize=(12,6))
sns.countplot(data_train['Numopen'])
```

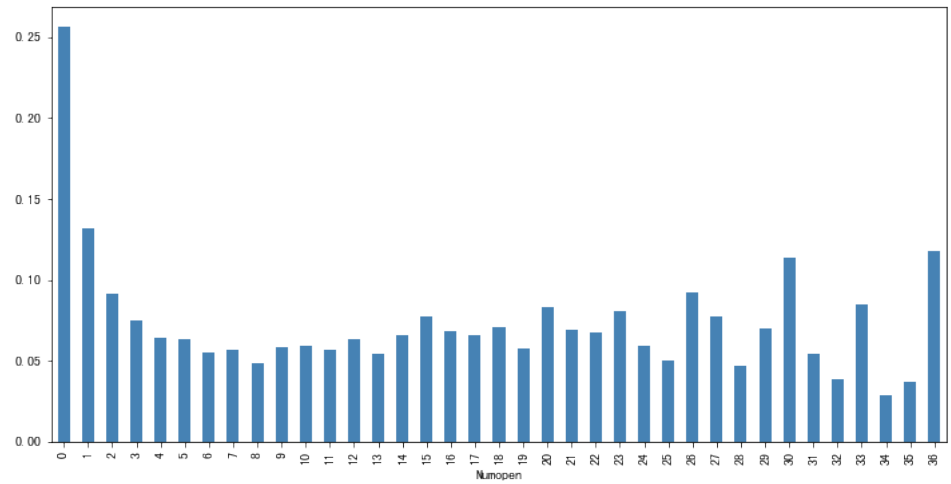
```
<matplotlib.axes._subplots.AxesSubplot at 0x1136d98d0>
```



可以看出大于36的数据过少，我们把大于36的数据和36合并，并查看违约率情况。

```
data_train.loc[data_train['Numopen']>36,'Numopen']=36
Numopen_dlq=data_train.groupby(['Numopen'])['Isdlq'].sum()
Numopen_total=data_train.groupby(['Numopen'])['Isdlq'].count()
Numopen_dlqratio=Numopen_dlq/Numopen_total
Numopen_dlqratio.plot(kind='bar',figsize=(12,6),color='#4682B4')

```

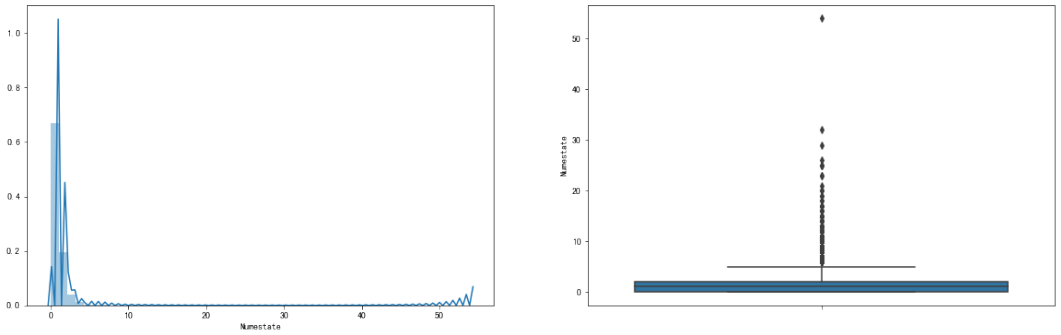
```
<matplotlib.axes._subplots.AxesSubplot at 0x112692dd0>
```



- **Numestate**

```
#数据分布
fig,[ax1,ax2]=plt.subplots(1,2,figsize=(20,6))
sns.distplot(data_train['Numestate'],ax=ax1)
sns.boxplot(y=data_train['Numestate'],ax=ax2)
```

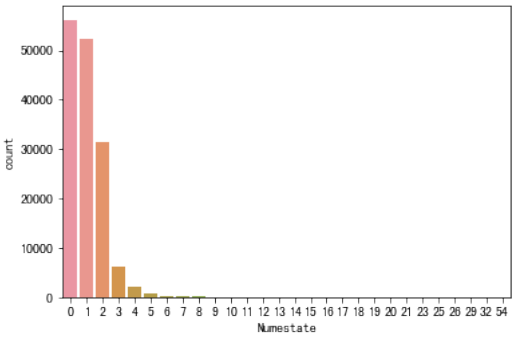
```
<matplotlib.axes._subplots.AxesSubplot at 0x111297110>
```



可看到超过50的点为明显的异常点。

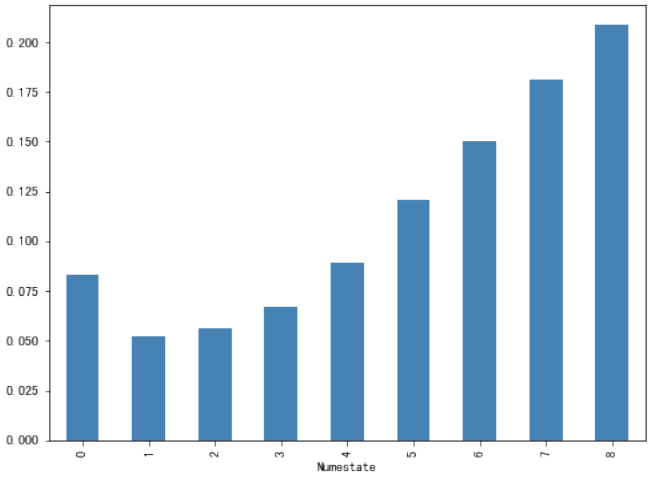
```
#查看各数据点数据大小分布
sns.countplot(data_train['Numestate'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x115cd9dd0>
```




```
#将大于8的数据和8合并后看一下违约率的情况
data_train.loc[data_train['Numestate']>8,'Numestate']=8
Numestate_dlq=data_train.groupby(['Numestate'])['Isdlq'].sum()
Numestate_total=data_train.groupby(['Numestate'])['Isdlq'].count()
Numestate_dlqratio=Numestate_dlq/Numestate_total
Numestate_dlqratio.plot(kind='bar',figsize=(8,6),color='#4682B4')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x11d4aeed0>
```

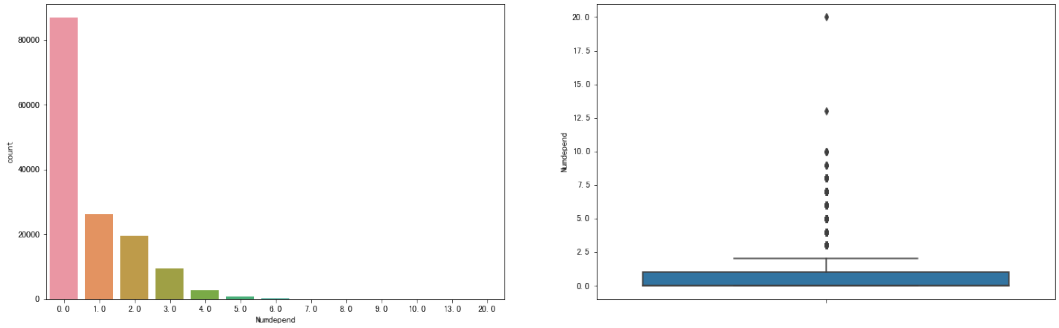


从Numopen和Numestate的违约率分布可以看出，贷款数量为0时并不是违约率最低的，不动产贷款数量为1时违约率最低，但随着打款数量增加，违约率也随着增高

- **Numdepend**

```
#Numdepend数据分布
fig,[ax1,ax2]=plt.subplots(1,2,figsize=(20,6))
sns.countplot(data_train['Numdepend'],ax=ax1)
sns.boxplot(y=data_train['Numdepend'],ax=ax2)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x11d765d10>
```



由2.1节的描述统计信息可知Numdepend中含有缺失值，查看缺失值情况：

```
D_nullNum=data_train['Numdepend'].isnull().sum()
print('The number of missing value: ',D_nullNum,'The ratio of missing value:
{0}%'.format(D_nullNum*100/data_train.shape[0]))
```

```
('The number of missing value: ', 3924, 'The ratio of missing value: 2.616%')
```

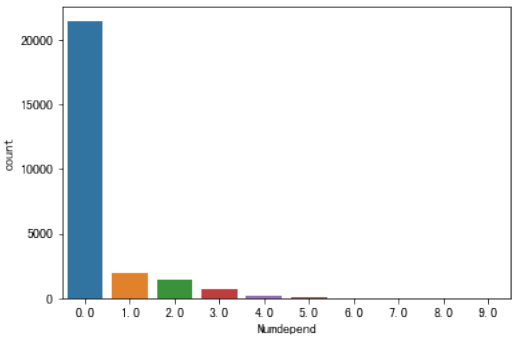
```
#查看MonthlyIncome和Numdepend的缺失是否有关联
data_train.loc[(data_train['Numdepend'].isnull())&(data_train['MonthlyIncome'].isnull()),:].shape[0]
```

```
3924
```

可以看出Numdepend缺失的，MonthlyIncome也同时缺失。所以，接下来看一下MonthlyIncome缺失，Numdepend不缺失的数据分布：

```
MonthNullDependNot=data_train.loc[(data_train['Numdepend'].notnull())&
(data_train['MonthlyIncome']).isnull(),:]
sns.countplot(MonthNullDependNot['Numdepend'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x115ceb590>
```

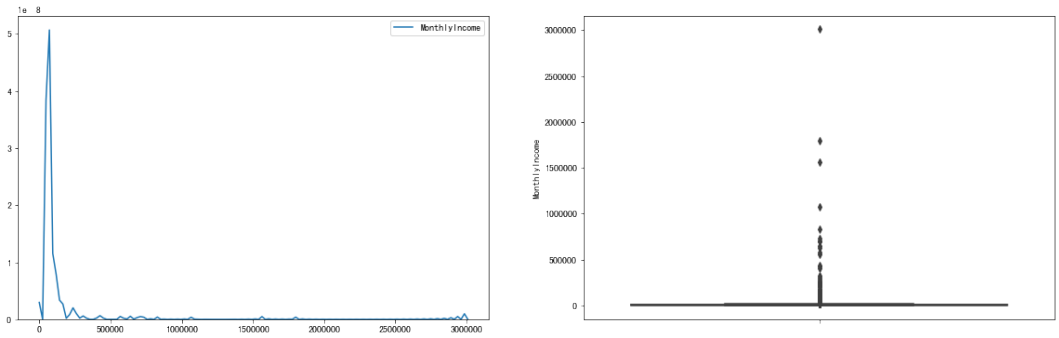


可看出MonthlyIncome缺失，Numdepend不缺失的数据中Numdepend大多取值0，所以我们将Numdepend的缺失值填充为0。

- **MonthlyIncome**

```
#MonthlyIncome数据分布
fig,[ax1,ax2]=plt.subplots(1,2,figsize=(20,6))
sns.kdeplot(data_train['MonthlyIncome'],ax=ax1)
sns.boxplot(y=data_train['MonthlyIncome'],ax=ax2)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x11e43d6d0>
```




```
#MonthlyIncome缺失值情况
M_nullNum=data_train['MonthlyIncome'].isnull().sum()
print('The number of missing value: ',M_nullNum,'The ratio of missing value:
{0}%'.format(M_nullNum*100/data_train.shape[0]))
```

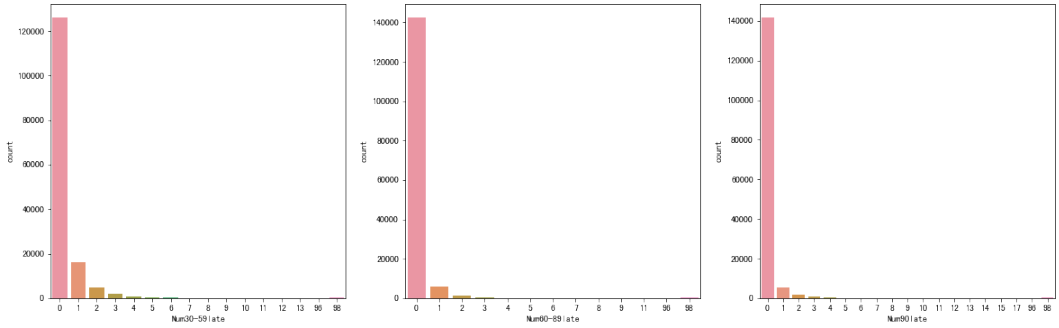
```
('The number of missing value: ', 29731, 'The ratio of missing value: 19.8206666667%')
```

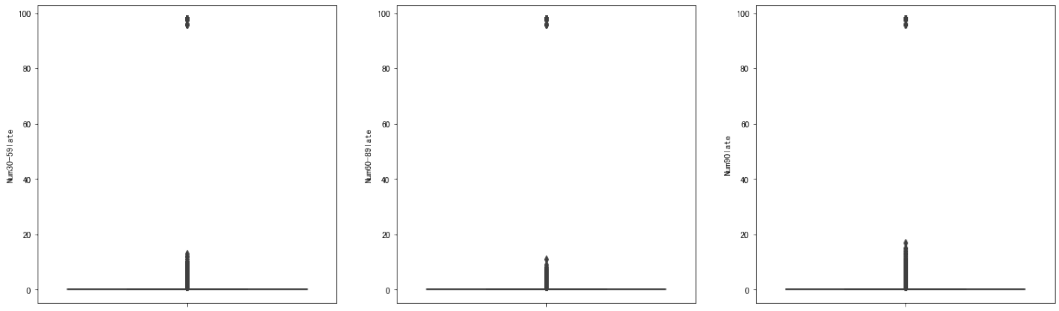
缺失比例接近20%，不能直接删除，后面采用随机森林填补缺失值。

- **Num30-59late Num60-89late Num90late**

```
fig,[ax1,ax2,ax3]=plt.subplots(1,3,figsize=(20,6))
sns.countplot(data_train['Num30-59late'],ax=ax1)
sns.countplot(data_train['Num60-89late'],ax=ax2)
sns.countplot(data_train['Num90late'],ax=ax3)

fig,[ax1,ax2,ax3]=plt.subplots(1,3,figsize=(20,6))
sns.boxplot(y=data_train['Num30-59late'],ax=ax1)
sns.boxplot(y=data_train['Num60-89late'],ax=ax2)
sns.boxplot(y=data_train['Num90late'],ax=ax3)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x12005bad0>
```





可看出大于90的明显为异常值。

3. 数据预处理

3.1 异常值处理

```
#age异常值处理
data_train=data_train[data_train['age']>0]

#Num30-59late Num60-89late Num90late异常值处理
data_train=data_train[data_train['Num30-59late']<90]
data_train=data_train[data_train['Num60-89late']<90]
data_train=data_train[data_train['Num90late']<90]

#Numestate异常值处理
data_train=data_train[data_train['Numestate']<50]
```

3.2 缺失值处理

```
#Numdepend缺失值处理
data_train['Numdepend']=data_train['Numdepend'].fillna('0')

#MonthlyIncome缺失值处理
#随机森林预测缺失值
data_Forest=data_train.iloc[:,[5,1,2,3,4,6,7,8,9]]
MonthlyIncome_isnull=data_Forest.loc[data_train['MonthlyIncome'].isnull(),:]
MonthlyIncome_notnull=data_Forest.loc[data_train['MonthlyIncome'].notnull(),:]

from sklearn.ensemble import RandomForestRegressor
X=MonthlyIncome_notnull.iloc[:,1:].values
y=MonthlyIncome_notnull.iloc[:,0].values
regr=RandomForestRegressor(max_depth=3, random_state=0,n_estimators=200,n_jobs=-1)
regr.fit(X,y)
MonthlyIncome_fillvalue=regr.predict(MonthlyIncome_isnull.iloc[:,1:].values).round(0)

#填充MonthlyIncome缺失值
data_train.loc[data_train['MonthlyIncome'].isnull(),'MonthlyIncome']=MonthlyIncome_fillvalue
```

4. 特征工程

4.1 特征提取

```
#衍生变量
data_train['AllNumlate']=data_train['Num30-59late']+data_train['Num60-89late']+data_train['Num90late']
data_train['Monthlypayment']=data_train['DebtRatio']*data_train['MonthlyIncome']
data_train['Withdepend']=data_train['Numdepend']
```

4.2 特征分箱

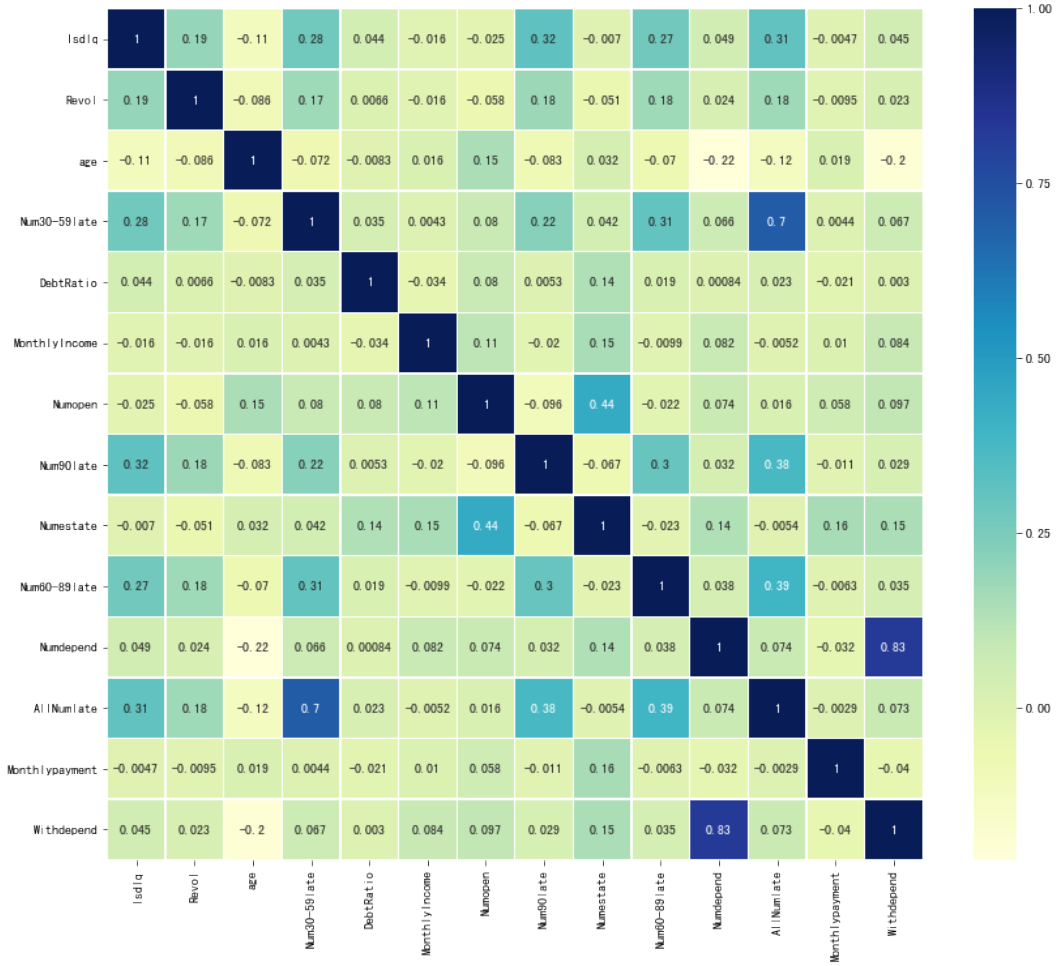
```
#数据类型转换
data_train['Numdepend']=data_train['Numdepend'].astype('int64')
data_train['Withdepend']=data_train['Withdepend'].astype('int64')
data_train['MonthlyIncome']=data_train['MonthlyIncome'].astype('int64')
data_train['Monthlypayment']=data_train['Monthlypayment'].astype('int64')

#Revol分箱
data_train.loc[(data_train['Revol']<1),'Revol']=0
data_train.loc[(data_train['Revol']>1)&(data_train['Revol']<=20),'Revol']=1
data_train.loc[(data_train['Revol']>20),'Revol']=0#根据前文EDA分析，将大于20的数据与0-1的数据合并

#DebtRatio分箱
data_train.loc[(data_train['DebtRatio']<1),'DebtRatio']=0
data_train.loc[(data_train['DebtRatio']>1)&(data_train['DebtRatio']<2),'DebtRatio']=1
data_train.loc[(data_train['DebtRatio']>=2),'DebtRatio']=0

#Num30-59late/Num60-89late/Num90late/Numestate/Numdepend
data_train.loc[(data_train['Num30-59late']>=8), 'Num30-59late'] = 8
data_train.loc[(data_train['Num60-89late']>=7), 'Num60-89late'] = 7
data_train.loc[(data_train['Num90late']>=10), 'Num90late'] = 10
data_train.loc[(data_train['Numestate']>=8), 'Numestate'] = 8
data_train.loc[(data_train['Numdepend']>=7), 'Numdepend'] = 7

#AllNumlate分箱
data_train.loc[(data_train['AllNumlate']>1),'AllNumlate']=1#分为逾期和未逾期两种情况

#Withdepend分箱
data_train.loc[(data_train['Withdepend']>1),'Withdepend']=1#分为独生子女和非独生子女
```

4.3 特征选择

4.3.1 根据相关系数查看各变量相关性

```
corr=data_train.corr()
plt.figure(figsize=(14,12))
sns.heatmap(corr,annot=True,linewidths=.3,cmap='YlGnBu')
```

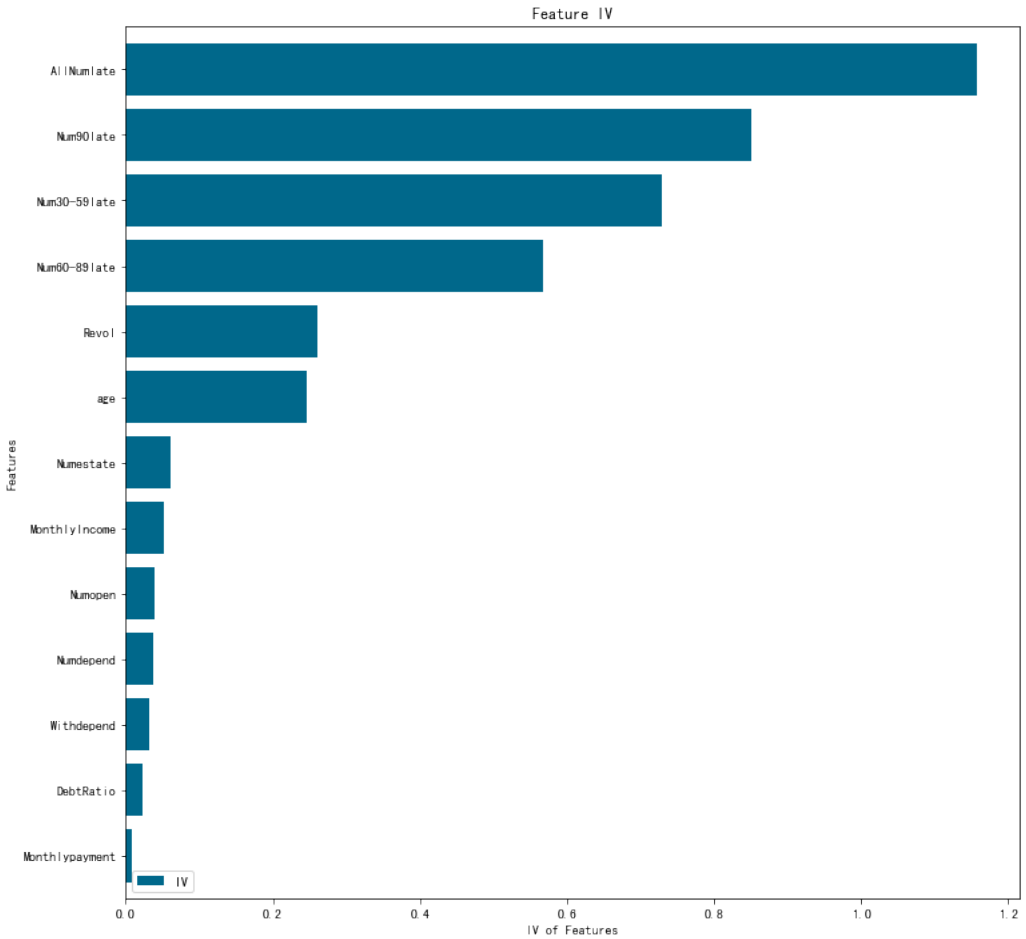
```
<matplotlib.axes._subplots.AxesSubplot at 0x11fa3e550>
```



4.3.2 WOE, IV值计算

```
def bin_woe(tar, var, n=None, cat=None):
    """
    连续自变量分箱,woe,iv变换
    tar:target目标变量
    var:进行woe,iv转换的自变量
    n:分组数量
    """
    total_bad = tar.sum()
    total_good =tar.count()-total_bad
    totalRate = total_good/total_bad

    if cat == 's':
        msheet = pd.DataFrame({tar.name:tar,var.name:var,'var_bins':pd.qcut(var, n,
duplicates='drop')})
        grouped = msheet.groupby(['var_bins'])
    elif (cat == 'd') and (n is None):
        msheet = pd.DataFrame({tar.name:tar,var.name:var})
        grouped = msheet.groupby([var.name])

    groupBad = grouped.sum()[tar.name]
    groupTotal = grouped.count()[tar.name]
    groupGood = groupTotal - groupBad
    groupRate = groupGood/groupBad
    groupBadRate = groupBad/groupTotal
    groupGoodRate = groupGood/groupTotal

    woe = np.log(groupRate/totalRate)
    iv = np.sum((groupGood/total_good-groupBad/total_bad)*woe)

    if cat == 's':
        new_var, cut = pd.qcut(var, n, duplicates='drop',retbins=True, labels=woe.tolist())
    elif cat == 'd':
        dictmap = {}
        for x in woe.index:
            dictmap[x] = woe[x]
        new_var, cut = var.map(dictmap), woe.index

    return woe.tolist(), iv, cut, new_var
```

```
38
39  # 确定变量类型，连续变量还是离散变量
40  dvar = ['Revol','DebtRatio','Num30-59late', 'Num60-89late','Num90late','AllNumlate','Withdepend',
41          'Numestate','Numdepend']
42
43  # 可视化woe得分和iv得分
44  def woe_vs(data):
45      cutdict = {}
46      ivdict = {}
47      woe_dict = {}
48      woe_var = pd.DataFrame()
49      for var in data.columns:
50          if var in dvar:
51              woe, iv, cut, new = bin_woe(data['Isdlq'], data[var], cat='d')
52              woe_dict[var] = woe
53              woe_var[var] = new
54              ivdict[var] = iv
55              cutdict[var] = cut
56          elif var in svar:
57              woe, iv, cut, new = bin_woe(data['Isdlq'], data[var], n=5, cat='s')
58              woe_dict[var] = woe
59              woe_var[var] = new
60              ivdict[var] = iv
61              cutdict[var] = cut
62
63      ivdict = sorted(ivdict.items(), key=lambda x:x[1], reverse=False)
64      iv_vs = pd.DataFrame([x[1] for x in ivdict],index=[x[0] for x in ivdict],columns=['IV'])
65      ax = iv_vs.plot(kind='barh',
66                      figsize=(12,12),
67                      title='Feature IV',
68                      fontsize=10,
69                      width=0.8,
70                      color='#00688B')
71      ax.set_ylabel('Features')
72      ax.set_xlabel('IV of Features')
73
74      return ivdict, woe_var, woe_dict, cutdict
75
76  # woe转化
77  ivinfo, woe_data, woe_dict, cut_dict = woe_vs(data_train)
```



筛选出IV值大于0.1的变量：'Num30-59late'，'Num60-89late'，'Num90late'，'AllNumlate'，'Revol'，'age'；从以上相关性分析结果看出，'Num30-59late'与'AllNumlate'具有强相关性（0.7），因此两者取IV值较高者'AllNumlate'。

4.4 定义（X,y）及交叉验证

```
from sklearn.model_selection import StratifiedKFold
# 定义 X 和 y
IV_info=['Num60-89late','Num90late','AllNumlate','Revol','age']
X=woe_data[IV_info]
y=data_train['Isdlq']
X = np.array(X.as_matrix())
y = np.array(y.tolist())
X_train,X_test,y_train,y_test=train_test_split(X,y,random_state=42)


# 检查数据
print X.shape
print X_train.shape
print X_test.shape
```

```
(149730, 5)
(112297, 5)
(37433, 5)
```

5. 定义评价指标

5.1 混淆矩阵

```
# 混淆矩阵绘图
def plot_confusion_matrix(cm, classes,
                          normalize = False,
                          title = 'Confusion matrix"',
                          cmap = plt.cm.Blues) :
    plt.imshow(cm, interpolation = 'nearest', cmap = cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation = 0)
    plt.yticks(tick_marks, classes)

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])) :
        plt.text(j, i, cm[i, j],
                 horizontalalignment = 'center',
                 color = 'white' if cm[i, j] > thresh else 'black')

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

5.2 Recall, Precision和F1_score

```
# 显示评估指标
def show_metrics():
    tp = cm[1,1]
    fn = cm[1,0]
    fp = cm[0,1]
    tn = cm[0,0]
    print('Precision =     {:.3f}'.format(tp/(tp+fp)))
    print('Recall    =     {:.3f}'.format(tp/(tp+fn)))
    print('F1_score  =     {:.3f}'.format(2*(((tp/(tp+fp))*(tp/(tp+fn)))/
                                           ((tp/(tp+fp))+(tp/(tp+fn))))))
```

5.3 Precision-Recall曲线

```
# 绘制 P-R 曲线
def plot_precision_recall():
    plt.step(recall, precision, color = 'b', alpha = 0.2,
             where = 'post')
    plt.fill_between(recall, precision, step ='post', alpha = 0.2,
                     color = 'b')

    plt.plot(recall, precision, linewidth=2)
    plt.xlim([0.0,1])
    plt.ylim([0.0,1.05])
```

```
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.title('Precision Recall Curve')
    plt.show();
```

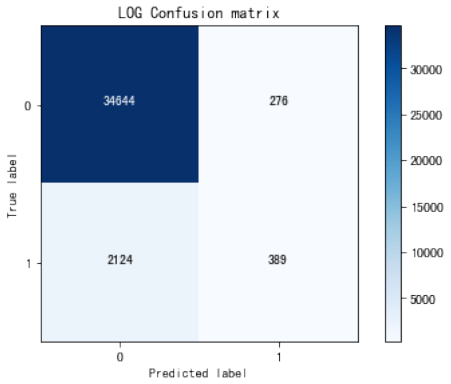
5.4 ROC 曲线

```
# 绘制 ROC 曲线
def plot_roc():
    plt.plot(fpr, tpr, label = 'AUC = %0.2f'%auc_score, linewidth = 2)
    plt.plot([0,1],[0,1], 'k--', linewidth = 2)
    plt.xlim([0.0,1])
    plt.ylim([0.0,1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend()
    plt.show();
```

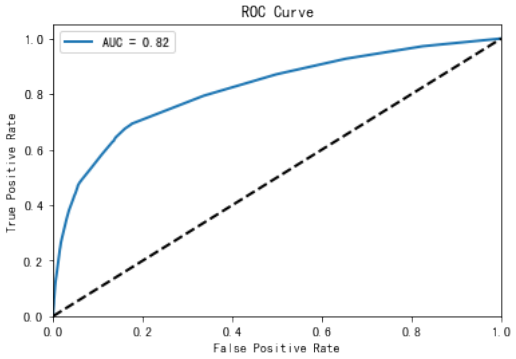
6. LogisticRegression: Train (AUC=0.82)

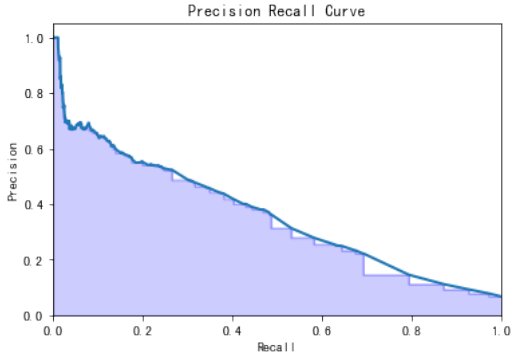
6.1 LOG - 未调优超参数

```
#Logistic模型建立
from sklearn.linear_model import LogisticRegression
# 逻辑斯蒂回归
log_cfl = LogisticRegression()

log_cfl.fit(X_train, y_train)
y_pred = log_cfl.predict(X_test)
y_score = log_cfl.decision_function(X_test)

# 混淆矩阵 & 评估指标
cm = confusion_matrix(y_test, y_pred)
class_names = [0,1]
plt.figure()
plot_confusion_matrix(cm,
                      classes = class_names,
                      title = 'LOG Confusion matrix')
plt.show()

cm = cm.astype(np.float64)

show_metrics()

# ROC 曲线
fpr, tpr, t = roc_curve(y_test, y_score)
auc_score = roc_auc_score(y_test, y_score)
plot_roc()

# Precision-recall 曲线
precision, recall, thresholds = precision_recall_curve(y_test, y_score)
plot_precision_recall()
```




```
Precision =     0.585
Recall    =     0.155
F1_score  =     0.245
```






```
# 查看当前参数
from pprint import pprint
print('Parameters currently in use:\n')
pprint(log_cfl.get_params())
```

```
Parameters currently in use:

{'C': 1.0,
 'class_weight': None,
 'dual': False,
 'fit_intercept': True,
 'intercept_scaling': 1,
 'max_iter': 100,
 'multi_class': 'warn',
 'n_jobs': None,
 'penalty': 'l2',
 'random_state': None,
 'solver': 'warn',
 'tol': 0.0001,
 'verbose': 0,
 'warm_start': False}
```

6.2 LOG - GridSearchCV 搜索超参数

```
# 使用GridSearchCV找到最佳的参数组合
from sklearn.model_selection import GridSearchCV
param_grid = {
            'C' : [0.001, 0.01, 0.1]
            }

CV_log_cfl = GridSearchCV(estimator = log_cfl, param_grid = param_grid , scoring = 'recall', verbose = 1, n_jobs = -1)
CV_log_cfl.fit(X_train, y_train)

best_parameters = CV_log_cfl.best_params_
print('The best parameters for using this model is', best_parameters)
```

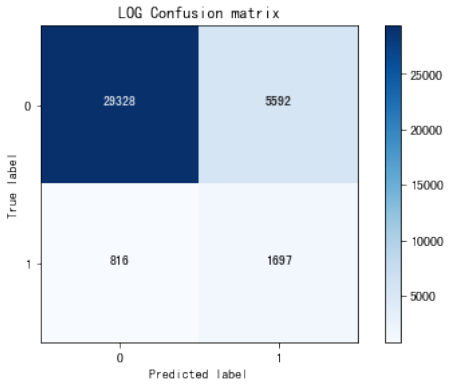
```
Fitting 3 folds for each of 3 candidates, totalling 9 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   9 out of   9 | elapsed:    5.0s finished
```

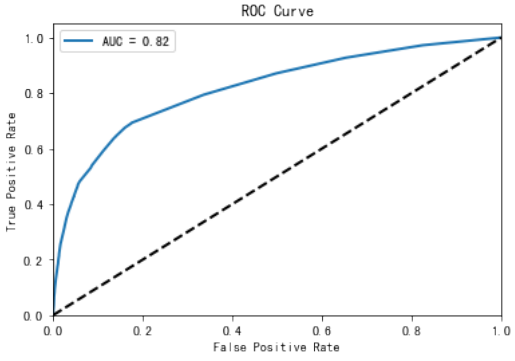
```
('The best parameters for using this model is', {'C': 0.01})
```

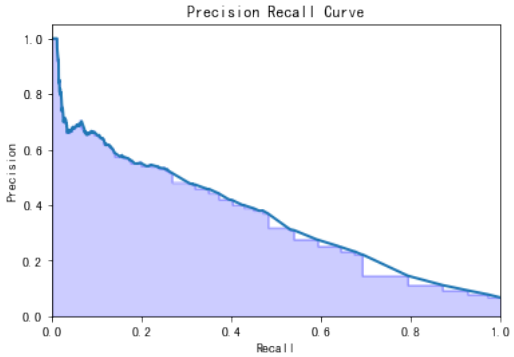
6.3 LOG - 超参数更新

```
# 使用搜索的超参数组合重新构建模型，将结果可视化
log_cfl = LogisticRegression(C = 0.01,
                             penalty = 'l2',
                             class_weight = 'balanced')
log_cfl.fit(X_train, y_train)
y_pred = log_cfl.predict(X_test)
y_score = log_cfl.decision_function(X_test)

# 混淆矩阵 & 评估指标
cm = confusion_matrix(y_test, y_pred)
class_names = [0,1]
plt.figure()
plot_confusion_matrix(cm,
                      classes=class_names,
                      title='LOG Confusion matrix')

plt.savefig('log_cfl_confusion_matrix.png')
plt.show()

cm = cm.astype(np.float64)

show_metrics()

# ROC 曲线
fpr, tpr, t = roc_curve(y_test, y_score)
plot_roc()

# Precision-recall 曲线
precision, recall, thresholds = precision_recall_curve(y_test, y_score)
plot_precision_recall()

fpr_log, tpr_log, t_log = fpr, tpr, t
precision_log, recall_log, thresholds_log = precision, recall, thresholds
```




```
Precision =     0.233
Recall    =     0.675
F1_score  =     0.346
```

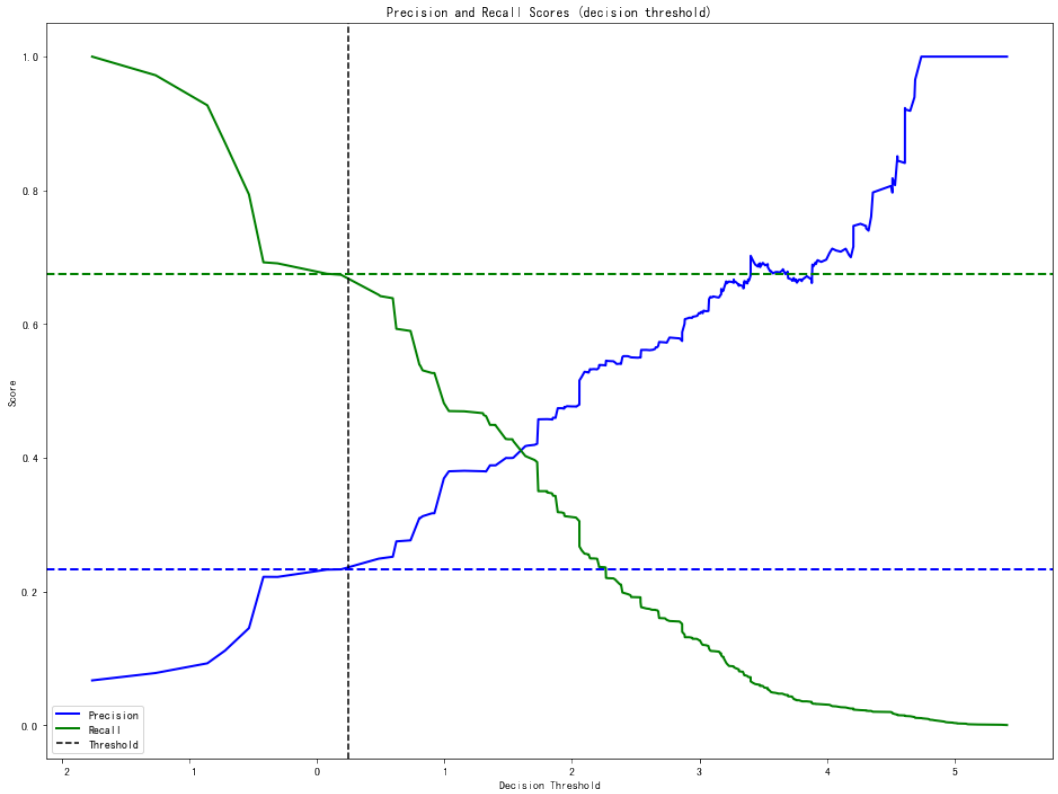




6.4 LOG - Precision - Recall - Threshold 曲线

```
pr = 0.233
rec = 0.675
t = 0.25

# Precision-recall-threshold 曲线 :
def plot_precision_recall_vs_threshold(precisions, recalls, thresholds):
    plt.figure(figsize=(16, 12))
    plt.title('Precision and Recall Scores (decision threshold)')
    plt.plot(thresholds, precisions[:-1], 'b-',linewidth=2, label='Precision')
    plt.plot(thresholds, recalls[:-1], 'g', linewidth=2, label='Recall')
    plt.axvline(t, color='k', linestyle='--', label='Threshold')
    plt.axhline(pr, color='blue', linewidth=2, linestyle='--')
    plt.axhline(rec, color='green', linewidth=2, linestyle='--')
    plt.ylabel('Score')
    plt.xlabel('Decision Threshold')
    plt.legend(loc='best')
    plt.savefig('prec_recc_threshold.png')
    plt.show();
```

```
plot_precision_recall_vs_threshold(precision, recall, thresholds)
```



可见当阈值为0.25时，模型表现最佳。

7. 制作评分卡

```
intercept=model.intercept_
coef=model.coef_
coe=coef[0].tolist()
```

```
coe_df=pd.DataFrame({'feature':IV_info,'coe':coe})

import math
B=20/math.log(2)
A=600+B*math.log(1/20)
#基础分
score=round(A-B*intercept[0],0)

featurelist = []
woelist = []
cutlist = []
for k,v in woe_dict.items():
    if k in IV_info:
        for n in range(0,len(v)):
            featurelist.append(k)
            woelist.append(v[n])
            cutlist.append(cut_dict[k][n])
scoreboard = pd.DataFrame({'feature':featurelist,'woe':woelist,'cut':cutlist},
                          columns=['feature','cut','woe'])

score_df=pd.merge(scoreboard,coe_df)
score_df['score']=-B*score_df['woe']*score_df['coe']
score_df['score'] = score_df['score'].round(decimals=0)
score_df.drop('coe',axis=1,inplace=True)
score_df
```

	feature	cut	woe	score
0	Num60-89late	0.0	0.274309	3.0
1	Num60-89late	1.0	-1.850365	-20.0
2	Num60-89late	2.0	-2.657322	-29.0
3	Num60-89late	3.0	-2.915869	-32.0
4	Num60-89late	4.0	-3.135674	-35.0
5	Num60-89late	5.0	-3.129739	-35.0
6	Num60-89late	6.0	-3.748779	-41.0
7	Num60-89late	7.0	-2.804317	-31.0
8	AllNumlate	0.0	0.923681	17.0
9	AllNumlate	1.0	-1.383442	-25.0
10	age	21.0	-0.487183	-11.0
11	age	39.0	-0.252557	-6.0
12	age	48.0	-0.078292	-2.0
13	age	56.0	0.430123	10.0
14	age	65.0	1.054168	25.0
15	Revol	0.0	0.119231	2.0
16	Revol	1.0	-2.226411	-38.0
17	Num90late	0.0	0.375825	5.0
18	Num90late	1.0	-1.971860	-28.0
19	Num90late	2.0	-2.646308	-37.0
20	Num90late	3.0	-2.961503	-42.0
21	Num90late	4.0	-3.358818	-47.0
22	Num90late	5.0	-3.197806	-45.0
23	Num90late	6.0	-3.055631	-43.0
24	Num90late	7.0	-4.138243	-58.0
25	Num90late	8.0	-3.566457	-50.0
26	Num90late	9.0	-3.679786	-52.0
27	Num90late	10.0	-2.817220	-40.0