week7 拼多多优惠券使用行为预测

1.数据概况分析

In [1]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['font.sans-serif']=['simhei']
```

In [2]:

```
pdd=pd.read_csv('C:\\Users\mac\Desktop\数据分析班\week7\拼多多优惠券数据.csv')
```

In [3]:

```
pdd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25317 entries, 0 to 25316
Data columns (total 10 columns):
 #   Column                      Non-Null Count  Dtype 
---  ------                      --------------  ----- 
 0   ID                          25317 non-null  int64 
 1   age                         25317 non-null  int64 
 2   job                         25317 non-null  object
 3   marital                     25317 non-null  object
 4   default                     25317 non-null  object
 5   returned                    25317 non-null  object
 6   loan                        25317 non-null  object
 7   coupon_used_in_last6_month  25317 non-null  int64 
 8   coupon_used_in_last_month   25317 non-null  int64 
 9   coupon_ind                  25317 non-null  int64 
dtypes: int64(5), object(5)
memory usage: 1.9+ MB
```

- 没有缺失值
- default，returned和loan需要转化为数字变量，以便以后的分析

In [4]:

```
pdd.head()
```

Out[4]:

	ID	age	job	marital	default	returned	loan	coupon_used_in_last6_month	coupon_us
0	1	43	management	married	no	yes	no	2	
1	2	42	technician	divorced	no	yes	no	1	
2	3	47	admin.	married	no	yes	yes	2	
3	4	28	management	single	no	yes	yes	2	
4	5	42	technician	divorced	no	yes	no	5	

In [5]:

```
pdd.describe()
```

Out[5]:

	ID	age	coupon_used_in_last6_month	coupon_used_in_last_month	coupo
count	25317.000000	25317.000000	25317.000000	25317.000000	25317.0

	ID	age	coupon_used_in_last6_month	coupon_used_in_last_month	coupo
mean	12659.000000	40.935379	2.772050	0.292847	0.1
std	7308.532719	10.634289	3.136097	0.765498	0.3
min	1.000000	18.000000	1.000000	0.000000	0.0
25%	6330.000000	33.000000	1.000000	0.000000	0.0
50%	12659.000000	39.000000	2.000000	0.000000	0.0
75%	18988.000000	48.000000	3.000000	0.000000	0.0
max	25317.000000	95.000000	55.000000	15.000000	1.0

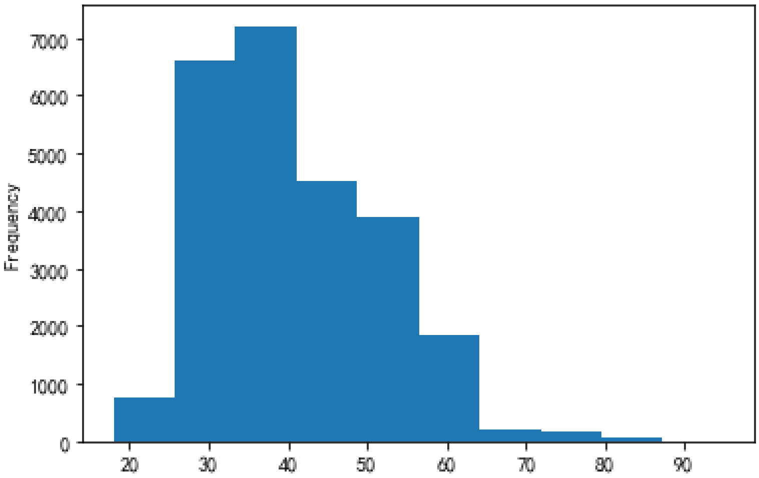
- age中最大值95有异常的可能

2.单变量分析

2.1年龄

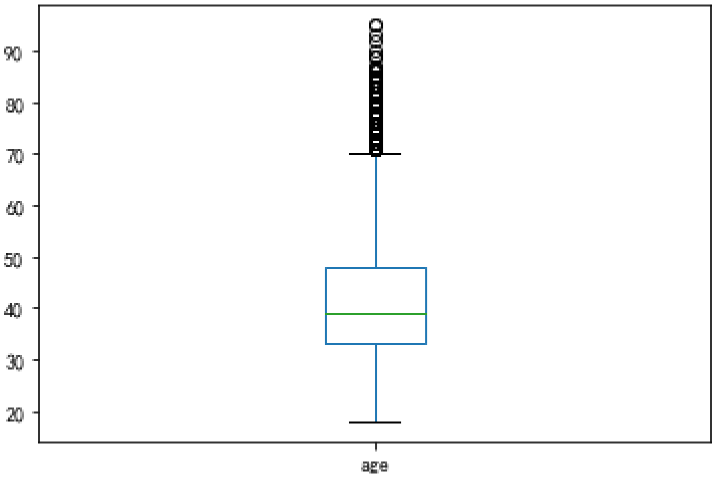
In [6]:

```
pdd['age'].plot(kind='hist');
```



In [7]:

```
pdd['age'].plot(kind='box');
```



- age在年龄较大的部分有离群的异常值存在

In [8]:

```
des_age=pdd['age'].describe()
IQR_age=des_age['75%']-des_age['25%']
max_age_should=des_age['75%']+1.5*IQR_age
max_age_should
```

Out[8]:

```
70.5
```

In [9]:

```
pdd[pdd['age']>max_age_should]
```

Out[9]:

	ID	age	job	marital	default	returned	loan	coupon_used_in_last6_month	coupon_
114	115	74	retired	married	no	no	no	3	
187	188	79	retired	divorced	no	no	no	2	
211	212	80	retired	divorced	no	no	no	8	
284	285	75	retired	divorced	no	no	no	1	
418	419	81	retired	divorced	no	no	no	1	
...	...	...	...	...	...	...	...	...	
25182	25183	72	retired	married	no	no	no	4	
25195	25196	77	retired	married	no	no	no	1	
25203	25204	78	retired	divorced	no	no	no	1	
25241	25242	72	retired	married	no	no	no	2	
25272	25273	75	retired	married	no	no	no	1	

284 rows × 10 columns

- 比例较小，可以除去

In [10]:

```
pdd=pdd[pdd['age']<max_age_should]
```

2.2婚姻状况

In [11]:

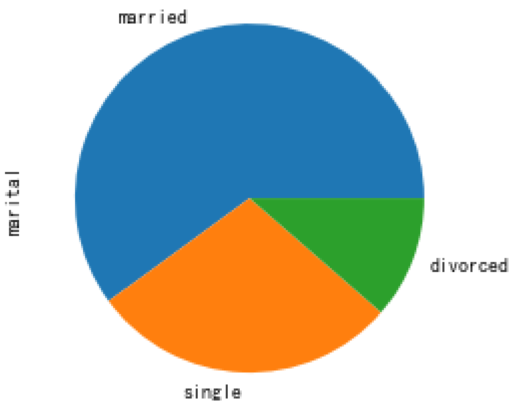
```
pdd['marital'].value_counts()
```

Out[11]:

```
married     15035
single       7148
divorced     2850
Name: marital, dtype: int64
```

In [12]:

```
pdd['marital'].value_counts().plot(kind='pie');
```



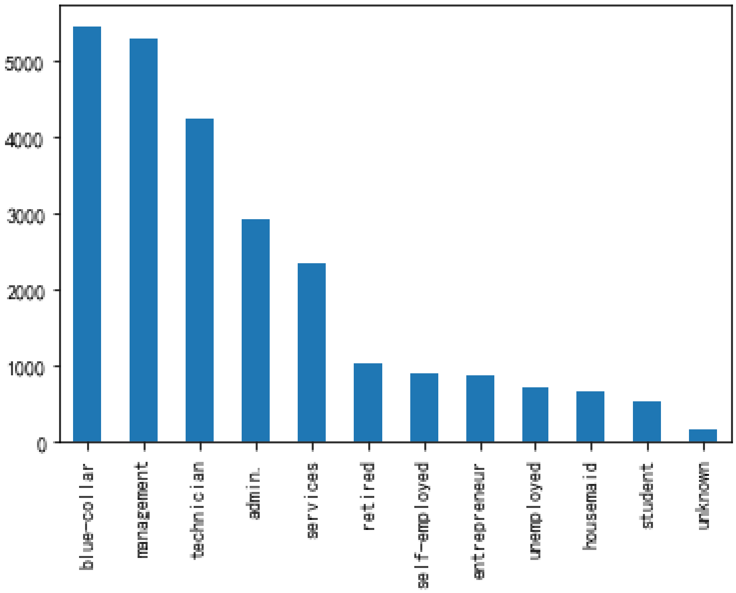
- 多数人是已婚的，其次是单身

2.3职业

In [13]:
```
pdd['job'].value_counts()
```

Out[13]:
```
blue-collar      5455
management       5287
technician       4239
admin.           2906
services         2342
retired          1026
self-employed     881
entrepreneur      855
unemployed        701
housemaid         650
student           533
unknown           158
Name: job, dtype: int64
```

In [14]:
```
pdd['job'].value_counts().plot(kind='bar');
```



- 使用拼多多的人中蓝领、管理层和从事技术工作的人占比较大

3.相关与可视化分析

3.1 数据预处理

In [15]:

```
dummy=pdd[['ID','default','returned','loan']]
dummy.head()
```

Out[15]:

	ID	default	returned	loan
0	1	no	yes	no
1	2	no	yes	no
2	3	no	yes	yes
3	4	no	yes	yes
4	5	no	yes	no

In [16]:

```
dummy=pd.get_dummies(dummy)
dummy.head()
```

Out[16]:

	ID	default_no	default_yes	returned_no	returned_yes	loan_no	loan_yes
0	1	1	0	0	1	1	0
1	2	1	0	0	1	1	0
2	3	1	0	0	1	0	1
3	4	1	0	0	1	0	1
4	5	1	0	0	1	1	0

In [17]:

```
dummy.drop(['default_no','returned_no','loan_no'],axis=1,inplace=True)
dummy.head()
```

Out[17]:

	ID	default_yes	returned_yes	loan_yes
0	1	0	1	0
1	2	0	1	0
2	3	0	1	1
3	4	0	1	1
4	5	0	1	0

In [18]:

```
tmp=pd.DataFrame.merge(pdd,dummy)
tmp.head()
```

Out[18]:

	ID	age	job	marital	default	returned	loan	coupon_used_in_last6_month	coupon_us
0	1	43	management	married	no	yes	no	2	
1	2	42	technician	divorced	no	yes	no	1	
2	3	47	admin.	married	no	yes	yes	2	
3	4	28	management	single	no	yes	yes	2	
4	5	42	technician	divorced	no	yes	no	5	

In [19]:

```
tmp.drop(['default','returned','loan'],axis=1,inplace=True)
tmp.head()
```

Out[19]:

	ID	age	job	marital	coupon_used_in_last6_month	coupon_used_in_last_month	coupon
0	1	43	management	married	2	0	
1	2	42	technician	divorced	1	1	
2	3	47	admin.	married	2	0	
3	4	28	management	single	2	0	
4	5	42	technician	divorced	5	0	

In [20]:

```
pdd_new=tmp
pdd_new.head()
```

Out[20]:

	ID	age	job	marital	coupon_used_in_last6_month	coupon_used_in_last_month	coupon
0	1	43	management	married	2	0	
1	2	42	technician	divorced	1	1	
2	3	47	admin.	married	2	0	
3	4	28	management	single	2	0	
4	5	42	technician	divorced	5	0	

3.2 概览

In [21]:

```
summary=pdd_new.groupby('coupon_ind')
summary.mean()
```

Out[21]:

	ID	age	coupon_used_in_last6_month	coupon_used_in_last_month	defau
coupon_ind					
0	11178.739888	40.569859	2.862175	0.25840	0.0
1	23841.391028	40.207700	2.128223	0.53338	0.0

In [22]:

```
summary.std()
```

Out[22]:

	ID	age	coupon_used_in_last6_month	coupon_used_in_last_month	defaul
coupon_ind					
0	6452.779974	9.751967	3.262437	0.743319	0.13
1	854.524900	11.526063	1.898340	0.866045	0.09

- 由以上数据可以看出
年龄对是否会使用优惠券的影响差距不大
过去六个月使用优惠券多的用户本次可能不使用优惠券的更多，而过去一个月使用优惠券多的本次更可能使用优惠券
有过违约、退货和信用卡付款的更多的预计在本次活动中不会使用优惠券

3.3 婚姻状况

In [23]:

```
pdd_new.groupby('coupon_ind')['marital'].value_counts()
```

Out[23]:

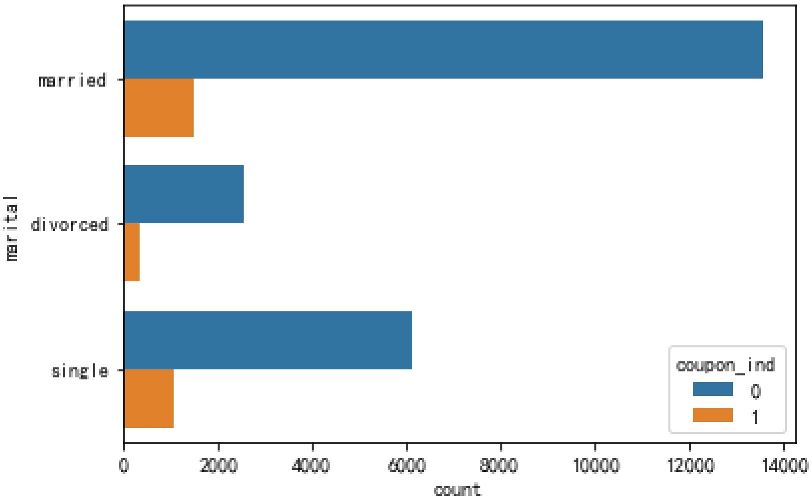
```
coupon_ind  marital
0           married     13567
            single       6102
            divorced     2533
1           married      1468
            single       1046
            divorced      317
Name: marital, dtype: int64
```

In [24]:

```
sns.countplot(y='marital',hue='coupon_ind',data=pdd_new)
```

Out[24]:

```
<AxesSubplot:xlabel='count', ylabel='marital'>
```



- 可以看出已婚的人多为不使用优惠券的人

3.4 职业

In [25]:

```
pdd_new.groupby('coupon_ind')['job'].value_counts()
```

Out[25]:

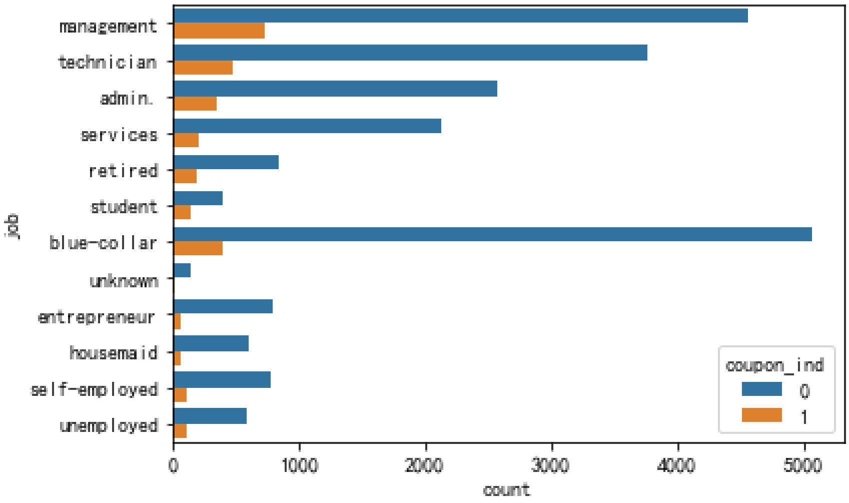
```
coupon_ind  job
0           blue-collar      5068
            management       4555
            technician       3759
            admin.           2566
            services         2131
            retired           843
            entrepreneur      788
            self-employed     778
            housemaid         597
            unemployed        587
            student           390
            unknown          140
1           management       732
            technician       480
            blue-collar      387
            admin.           340
            services         211
            retired          183
            student          143
            unemployed       114
            self-employed    103
            entrepreneur      67
            housemaid         53
            unknown           18
Name: job, dtype: int64
```

In [26]:

```
sns.countplot(y='job',hue='coupon_ind',data=pdd_new)
```

Out[26]:

```
<AxesSubplot:xlabel='count', ylabel='job'>
```



- 可以看出蓝领、管理层和技术工作人员中不使用优惠券的人群的占比较大

3.5 相关性分析

In [27]:

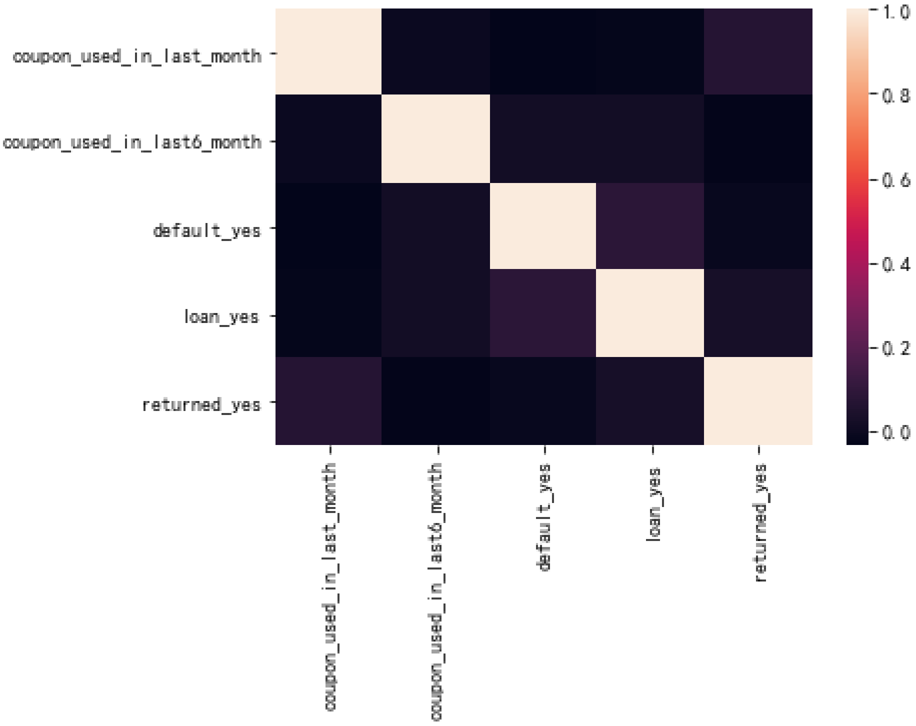
```
pdd_new.corr()[['coupon_ind']].sort_values('coupon_ind',ascending=False)
```

Out[27]:

	coupon_ind
coupon_ind	1.000000
ID	0.550376
coupon_used_in_last_month	0.114116
age	-0.011506
default_yes	-0.024337
loan_yes	-0.061545
coupon_used_in_last6_month	-0.073873
returned_yes	-0.135141

In [28]:

```
q1=['coupon_used_in_last_month','coupon_used_in_last6_month','default_yes','loan_yes','retur
sns.heatmap(pdd_new[q1].corr());
```



·由上可知：
本次是否会使用优惠券的预测结果与过去一个月使用优惠券的次数正相关
与是否违约、退货、使用信用卡付款和过去六个月使用优惠券的次数负相关

4.逻辑回归

4.1 建立模型

In [29]:

```
y=pdd_new['coupon_ind']
x=pdd_new[['coupon_used_in_last_month','coupon_used_in_last6_month','default_yes','loan_yes'
```

In [30]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=100)
```

In [31]:

```
from sklearn import linear_model as lrmd
lr=lrmd.LogisticRegression()
```

In [32]:

```
lr.fit(x_train,y_train)
```

Out[32]:

```
LogisticRegression()
```

In [33]:

```
lr.intercept_
```

Out[33]:

```
array([-1.2524545])
```

In [34]:

```
lr.coef_
```

Out[34]:

```
array([[ 0.44012769, -0.18450179, -0.66809835, -0.59855371, -0.95154737]])
```

- 与3.5中的结果一致

In [35]:

```
y_pred_train=lr.predict(x_train)
y_pred_test=lr.predict(x_test)
print(y_pred_train)
```

```
[0 0 0 ... 0 0 0]
```

4.2 模型评估

In [36]:

```
# 计算训练集的准确度
import sklearn.metrics as metrics
metrics.accuracy_score(y_train,y_pred_train)
```

Out[36]:

```
0.8861496319123437
```

In [37]:

```
#计算测试集准确率
metrics.accuracy_score(y_test,y_pred_test)
```

Out[37]:

```
0.8868175765645806
```

- 比训练集准确度稍高

4.3 模型优化

调整参数

In [38]:

```
x_1_train,x_1_test,y_1_train,y_1_test=train_test_split(x,y,test_size=0.5,random_state=100)
mod=lr.fit(x_1_train,y_1_train)
mod
```

Out[38]:

```
LogisticRegression()
```

In [39]:

```
lr.intercept_
```

Out[39]:

```
array([-1.26135287])
```

In [40]:

```
lr.coef_
```

Out[40]:

```
array([[ 0.43023751, -0.19497695, -0.57867384, -0.54953283, -0.8943783 ]])
```

In [41]:

```
y_1_pred_train=lr.predict(x_1_train)
y_1_pred_test=lr.predict(x_1_test)
print(y_1_pred_train)
```

```
[0 0 0 ... 0 0 0]
```

In [42]:

```
metrics.accuracy_score(y_1_train,y_1_pred_train)
```

Out[42]:

```
0.8874240971556407
```

In [43]:

```
metrics.accuracy_score(y_1_test,y_1_pred_test)
```

```
Out[43]: 0.8858352640409044
```

- 训练集准确度上升，测试集准确度下降，说明0.3比0.5更好

5.业务解读与结论

根据测试集数量为30%时候的数据：

coupon_used_in_last_month,coupon_used_in_last6_month,default_yes,loan_yes,ret
五个变量的回归系数分别为0.43329545, -0.16767374, -0.53899875,
-0.53307719, -0.98864659

```
In [44]: import numpy as np
```

```
In [45]: np.exp([[ 0.43329545, -0.16767374, -0.53899875, -0.53307719, -0.98864659]])
```

```
Out[45]: array([[1.54233184, 0.84562968, 0.58333202, 0.5867965 , 0.37207993]])
```

根据系数解读：
过去一个月使用过优惠券的用户，在本次活动使用优惠券的可能性是近一个月没有使用优惠券的 1.54 倍
而过去一个月使用过优惠券以及有过违约、信用卡支付、退货的用户，在本次活动中使用优惠券的可能性不如没有的

业务建议

为在一个月内没使用优惠券的用户提供高折扣的优惠券