Fintech Assignment 02

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Content

Notebook and related Resource:
https://github.com/Lawrence-Lu/Jupyter_git.git (https://github.com/Lawrence-Lu/Jupyter_git.git)

1.Renrendai loans

1.1 Data Summary

In this part we overlook all the data in "Renrendai". And I will look at the whole picture of the data. Lately in 1.2 I will kick start some detailed feature engeneering based on the problem we are facing

(1) Data Description
We found there are total 10k records X 25 features.
Most of the features contained clean data except serval features contain incomplete data
(EDUCATION 9996 non-null float64
WORKTIME 9994 non-null float64
INCOME 9998 non-null float64
IND 9318 non-null object
CITY 9857 non-null object
PURPOSE 9994 non -null object)

(2)Feature transforming
There are 10 features are objects including: STATUS, IND-Industry, City, Purpose, Marry, Open time, Readytime, Title

Description, nickname. I transform theses two types of data since it may be useful
2.1) I transform time value from time to integer for further study,only keeping duration(Ready time -Open time)
2.2) Create dummy variables for Lable feature with few types including: Marry, Purpose, IND

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In [16]:

```
import pandas as pd
import numpy as np
import math
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import Pipeline
import statsmodels.api as sm
import statsmodels.formula.api as smf
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

In [17]:

```
data = pd.read_csv(r"..\Week 2 Assignment\loanraw.csv",encoding="gbk")
data.head()
```

Out[17]:

	loanId	STATUS	BIDS	DEFAULT	AMOUNT	INTEREST	MONTHS	CREDIT	HOUSE	CAR	.
0	2	CLOSED	9	0	3000	5.0	6	7	1	1	.
1	11	CLOSED	8	0	3000	18.0	3	3	0	0	.
2	16	CLOSED	8	0	3000	12.0	12	3	0	0	.
3	19	CLOSED	11	0	3000	8.8	12	7	1	1	.
4	20	CLOSED	15	0	5000	15.0	12	7	0	1	.

5 rows × 25 columns

In [18]:

```
data.shape
```

Out[18]:

```
(10000, 25)
```

In [19]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 25 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   loanId       10000 non-null  int64  
 1   STATUS       10000 non-null  object 
 2   BIDS         10000 non-null  int64  
 3   DEFAULT      10000 non-null  int64  
 4   AMOUNT       10000 non-null  int64  
 5   INTEREST     10000 non-null  float64
 6   MONTHS       10000 non-null  int64  
 7   CREDIT       10000 non-null  int64  
 8   HOUSE        10000 non-null  int64  
 9   CAR          10000 non-null  int64  
 10  HOUSE_L      10000 non-null  int64  
 11  CAR_L        10000 non-null  int64  
 12  EDUCATION    9996 non-null   float64
 13  WORKTIME     9994 non-null   float64
 14  INCOME       9998 non-null   float64
 15  IND          9318 non-null   object 
 16  CITY         9857 non-null   object 
 17  PURPOSE      9994 non-null   object 
 18  MARRY        10000 non-null  object 
 19  AGE          10000 non-null  int64  
 20  opentime     10000 non-null  object 
 21  readytime    10000 non-null  object 
 22  title        10000 non-null  object 
 23  description  10000 non-null  object 
 24  nickName     10000 non-null  object 
dtypes: float64(4), int64(11), object(10)
memory usage: 1.9+ MB
```

Construct new feature "duration"

based on the gap between "readytime" and "opentime" (accurate to hour), using day as unit

In [20]:

```
data['duration'] = (pd.to_datetime(data["readytime"]) - pd.to_datetime(data["opentime"])).a
data.describe()['duration']
```

Out[20]:

```
count    10000.000000
mean         3.769125
std          4.548706
min         -0.500000
25%          0.000000
50%          2.625000
75%          5.708333
max         37.375000
Name: duration, dtype: float64
```

Construct new dummy variables for label features

MARRY: 4 possible status PURPOSE: 10 possible status IND : 20 possible status

In [21]:

```
data_2 = pd.get_dummies(data,columns=["MARRY","PURPOSE","IND"])
```

In [22]:

```
data_2.columns
```

Out[22]:

```
Index(['loanId', 'STATUS', 'BIDS', 'DEFAULT', 'AMOUNT', 'INTEREST', 'MONTH
S',
       'CREDIT', 'HOUSE', 'CAR', 'HOUSE_L', 'CAR_L', 'EDUCATION', 'WORKTIM
E',
       'INCOME', 'CITY', 'AGE', 'opentime', 'readytime', 'title',
       'description', 'nickName', 'duration', 'MARRY_丧偶', 'MARRY_已婚',
       'MARRY_未婚', 'MARRY_离异', 'PURPOSE_个人消费', 'PURPOSE_其他借款', 'PUR
POSE_医疗支出',
       'PURPOSE_婚礼筹备', 'PURPOSE_投资创业', 'PURPOSE_教育培训', 'PURPOSE_短
期周转',
       'PURPOSE_装修借款', 'PURPOSE_购房借款', 'PURPOSE_购车借款', 'IND_IT', 'I
ND_交通运输业',
       'IND_体育/艺术', 'IND_公共事业', 'IND_公益组织', 'IND_其它', 'IND_农业',
'IND_制造业',
       'IND_医疗/卫生/保健', 'IND_娱乐服务业', 'IND_媒体/广告', 'IND_建筑工程',
'IND_房地产业',
       'IND_政府机关', 'IND_教育/培训', 'IND_能源业', 'IND_计算机系统', 'IND_金
融/法律',
       'IND_零售/批发', 'IND_餐饮/旅馆业'],
      dtype='object')
```

Data summary based on experience

Bowrrer characteristics: Credit, car, house, education, worktime, Income

Loan characteristics: Amount, interest,MONTHS, duration

In [23]:

```
data_2.describe()[["CREDIT","CAR","HOUSE","EDUCATION","INCOME","WORKTIME"]]
```

Out[23]:

	CREDIT	CAR	HOUSE	EDUCATION	INCOME	WORKTIME
count	10000.00000	10000.000000	10000.000000	9996.000000	9998.000000	9994.000000
mean	2.14630	0.391700	0.564500	2.165966	4.309162	2.838003
std	1.53099	0.488155	0.495847	0.818108	1.335842	0.992755
min	1.00000	0.000000	0.000000	1.000000	1.000000	1.000000
25%	1.00000	0.000000	0.000000	2.000000	3.000000	2.000000
50%	2.00000	0.000000	1.000000	2.000000	4.000000	3.000000
75%	3.00000	1.000000	1.000000	3.000000	5.000000	4.000000
max	7.00000	1.000000	1.000000	4.000000	7.000000	4.000000

In [24]:

```
data_2.describe()[["AMOUNT","INTEREST","MONTHS","duration"]]
```

Out[24]:

	AMOUNT	INTEREST	MONTHS	duration
count	10000.000000	10000.000000	10000.00000	10000.000000
mean	24545.835000	12.621900	12.23730	3.769125
std	38280.756524	2.273689	8.09109	4.548706
min	3000.000000	5.000000	3.00000	-0.500000
25%	8000.000000	11.000000	6.00000	0.000000
50%	14400.000000	12.000000	12.00000	2.625000
75%	26000.000000	13.000000	12.00000	5.708333
max	500000.000000	24.400000	36.00000	37.375000

1.2 Feature cleaning and engineering

1.2.1 On Default regression

(1) correlation test

Based on the correlation result, I just take the four features ahead of loanId for two reasons.
a) loanId is not supposed to related to the likelihood of default based on basic bussiness logic. So I only take

features defeat loanId
b) Based on my own experience, usually, features show a rate above 0.1 are likely to have a good performance in models

(2) Data Cleaning
EDUCATION feature needs to be clean up: Because the number of missing records is small it belongs to discrete feature. I simply use median to fill the null value

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There are no missing records in BIDS

In [25]:

```
data_2["DEFAULT"].value_counts()
```

Out[25]:

```
0    8487
1    1513
Name: DEFAULT, dtype: int64
```

Correlatin test
Based on the result, I pick top 10 for further discussion

In [26]:

```
abs(data_2.corr()["DEFAULT"]).sort_values(ascending=False)[0:41]
```

Out[26]:

```
DEFAULT         1.000000
CREDIT          0.292815
MONTHS          0.274555
EDUCATION       0.154944
CAR             0.095841
loanId          0.094200
INTEREST        0.082417
MARRY_离异        0.080191
PURPOSE_装修借款      0.072103
HOUSE_L         0.070177
PURPOSE_购车借款      0.059450
PURPOSE_短期周转      0.054436
IND_IT          0.053042
duration        0.047243
PURPOSE_个人消费      0.044998
HOUSE           0.036634
IND_交通运输业        0.033180
IND_零售/批发       0.032275
AGE             0.026891
PURPOSE_投资创业      0.026225
IND_金融/法律       0.026032
CAR_L           0.024758
WORKTIME        0.023593
IND_制造业         0.022934
IND_农业          0.020576
PURPOSE_教育培训      0.020135
PURPOSE_其他借款      0.020104
IND_政府机关        0.018748
MARRY_未婚        0.017888
IND_能源业         0.016393
BIDS            0.015241
IND_其它          0.014405
IND_体育/艺术       0.014041
IND_建筑工程        0.013458
MARRY_已婚        0.013389
IND_教育/培训       0.011902
IND_餐饮/旅馆业      0.010136
IND_医疗/卫生/保健    0.009476
PURPOSE_购房借款      0.009074
IND_公益组织        0.007794
INCOME          0.007781
Name: DEFAULT, dtype: float64
```

In [27]:

```
abs(data_2.corr()["DEFAULT"]).sort_values(ascending=False)[0:11]
index = abs(data_2.corr()["DEFAULT"]).sort_values(ascending=False)[1:11].index
```

Out[27]:

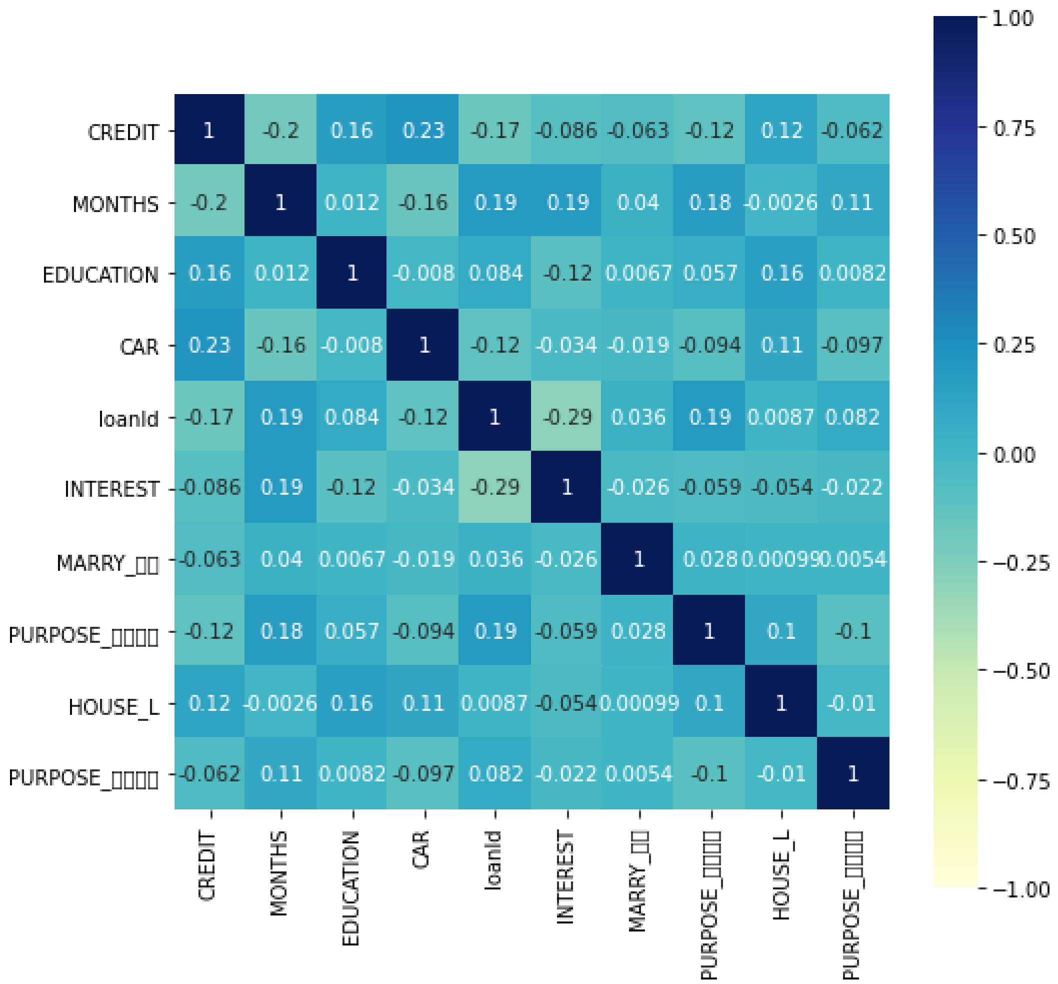
```
DEFAULT        1.000000
CREDIT         0.292815
MONTHS         0.274555
EDUCATION      0.154944
CAR            0.095841
loanId         0.094200
INTEREST       0.082417
MARRY_离异       0.080191
PURPOSE_装修借款     0.072103
HOUSE_L        0.070177
PURPOSE_购车借款     0.059450
Name: DEFAULT, dtype: float64
```

In [38]:

```
fig, ax = plt.subplots(figsize = (8,8))
sns.heatmap(data_2[index].corr(),annot=True, vmax=1, vmin=-1,square=True,cmap="YlGnBu")
```

Out[38]:

<AxesSubplot:>



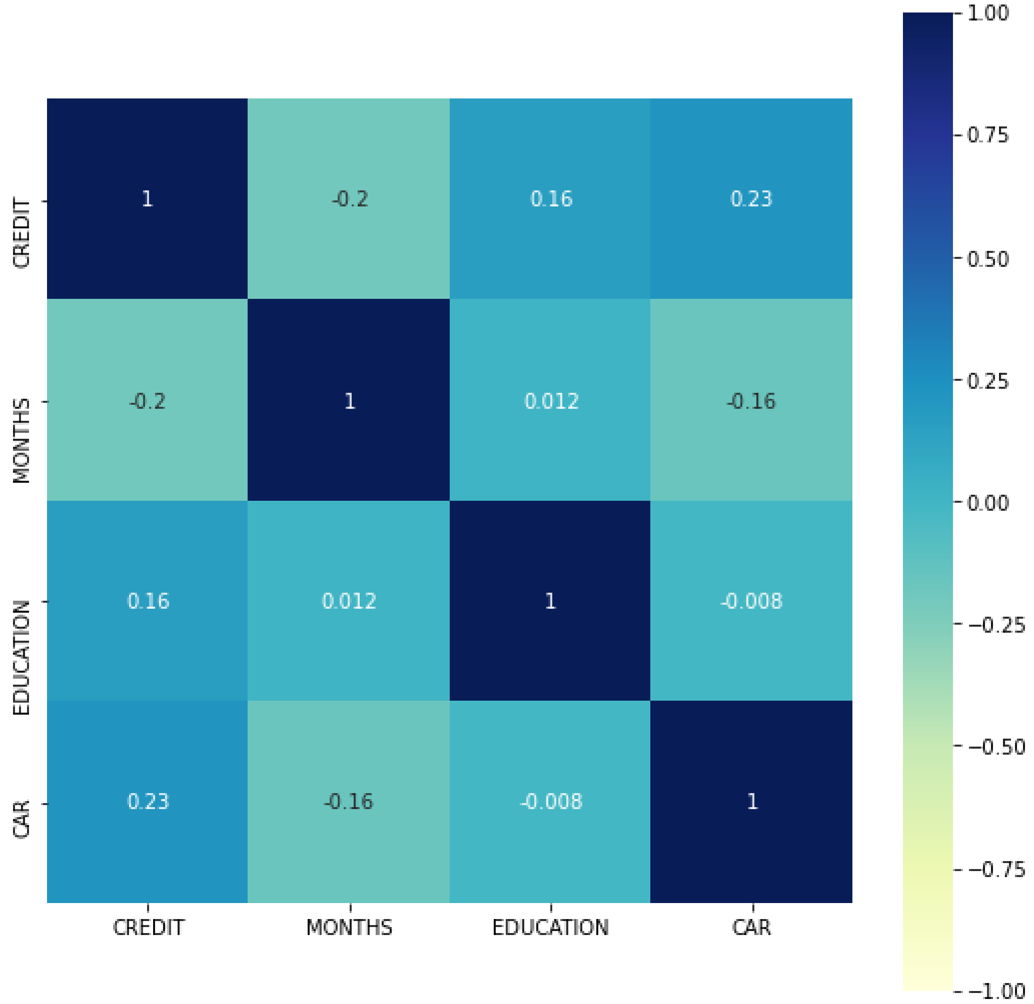
Heatmap for rank 10 features In these 10 features, they are not highly related to each other, So I do not drop a feature

In [29]:

```
fig, ax = plt.subplots(figsize = (9,9))
sns.heatmap(data_2[["CREDIT","MONTHS","EDUCATION","CAR"]].corr(),annot=True, vmax=1, vmin=-
```

Out[29]:

```
<AxesSubplot:>
```



Heatmap for rank 4 features (features beat loan id)
To show the data better I draw a heatmap only for 4 high ranked features.
In these four features, they are not highly related to each other, So I do not drop a feature

In [30]:

```
data_2.describe()[["CREDIT","MONTHS","EDUCATION","CAR"]]
```

Out[30]:

	CREDIT	MONTHS	EDUCATION	CAR
count	10000.00000	10000.00000	9996.000000	10000.000000
mean	2.14630	12.23730	2.165966	0.391700
std	1.53099	8.09109	0.818108	0.488155
min	1.00000	3.00000	1.000000	0.000000
25%	1.00000	6.00000	2.000000	0.000000
50%	2.00000	12.00000	2.000000	0.000000
75%	3.00000	12.00000	3.000000	1.000000
max	7.00000	36.00000	4.000000	1.000000

Filling null value in EDUCATION feature

In [31]:

```
data_2["EDUCATION"][data_2["EDUCATION"].isnull()] = data_2["EDUCATION"].median()
```

```
<ipython-input-31-2bafad20e43f>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  data_2["EDUCATION"][data_2["EDUCATION"].isnull()] = data_2["EDUCATION"].me
dian()
```

In [32]:

```
data_2.describe()[["CREDIT","MONTHS","EDUCATION","CAR"]]
```

Out[32]:

	CREDIT	MONTHS	EDUCATION	CAR
count	10000.00000	10000.00000	10000.000000	10000.000000
mean	2.14630	12.23730	2.165900	0.391700
std	1.53099	8.09109	0.817951	0.488155
min	1.00000	3.00000	1.000000	0.000000
25%	1.00000	6.00000	2.000000	0.000000
50%	2.00000	12.00000	2.000000	0.000000
75%	3.00000	12.00000	3.000000	1.000000
max	7.00000	36.00000	4.000000	1.000000

1.2.2 On Bids regression

(1) correlation test
I found there are far more features are highly relevant to BIDS
I select features ranking high from highest AMOUNT to INTEREST。 Then I also create a heat map to filter the features again inorder to avoid multicollinearity

(2) Filling missing records
There are few missing records in INCOME and WORKTIME. Since they are label features.
Similar to CAR, I simply use median value to fill the records.

(3) Feature visualization
Because I am about to conduct an OLS regression on the data samle, before that I draw a line based on the top there related features to illustrate how it affects BIDS. However, since it is not a one to one mapping, the line could be messy. Therefore I conduct the **portfolio approach** to illustrate the result.
Based on the graphs bids increase as long as amount and age increases while income shows a rebound relationship with bids.

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There are no missing records in BIDS

In [33]:

```
data_2.describe()['BIDS']
```

Out[33]:

```
count    10000.000000
mean        24.150600
std         41.342608
min          1.000000
25%          9.000000
50%         15.000000
75%         24.000000
max        592.000000
Name: BIDS, dtype: float64
```

In [34]:

```
abs(data_2.corr()["BIDS"]).sort_values(ascending=False)[1:13]
bidsIndex_0 = abs(data_2.corr()["BIDS"]).sort_values(ascending=False)[1:13].index
```

Out[34]:

```
AMOUNT          0.809234
INCOME          0.357055
AGE             0.257725
IND_制造业         0.188173
CAR             0.183072
loanId          0.159011
WORKTIME        0.139645
CREDIT          0.122454
MARRY_已婚        0.122299
MARRY_未婚        0.117044
PURPOSE_其他借款    0.105537
INTEREST        0.097306
Name: BIDS, dtype: float64
```

According to the heatmap

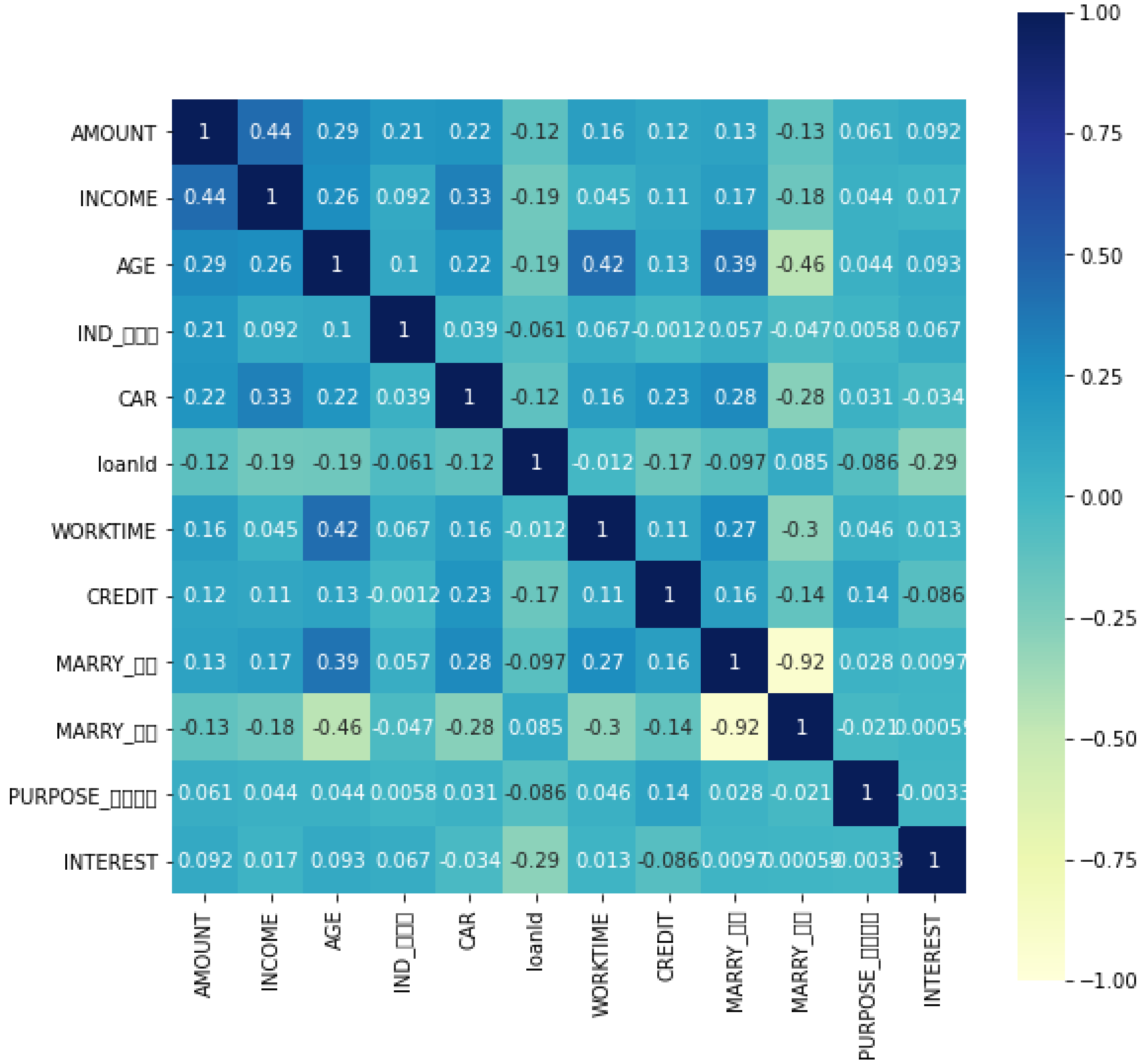
I found two status of marriage is highly related, So I drop the dismarriaged feature

In [36]:

```
fig, ax = plt.subplots(figsize = (9,9))
sns.heatmap(data_2[bidsIndex_0].corr(),annot=True, vmax=1, vmin=-1,square=True,cmap="YlGnBu
```

Out[36]:

<AxesSubplot:>



In [21]:

```
bidsIndex_0 = bidsIndex_0.drop("MARRY_未婚")
bidsIndex_0
```

Out[21]:

```
Index(['AMOUNT', 'INCOME', 'AGE', 'IND_制造业', 'CAR', 'loanId', 'WORKTIME',
       'CREDIT', 'MARRY_已婚', 'PURPOSE_其他借款', 'INTEREST'],
      dtype='object')
```

In [22]:

```
data_2.describe()[bidsIndex_0]
```

Out[22]:

	AMOUNT	INCOME	AGE	IND_制造业	CAR	loanId	W
count	10000.000000	9998.000000	10000.000000	10000.000000	10000.000000	1.000000e+04	9
mean	24545.835000	4.309162	34.755500	0.199700	0.391700	4.188469e+05	
std	38280.756524	1.335842	6.682708	0.399795	0.488155	4.464326e+05	
min	3000.000000	1.000000	24.000000	0.000000	0.000000	2.000000e+00	
25%	8000.000000	3.000000	30.000000	0.000000	0.000000	8.463525e+04	
50%	14400.000000	4.000000	33.000000	0.000000	0.000000	3.219450e+05	
75%	26000.000000	5.000000	38.000000	0.000000	1.000000	5.829305e+05	
max	500000.000000	7.000000	53.000000	1.000000	1.000000	2.086049e+06	

Filling missing records for INCOME and WORKTIME

In [23]:

```
data_2["INCOME"][data_2["INCOME"].isnull()] = data_2["INCOME"].median()
data_2["WORKTIME"][data_2["WORKTIME"].isnull()] = data_2["WORKTIME"].median()
data_2.describe()[bidsIndex_0]
```

```
 caveats in the documentation: https://pandas.pydata.org/pandas-doc
e/user_guide/indexing.html#returning-a-view-versus-a-copy (https://
pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
rsus-a-copy)
2["WORKTIME"][data_2["WORKTIME"].isnull()] = data_2["WORKTIME"].med
```

:

AMOUNT	INCOME	AGE	IND_制造业	CAR	loanId	WORKTIME	CRED
10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	1.000000e+04	10000.000000	10000.000
24545.835000	4.309100	34.755500	0.199700	0.391700	4.188469e+05	2.838100	2.146
38280.756524	1.335715	6.682708	0.399795	0.488155	4.464326e+05	0.992465	1.530
3000.000000	1.000000	24.000000	0.000000	0.000000	2.000000e+00	1.000000	1.000
8000.000000	3.000000	30.000000	0.000000	0.000000	8.463525e+04	2.000000	1.000

To illustrate the relationship better we plot the figure

Relationship between BIDS and threee most significant features using portfolio approach

Cutting data

In [24]:

```
data_2.loc[:,"AMOUNTLABEL"] = pd.cut(data["AMOUNT"],5)
data_2.loc[:,"AGELABEL"] = pd.cut(data["AGE"],3)
```

In [25]:

```
data_2["AMOUNTLABEL"].value_counts()
data_2["AGELABEL"].value_counts()
```

Out[25]:

```
(2503.0, 102400.0]      9732
(102400.0, 201800.0]     186
(201800.0, 301200.0]      63
(400600.0, 500000.0]      11
(301200.0, 400600.0]       8
Name: AMOUNTLABEL, dtype: int64
```

Out[25]:

```
(23.971, 33.667]    5053
(33.667, 43.333]    3702
(43.333, 53.0]      1245
Name: AGELABEL, dtype: int64
```

In [26]:

```
amountLabels = []
for label in data_2["AMOUNTLABEL"].value_counts().index:
    amountLabels.append(str(label))

incomeLabels = [1,2,3,4,5,6,7]
ageLabels = ["23-33","33-43","43-53"]
```

Feature visualization

Because I am about to conduct an OLS regression on the data samle, before that I draw a line based on the top there related features to illustrate how it affects BIDS. However, since it is not a one to one mapping, the line could be messy. Therefore I conduct the **portfolio approach** to illustrate the result.

Based on the graphs bids increase as long as amount and age increases while income shows a rebound relationship with bids.

In [27]:

```
plt.figure(figsize=[14, 8])
grid = plt.GridSpec(12, 8, wspace=0.5, hspace=0.5)
plt.subplot(grid[0:6,0:5])

plt.plot(amountLabels,data_2.groupby(["AMOUNTLABEL"])["BIDS"].mean(),"b--.")

plt.xlabel("AMOUNT")
plt.ylabel("BIDS")

plt.subplot(grid[7:12,0:5])

plt.plot(incomeLabels,data_2.groupby(["INCOME"])["BIDS"].mean(),"r--*")
plt.xlabel("INCOME")


plt.subplot(grid[0:12,5:8])

plt.plot(ageLabels,data_2.groupby(["AGELABEL"])["BIDS"].mean(),"g--*")
plt.xlabel("AGE")
plt.show
```

Out[27]:

```
<Figure size 1008x576 with 0 Axes>
```

Out[27]:

```
<AxesSubplot:>
```

Out[27]:

```
[<matplotlib.lines.Line2D at 0x22753dcaa90>]
```

Out[27]:

```
Text(0.5, 0, 'AMOUNT')
```

Out[27]:

```
Text(0, 0.5, 'BIDS')
```

Out[27]:

```
<AxesSubplot:>
```

Out[27]:

```
[<matplotlib.lines.Line2D at 0x22753e08280>]
```

Out[27]:

```
Text(0.5, 0, 'INCOME')
```

Out[27]:

```
<AxesSubplot:>
```

Out[27]:

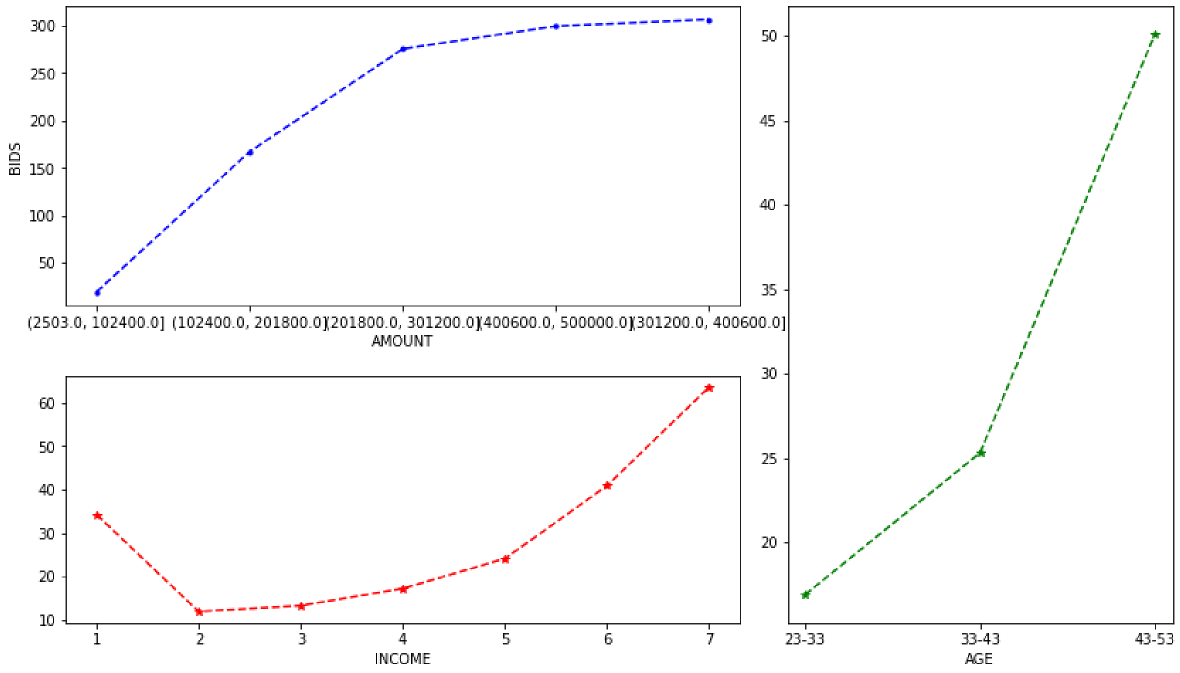
```
[<matplotlib.lines.Line2D at 0x22753e2fc70>]
```

Out[27]:

```
Text(0.5, 0, 'AGE')
```

Out[27]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



1.3 Logit Regression

- 1.3.1 Logit regression Model selection
- 1.3.2 Logit regression Conlusion

1.3 .1Logit Regression Model Selecion

In this part I fit the model with the features adpoted from the last step.
Then I select features and improve models based on each result namely, R-squared score , p-value of feature etc.

1. The first model contains all the features, but several features in it is not significant such as CAR, two purpose and so on
2. The second model remove CAR feature
3. The third model remove purpose-购车借款
4. Remove loan id which is not relevant to the result based on life experience
5. Remove interest because it is now insignificant. Now the fifth model seems perfect with no useless features and rather high R-square
6. Remove the only remained not bowrrower characteristic feature-Months, find the result was badly infected.
7. Therefore the fifth model is the final model we get.

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Add Intercet into data

In [28]:

```
data_2["intercept"] = 1.0
```

In [29]:

```
cols = []
for x in index: cols.append(str(x))
cols.append("intercept")
cols
```

Out[29]:

```
['CREDIT',
 'MONTHS',
 'EDUCATION',
 'CAR',
 'loanId',
 'INTEREST',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'PURPOSE_购车借款',
 'intercept']
```

Fit the first logit model with all variables

In [30]:

```
model = sm.Logit(data_2['DEFAULT'],data_2[cols])
result1 = model.fit()
result1.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.300684
         Iterations 9
```

Out[30]:

Logit Regression Results

Dep. Variable:	DEFAULT	**No. Observations:**	10000
Model:	Logit	**Df Residuals:**	9989
Method:	MLE	**Df Model:**	10
Date:	Mon, 27 Sep 2021	**Pseudo R-squ.:**	0.2924
Time:	16:43:37	**Log-Likelihood:**	-3006.8
converged:	True	**LL-Null:**	-4249.6
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
CREDIT	-1.9959	0.088	-22.628	0.000	-2.169	-1.823
MONTHS	0.0739	0.004	19.270	0.000	0.066	0.081
EDUCATION	-0.5459	0.043	-12.640	0.000	-0.631	-0.461
CAR	0.0388	0.072	0.538	0.591	-0.103	0.180
loanId	8.013e-07	7.72e-08	10.377	0.000	6.5e-07	9.53e-07
INTEREST	0.0645	0.016	3.974	0.000	0.033	0.096
MARRY_离异	0.8014	0.141	5.671	0.000	0.524	1.078
PURPOSE_装修借款	0.1959	0.082	2.404	0.016	0.036	0.356
HOUSE_L	-0.3119	0.088	-3.560	0.000	-0.484	-0.140
PURPOSE_购车借款	0.2600	0.134	1.935	0.053	-0.003	0.523
intercept	-0.1468	0.261	-0.563	0.573	-0.657	0.364

In [31]:

```
cols.pop(3)
cols
```

Out[31]:

```
'CAR'
```

Out[31]:

```
['CREDIT',
 'MONTHS',
 'EDUCATION',
 'loanId',
 'INTEREST',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'PURPOSE_购车借款',
 'intercept']
```

Fit the second model droping CAR

In [32]:

```
model = sm.Logit(data_2['DEFAULT'],data_2[cols])
result2 = model.fit()
result2.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.300698
         Iterations 9
```

Out[32]:

Logit Regression Results

Dep. Variable:	DEFAULT	**No. Observations:**	10000
Model:	Logit	**Df Residuals:**	9990
Method:	MLE	**Df Model:**	9
Date:	Mon, 27 Sep 2021	**Pseudo R-squ.:**	0.2924
Time:	16:43:37	**Log-Likelihood:**	-3007.0
converged:	True	**LL-Null:**	-4249.6
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
CREDIT	-1.9934	0.088	-22.635	0.000	-2.166	-1.821
MONTHS	0.0737	0.004	19.300	0.000	0.066	0.081
EDUCATION	-0.5457	0.043	-12.636	0.000	-0.630	-0.461
loanId	7.994e-07	7.71e-08	10.362	0.000	6.48e-07	9.51e-07
INTEREST	0.0641	0.016	3.956	0.000	0.032	0.096
MARRY_离异	0.8016	0.141	5.672	0.000	0.525	1.079
PURPOSE_装修借款	0.1926	0.081	2.370	0.018	0.033	0.352
HOUSE_L	-0.3059	0.087	-3.521	0.000	-0.476	-0.136
PURPOSE_购车借款	0.2533	0.134	1.893	0.058	-0.009	0.516
intercept	-0.1299	0.259	-0.502	0.616	-0.637	0.377

In [33]:

```
cols.pop(8)
cols
```

Out[33]:

```
'PURPOSE_购车借款'
```

Out[33]:

```
['CREDIT',
 'MONTHS',
 'EDUCATION',
 'loanId',
 'INTEREST',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'intercept']
```

Fit the Third model droping PURPOSE_购车借款

In [34]:

```
model = sm.Logit(data_2['DEFAULT'],data_2[cols])
result3 = model.fit()
result3.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.300875
         Iterations 9
```

Out[34]:

Logit Regression Results

Dep. Variable:	DEFAULT	**No. Observations:**	10000
Model:	Logit	**Df Residuals:**	9991
Method:	MLE	**Df Model:**	8
Date:	Mon, 27 Sep 2021	**Pseudo R-squ.:**	0.2920
Time:	16:43:37	**Log-Likelihood:**	-3008.7
converged:	True	**LL-Null:**	-4249.6
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
CREDIT	-1.9960	0.088	-22.657	0.000	-2.169	-1.823
MONTHS	0.0747	0.004	19.715	0.000	0.067	0.082
EDUCATION	-0.5454	0.043	-12.634	0.000	-0.630	-0.461
loanId	8.041e-07	7.71e-08	10.429	0.000	6.53e-07	9.55e-07
INTEREST	0.0630	0.016	3.893	0.000	0.031	0.095
MARRY_离异	0.8019	0.141	5.678	0.000	0.525	1.079
PURPOSE_装修借款	0.1684	0.080	2.098	0.036	0.011	0.326
HOUSE_L	-0.3068	0.087	-3.530	0.000	-0.477	-0.136
intercept	-0.1093	0.258	-0.423	0.672	-0.616	0.397

In [35]:

```
cols.pop(3)
cols
```

Out[35]:

```
'loanId'
```

Out[35]:

```
['CREDIT',
 'MONTHS',
 'EDUCATION',
 'INTEREST',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'intercept']
```

Fit the Fourth model droping loanId

In [36]:

```
model = sm.Logit(data_2['DEFAULT'],data_2[cols])
result4 = model.fit()
result4.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.306135
         Iterations 9
```

Out[36]:

Logit Regression Results

Dep. Variable:	DEFAULT	**No. Observations:**	10000
Model:	Logit	**Df Residuals:**	9992
Method:	MLE	**Df Model:**	7
Date:	Mon, 27 Sep 2021	**Pseudo R-squ.:**	0.2796
Time:	16:43:37	**Log-Likelihood:**	-3061.4
converged:	True	**LL-Null:**	-4249.6
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
CREDIT	-1.8746	0.084	-22.218	0.000	-2.040	-1.709
MONTHS	0.0789	0.004	21.000	0.000	0.072	0.086
EDUCATION	-0.5103	0.042	-12.042	0.000	-0.593	-0.427
INTEREST	0.0099	0.016	0.639	0.523	-0.021	0.040
MARRY_离异	0.8011	0.140	5.708	0.000	0.526	1.076
PURPOSE_装修借款	0.2557	0.079	3.223	0.001	0.100	0.411
HOUSE_L	-0.3273	0.086	-3.788	0.000	-0.497	-0.158
intercept	0.6634	0.248	2.680	0.007	0.178	1.149

In [37]:

```
cols.pop(3)
cols
```

Out[37]:

```
'INTEREST'
```

Out[37]:

```
['CREDIT',
 'MONTHS',
 'EDUCATION',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'intercept']
```

Fit the Fifth model droping Interest

In [38]:

```
model = sm.Logit(data_2['DEFAULT'],data_2[cols])
result5 = model.fit()
result5.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.306155
         Iterations 9
```

Out[38]:

Logit Regression Results

Dep. Variable:	DEFAULT	**No. Observations:**	10000
Model:	Logit	**Df Residuals:**	9993
Method:	MLE	**Df Model:**	6
Date:	Mon, 27 Sep 2021	**Pseudo R-squ.:**	0.2796
Time:	16:43:38	**Log-Likelihood:**	-3061.6
converged:	True	**LL-Null:**	-4249.6
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
CREDIT	-1.8790	0.084	-22.319	0.000	-2.044	-1.714
MONTHS	0.0793	0.004	21.346	0.000	0.072	0.087
EDUCATION	-0.5124	0.042	-12.123	0.000	-0.595	-0.430
MARRY_离异	0.7979	0.140	5.691	0.000	0.523	1.073
PURPOSE_装修借款	0.2514	0.079	3.182	0.001	0.097	0.406
HOUSE_L	-0.3275	0.086	-3.791	0.000	-0.497	-0.158
intercept	0.7967	0.133	5.981	0.000	0.536	1.058

In [39]:

```
cols.pop(1)
cols
```

Out[39]:

```
'MONTHS'
```

Out[39]:

```
['CREDIT', 'EDUCATION', 'MARRY_离异', 'PURPOSE_装修借款', 'HOUSE_L', 'intercep
t']
```

Fit the Sixth model droping MONTHS

In [40]:

```
model = sm.Logit(data_2['DEFAULT'],data_2[cols])
result6 = model.fit()
result6.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.330429
         Iterations 9
```

Out[40]:

Logit Regression Results

Dep. Variable:	DEFAULT	**No. Observations:**	10000
Model:	Logit	**Df Residuals:**	9994
Method:	MLE	**Df Model:**	5
Date:	Mon, 27 Sep 2021	**Pseudo R-squ.:**	0.2224
Time:	16:43:38	**Log-Likelihood:**	-3304.3
converged:	True	**LL-Null:**	-4249.6
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
CREDIT	-1.8938	0.083	-22.838	0.000	-2.056	-1.731
EDUCATION	-0.4481	0.040	-11.238	0.000	-0.526	-0.370
MARRY_离异	0.8082	0.133	6.059	0.000	0.547	1.070
PURPOSE_装修借款	0.4790	0.075	6.386	0.000	0.332	0.626
HOUSE_L	-0.3142	0.083	-3.806	0.000	-0.476	-0.152
intercept	1.7775	0.123	14.459	0.000	1.537	2.018

In [41]:

```
final_cols = ['CREDIT', 'MONTHS','EDUCATION', 'MARRY_离异', 'PURPOSE_装修借款', 'HOUSE_L', '
```

In [42]:

```
model = sm.Logit(data_2['DEFAULT'],data_2[final_cols])
result7 = model.fit()
result7.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.306155
         Iterations 9
```

Out[42]:

Logit Regression Results

Dep. Variable:	DEFAULT	**No. Observations:**	10000
Model:	Logit	**Df Residuals:**	9993
Method:	MLE	**Df Model:**	6
Date:	Mon, 27 Sep 2021	**Pseudo R-squ.:**	0.2796
Time:	16:43:38	**Log-Likelihood:**	-3061.6
converged:	True	**LL-Null:**	-4249.6
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
CREDIT	-1.8790	0.084	-22.319	0.000	-2.044	-1.714
MONTHS	0.0793	0.004	21.346	0.000	0.072	0.087
EDUCATION	-0.5124	0.042	-12.123	0.000	-0.595	-0.430
MARRY_离异	0.7979	0.140	5.691	0.000	0.523	1.073
PURPOSE_装修借款	0.2514	0.079	3.182	0.001	0.097	0.406
HOUSE_L	-0.3275	0.086	-3.791	0.000	-0.497	-0.158
intercept	0.7967	0.133	5.981	0.000	0.536	1.058

1.3.2 Logit model Sum up

Finally, we get illustrate all the models in a table we can draw the conclusion.

(1) Compated to other model the senventh model is the final model. It contains no insignificant features and contains a rather satifactory score.

Among all the features left, credit, education, house_L has negative effect on Default. It means if someone has higher credits, or better education background or house_L he is less likely to default.
Months,Marry_离异,Purpose_装修借款， has positive effect on Default likelihood.

(2) However, if we can only include bowrrowers' characteristic instead of features about the trade. We should use model 6.

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In [43]:

```
def sum_up(result_list):
    for m in range(len(result_list)):
        temp = []
        result = result_list[m]
        for i in range(len(result.params)):
            text = str('{:.3e}'.format(result.params[i])) + "    " + "( " + result.pvalues[i
            temp.append(text)
        if m==0:
            df = pd.DataFrame({"Model 1" : temp},index = result.params.index)
        else:
            column = "Model " + str(m+1)
            df = df.join(pd.DataFrame({column : temp},index = result.params.index))
    return df
```

In [44]:

```
result_list = [result1,result2,result3,result4,result5,result6,result7]
df = sum_up(result_list)
r_squares = []
for result in result_list:
    r_squares.append('{:.4f}'.format(result.prsquared))
pd.concat([df,pd.DataFrame([r_squares],columns=["Model 1","Model 2","Model 3","Model 4","Mo
```

Out[44]:

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
CREDIT	-1.996e+00 (0.0)	-1.993e+00 (0.0)	-1.996e+00 (0.0)	-1.875e+00 (0.0)	-1.879e+00 (0.0)	-1.894e+00 (0.0)	-1.879e+00 (0.0)
MONTHS	7.391e-02 (0.0)	7.373e-02 (0.0)	7.467e-02 (0.0)	7.893e-02 (0.0)	7.931e-02 (0.0)	NaN	7.931e-02 (0.0)
EDUCATION	-5.459e-01 (0.0)	-5.457e-01 (0.0)	-5.454e-01 (0.0)	-5.103e-01 (0.0)	-5.124e-01 (0.0)	-4.481e-01 (0.0)	-5.124e-01 (0.0)
CAR	3.878e-02 (0.591)	NaN	NaN	NaN	NaN	NaN	NaN
loanId	8.013e-07 (0.0)	7.994e-07 (0.0)	8.041e-07 (0.0)	NaN	NaN	NaN	NaN
INTEREST	6.446e-02 (0.0)	6.410e-02 (0.0)	6.304e-02 (0.0)	9.946e-03 (0.523)	NaN	NaN	NaN
MARRY_离异	8.014e-01 (0.0)	8.016e-01 (0.0)	8.019e-01 (0.0)	8.011e-01 (0.0)	7.979e-01 (0.0)	8.082e-01 (0.0)	7.979e-01 (0.0)
PURPOSE_装修借款	1.959e-01 (0.016)	1.926e-01 (0.018)	1.684e-01 (0.036)	2.557e-01 (0.001)	2.514e-01 (0.001)	4.790e-01 (0.0)	2.514e-01 (0.001)
HOUSE_L	-3.119e-01 (0.0)	-3.059e-01 (0.0)	-3.068e-01 (0.0)	-3.273e-01 (0.0)	-3.275e-01 (0.0)	-3.142e-01 (0.0)	-3.275e-01 (0.0)
PURPOSE_购车借款	2.600e-01 (0.053)	2.533e-01 (0.058)	NaN	NaN	NaN	NaN	NaN
intercept	-1.468e-01 (0.573)	-1.299e-01 (0.616)	-1.093e-01 (0.672)	6.634e-01 (0.007)	7.967e-01 (0.0)	1.778e+00 (0.0)	7.967e-01 (0.0)
R-Square	0.2924	0.2924	0.2920	0.2796	0.2796	0.2224	0.2796

1.3.3 Further study a comparison between logit regression and random forest

(1) [Comparing logit models from machine learning angle]
(2) [Tranning and adjusting the paramater of Randomforest]
(3) [Comparing logit model and randomforest]

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(1) Comparing logit models from machine learning angle

As a result I found after model selection. with fewer features. the final model has better performance than the first model

In [66]:

```
Y =data_2["DEFAULT"]
X = data_2[['CREDIT',
 'MONTHS',
 'EDUCATION',
 'CAR',
 'loanId',
 'INTEREST',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'PURPOSE_购车借款']]
X_train,X_test,y_train,y_test= train_test_split(X,Y,test_size=0.25,random_state=0)
```

In [68]:

```
lg = LogisticRegression()
lg.fit(X_train,y_train)
lg.score(X_train,y_train)
lg.score(X_test,y_test)
```

Out[68]:

```
LogisticRegression()
```

Out[68]:

```
0.8492
```

Out[68]:

```
0.8472
```

In [69]:

```
Y = data_2["DEFAULT"]
X = data_2[final_cols]
X_train,X_test,y_train,y_test= train_test_split(X,Y,test_size=0.25,random_state=0)
lg = LogisticRegression()
lg.fit(X_train,y_train)
lg.score(X_train,y_train)
lg.score(X_test,y_test)
```

Out[69]:

```
LogisticRegression()
```

Out[69]:

```
0.8621333333333333
```

Out[69]:

```
0.8568
```

(2) Randomforest Training

Since there are few features remained for randomforest,
I just drop the illogic feature-loanId, and fit the model with better parameter instead of further feature filtering

Without setting the parm, the score between train set and test set is much larger

To fix the overfitting problem, adjust parm: "max-depth"

Draw the result at last socre-different max depth

Come to a conclusion, max - depth =6 is the best parm.

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In [86]:

```
score_train = []
score_test = []
```

In [87]:

```
Y =data_2["DEFAULT"]
X = data_2[['CREDIT',
 'MONTHS',
 'EDUCATION',
 'CAR',
 'INTEREST',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'PURPOSE_购车借款']]
X_train,X_test,y_train,y_test= train_test_split(X,Y,test_size=0.25,random_state=0)
clf = RandomForestClassifier( random_state=0)
clf.fit(X_train,y_train)
clf.score(X_train,y_train)
clf.score(X_test,y_test)
score_train.append(clf.score(X_train,y_train))
score_test.append(clf.score(X_test,y_test))
```

Out[87]:

```
RandomForestClassifier(random_state=0)
```

Out[87]:

```
0.8906666666666667
```

Out[87]:

```
0.8528
```

In [88]:

```
Y =data_2["DEFAULT"]
X = data_2[['CREDIT',
 'MONTHS',
 'EDUCATION',
 'CAR',
 'INTEREST',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'PURPOSE_购车借款']]
X_train,X_test,y_train,y_test= train_test_split(X,Y,test_size=0.25,random_state=0)
clf = RandomForestClassifier( max_depth=2,random_state=0)
clf.fit(X_train,y_train)
clf.score(X_train,y_train)
clf.score(X_test,y_test)
score_train.append(clf.score(X_train,y_train))
score_test.append(clf.score(X_test,y_test))
```

Out[88]:

```
RandomForestClassifier(max_depth=2, random_state=0)
```

Out[88]:

```
0.8492
```

Out[88]:

```
0.8472
```

In [89]:

```
Y =data_2["DEFAULT"]
X = data_2[['CREDIT',
 'MONTHS',
 'EDUCATION',
 'CAR',
 'INTEREST',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'PURPOSE_购车借款']]
X_train,X_test,y_train,y_test= train_test_split(X,Y,test_size=0.25,random_state=0)
clf = RandomForestClassifier( max_depth=4,random_state=0)
clf.fit(X_train,y_train)
clf.score(X_train,y_train)
clf.score(X_test,y_test)
score_train.append(clf.score(X_train,y_train))
score_test.append(clf.score(X_test,y_test))
```

Out[89]:

```
RandomForestClassifier(max_depth=4, random_state=0)
```

Out[89]:

```
0.8516
```

Out[89]:

```
0.8476
```

In [90]:

```
Y =data_2["DEFAULT"]
X = data_2[['CREDIT',
 'MONTHS',
 'EDUCATION',
 'CAR',
 'INTEREST',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'PURPOSE_购车借款']]
X_train,X_test,y_train,y_test= train_test_split(X,Y,test_size=0.25,random_state=0)
clf = RandomForestClassifier( max_depth=6,random_state=0)
clf.fit(X_train,y_train)
clf.score(X_train,y_train)
clf.score(X_test,y_test)
score_train.append(clf.score(X_train,y_train))
score_test.append(clf.score(X_test,y_test))
```

Out[90]:

```
RandomForestClassifier(max_depth=6, random_state=0)
```

Out[90]:

```
0.8668
```

Out[90]:

```
0.8652
```

In [91]:

```
Y =data_2["DEFAULT"]
X = data_2[['CREDIT',
 'MONTHS',
 'EDUCATION',
 'CAR',
 'INTEREST',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'PURPOSE_购车借款']]
X_train,X_test,y_train,y_test= train_test_split(X,Y,test_size=0.25,random_state=0)
clf = RandomForestClassifier( max_depth=8,random_state=0)
clf.fit(X_train,y_train)
clf.score(X_train,y_train)
clf.score(X_test,y_test)
score_train.append(clf.score(X_train,y_train))
score_test.append(clf.score(X_test,y_test))
```

Out[91]:

```
RandomForestClassifier(max_depth=8, random_state=0)
```

Out[91]:

```
0.8733333333333333
```

Out[91]:

```
0.862
```

In [92]:

```
Y =data_2["DEFAULT"]
X = data_2[['CREDIT',
 'MONTHS',
 'EDUCATION',
 'CAR',
 'INTEREST',
 'MARRY_离异',
 'PURPOSE_装修借款',
 'HOUSE_L',
 'PURPOSE_购车借款']]
X_train,X_test,y_train,y_test= train_test_split(X,Y,test_size=0.25,random_state=0)
clf = RandomForestClassifier( max_depth=10,random_state=0)
clf.fit(X_train,y_train)
clf.score(X_train,y_train)
clf.score(X_test,y_test)
score_train.append(clf.score(X_train,y_train))
score_test.append(clf.score(X_test,y_test))
```

Out[92]:

```
RandomForestClassifier(max_depth=10, random_state=0)
```

Out[92]:

```
0.8805333333333333
```

Out[92]:

```
0.8592
```

Draw the result at last socre-different max depth

Come to a conclusion, max - depth =6 is the best parm. Because, it the test point reaches a local maximizer. Besides, it is fairly close to figure of trainset leading to no concern of overfitting problem.

In [105]:

```
plt.figure(figsize=[7, 6])
x_plot = [0,2,4,6,8,10]
plt.plot(x_plot,score_train,"b--*",label="Train Score")
plt.plot(x_plot,score_test,"r--.",label="Test Score")
plt.xlabel("Max Depth")
plt.ylabel("Score")
plt.title("Score - Max Depth")
plt.legend()
plt.show()
```

Out[105]:

```
<Figure size 504x432 with 0 Axes>
```

Out[105]:

```
[<matplotlib.lines.Line2D at 0x227563086a0>]
```

Out[105]:

```
[<matplotlib.lines.Line2D at 0x22756308ac0>]
```

Out[105]:

```
Text(0.5, 0, 'Max Depth')
```

Out[105]:

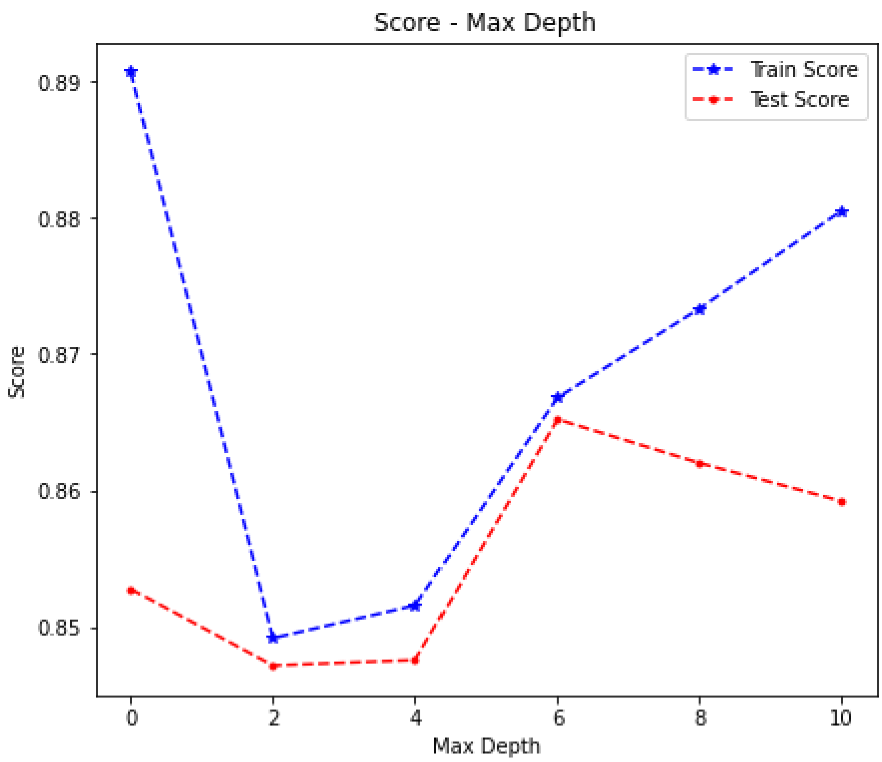
```
Text(0, 0.5, 'Score')
```

Out[105]:

```
Text(0.5, 1.0, 'Score - Max Depth')
```

Out[105]:

```
<matplotlib.legend.Legend at 0x22756308d60>
```



(3) Comparing logit and randomforest

From the table we can come to the conclusion that: Randomforest model scores (0.0047) better on the train set Randomforest model scores 0.0085 better on the test set. Obviously logit model has quiet similar performance compared to the random forest model. I assume there are two reasons:

(1) The logit model is excellently fitted
(2) The data sample is not perfect for randomforest because there are not enough featues and records.

Although random forest has better performance, it can not explain how each feature affect the result very well

Back to 1.3.3

In [108]:

```
pd.DataFrame({
    "Logit":[0.8621,0.8568],
    "RandomForest":[0.8668,0.8652]},
    index = ["Train set score","Test set score"]
l
)
```

Out[108]:

	Logit	RandomForest
Train set score	0.8621	0.8668
Test set score	0.8568	0.8652

In [110]:

```
0.8668 - 0.8621
0.8652 - 0.8568
```

Out[110]:

```
0.0047000000000000375
```

Out[110]:

```
0.008399999999999963
```

1.4 OLS Regression

(1) First Model
According to the note 2 in the result, I found there are some series problem in the model leading to an irregular large condition number.
At the same time when we plot the residual graph, the figure is not like a line,but varied among observations

(2) Second Model
Based on the tips I assume there is multicollinearity in the model, and based on the correlation test I have done, I have already removed close features. However I keep one feature AMOUNT which is highly related(0.809) to BIDS. I assume it is the reason causing the problem, and it is also rational that there is mullticollinearity between amount and bids from life experience. Since the amount is a result of bids

The result is a little better, but it still involve a large condition number.

(3) Third Model

Since there is still a same problem, I assume its cause is another issue-numerical problem. When I look up to the data statistc of the features, I found the feature loan Id is make up of significantly large number compared to other features. And it should not be a explainable based on life experience, so I simply drop it.
Finally we get model no longer report a large condition number.

(4) Fourth and d Fifth Model

In these two models I drop insignificant feature a.dummy variable _已婚 and b.Intereset.
After that I plot a residual graph of the final model. Compared to the model earlier, the line is much more smooth

Back to content

In [354]:

```
bidsIndex = bidsIndex_0
```

(1) The First Model

According to the note 2 in the result, I found there are some series problem in the model leading to an irregular large condition number.
At the same time when we plot the residual graph, the figure is not like a line,but varied among observations

In [355]:

```
X = data_2[bidsIndex]
Y = data_2["BIDS"]
X = sm.add_constant(X)
model = sm.OLS(Y,X)
result_ols = model.fit()
result_ols.summary()
```

Out[355]:

OLS Regression Results

Dep. Variable:	BIDS	**R-squared:**	0.662
Model:	OLS	**Adj. R-squared:**	0.662
Method:	Least Squares	**F-statistic:**	1782.
Date:	Fri, 24 Sep 2021	**Prob (F-statistic):**	0.00
Time:	17:36:39	**Log-Likelihood:**	-45978.
No. Observations:	10000	**AIC:**	9.198e+04
Df Residuals:	9988	**BIC:**	9.207e+04
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.2743	2.203	0.124	0.901	-4.044	4.593
AMOUNT	0.0009	7.3e-06	117.345	0.000	0.001	0.001
INCOME	-0.1936	0.212	-0.913	0.361	-0.609	0.222
AGE	0.0829	0.044	1.879	0.060	-0.004	0.169
IND_制造业	1.9705	0.617	3.196	0.001	0.762	3.179
CAR	-0.4390	0.550	-0.798	0.425	-1.517	0.639
loanId	-5.279e-06	5.91e-07	-8.929	0.000	-6.44e-06	-4.12e-06
WORKTIME	0.1738	0.273	0.636	0.524	-0.362	0.709
CREDIT	0.1792	0.167	1.073	0.283	-0.148	0.507
MARRY_已婚	0.3358	0.562	0.597	0.551	-0.767	1.438
PURPOSE_其他借款	9.9002	1.149	8.617	0.000	7.648	12.152
INTEREST	0.0981	0.113	0.870	0.384	-0.123	0.319

Omnibus:	6829.156	**Durbin-Watson:**	1.652
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	991338.826
Skew:	2.351	**Prob(JB):**	0.00
Kurtosis:	51.550	**Cond. No.**	5.62e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 5.62e+06. This might indicate that there are strong multicollinearity or other numerical problems.

In [356]:

```
x = np.linspace(0,1000,len(Y))
y_fitted = result_ols.fittedvalues
res = Y - y_fitted
res = (res-res.mean())/res.std()
fig, ax = plt.subplots(figsize=(8,6))
ax.plot(x, Y, 'o', label='data')
ax.plot(x, res, 'r--.',label='OLS')
ax.legend(loc='best')
```

Out[356]:

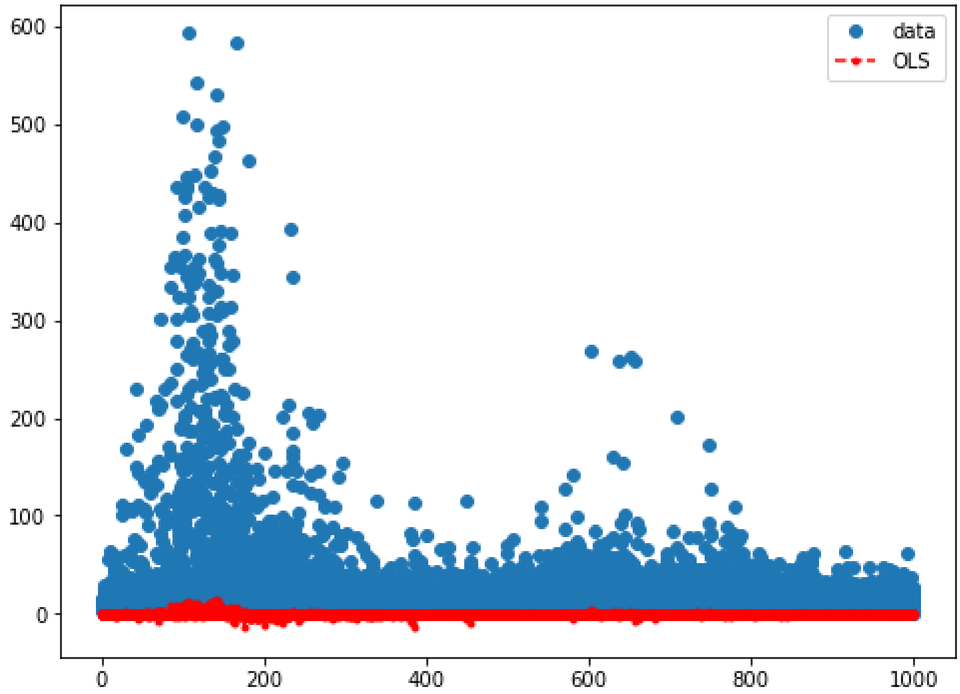
```
[<matplotlib.lines.Line2D at 0x1de84d0fca0>]
```

Out[356]:

```
[<matplotlib.lines.Line2D at 0x1de84d1d100>]
```

Out[356]:

```
<matplotlib.legend.Legend at 0x1de84d0fee0>
```



(2) The Second Model

Based on the tips I assume there is multicollinearity in the model, and based on the correlation test I have done, I have already removed close features. However I keep one feature AMOUNT which is highly related(0.809) to BIDS. I assume it is the reason causing the problem, and it is also rational that there is mullticollinearity between amount and bids from life experience. Since the amount is a result of bids

The result is a little better, but it still involve a large condition number.

In [342]:

```
bidsIndex = bidsIndex_0
bidsIndex = bidsIndex.drop(['AMOUNT'])
bidsIndex
```

Out[342]:

```
Index(['INCOME', 'AGE', 'IND_制造业', 'CAR', 'loanId', 'WORKTIME', 'CREDIT',
       'MARRY_已婚', 'PURPOSE_其他借款', 'INTEREST'],
      dtype='object')
```

In [343]:

```
X = data_2[bidsIndex]
Y = data_2["BIDS"]
X = sm.add_constant(X)
model = sm.OLS(Y,X)
result_ols = model.fit()
result_ols.summary()
```

Out[343]:

OLS Regression Results

Dep. Variable:	BIDS	**R-squared:**	0.197
Model:	OLS	**Adj. R-squared:**	0.196
Method:	Least Squares	**F-statistic:**	245.2
Date:	Fri, 24 Sep 2021	**Prob (F-statistic):**	0.00
Time:	17:31:21	**Log-Likelihood:**	-50310.
No. Observations:	10000	**AIC:**	1.006e+05
Df Residuals:	9989	**BIC:**	1.007e+05
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-67.3928	3.279	-20.552	0.000	-73.821	-60.965
INCOME	8.7481	0.305	28.667	0.000	8.150	9.346
AGE	0.7695	0.067	11.418	0.000	0.637	0.902
IND_制造业	14.3086	0.937	15.273	0.000	12.472	16.145
CAR	3.1661	0.847	3.738	0.000	1.506	4.826
loanId	-3.323e-06	9.11e-07	-3.646	0.000	-5.11e-06	-1.54e-06
WORKTIME	2.2428	0.420	5.336	0.000	1.419	3.067
CREDIT	1.4875	0.257	5.788	0.000	0.984	1.991
MARRY_已婚	-1.8969	0.867	-2.188	0.029	-3.596	-0.197
PURPOSE_其他借款	14.3378	1.771	8.096	0.000	10.866	17.809
INTEREST	1.2182	0.173	7.032	0.000	0.879	1.558

Omnibus:	11478.210	**Durbin-Watson:**	1.772
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1254822.334
Skew:	6.011	**Prob(JB):**	0.00
Kurtosis:	56.545	**Cond. No.**	5.43e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.43e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

(3) The Third Model

Since there is still a same problem, I assume its cause is another issue-numerical problem. When I look up to the data statistc of the features, I found the feature loan Id is make up of significantly large number compared to other features. And it should not be a explainable based on life experience, so I simply drop it.
Finally we get model no longer report a large condition number.

In [344]:

```
bidsIndex = bidsIndex_0
bidsIndex = bidsIndex.drop(['AMOUNT',"loanId"])
bidsIndex
```

Out[344]:

```
Index(['INCOME', 'AGE', 'IND_制造业', 'CAR', 'WORKTIME', 'CREDIT', 'MARRY_已
婚',
       'PURPOSE_其他借款', 'INTEREST'],
      dtype='object')
```

In [345]:

```
X = data_2[bidsIndex]
Y = data_2["BIDS"]
X = sm.add_constant(X)
model = sm.OLS(Y,X)
result_ols = model.fit()
result_ols.summary()
```

Out[345]:

OLS Regression Results

Dep. Variable:	BIDS	**R-squared:**	0.196
Model:	OLS	**Adj. R-squared:**	0.195
Method:	Least Squares	**F-statistic:**	270.6
Date:	Fri, 24 Sep 2021	**Prob (F-statistic):**	0.00
Time:	17:32:29	**Log-Likelihood:**	-50317.
No. Observations:	10000	**AIC:**	1.007e+05
Df Residuals:	9990	**BIC:**	1.007e+05
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-72.8437	2.920	-24.945	0.000	-78.568	-67.120
INCOME	8.8799	0.303	29.288	0.000	8.286	9.474
AGE	0.7974	0.067	11.902	0.000	0.666	0.929
IND_制造业	14.3857	0.937	15.350	0.000	12.549	16.223
CAR	3.2746	0.847	3.866	0.000	1.614	4.935
WORKTIME	2.1242	0.419	5.066	0.000	1.302	2.946
CREDIT	1.6431	0.254	6.479	0.000	1.146	2.140
MARRY_已婚	-1.8746	0.867	-2.161	0.031	-3.575	-0.174
PURPOSE_其他借款	14.7318	1.769	8.329	0.000	11.265	18.199
INTEREST	1.4109	0.165	8.547	0.000	1.087	1.735

Omnibus:	11478.053	**Durbin-Watson:**	1.775
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1253172.136
Skew:	6.012	**Prob(JB):**	0.00
Kurtosis:	56.507	**Cond. No.**	300.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

(4) The Fourth Model

In these two models I drop insignificant feature a.dummy variable _已婚

In [346]:

```
bidsIndex = bidsIndex_0
bidsIndex = bidsIndex.drop(['AMOUNT',"loanId","MARRY_已婚"])
bidsIndex
```

Out[346]:

```
Index(['INCOME', 'AGE', 'IND_制造业', 'CAR', 'WORKTIME', 'CREDIT', 'PURPOSE_
其他借款',
       'INTEREST'],
      dtype='object')
```

In [347]:

```
X = data_2[bidsIndex]
Y = data_2["BIDS"]
X = sm.add_constant(X)
model = sm.OLS(Y,X)
result_ols = model.fit()
result_ols.summary()
```

Out[347]:

OLS Regression Results

Dep. Variable:	BIDS	**R-squared:**	0.196
Model:	OLS	**Adj. R-squared:**	0.195
Method:	Least Squares	**F-statistic:**	303.7
Date:	Fri, 24 Sep 2021	**Prob (F-statistic):**	0.00
Time:	17:33:21	**Log-Likelihood:**	-50319.
No. Observations:	10000	**AIC:**	1.007e+05
Df Residuals:	9991	**BIC:**	1.007e+05
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-72.1526	2.903	-24.853	0.000	-77.844	-66.462
INCOME	8.8659	0.303	29.243	0.000	8.272	9.460
AGE	0.7574	0.064	11.761	0.000	0.631	0.884
IND_制造业	14.3604	0.937	15.321	0.000	12.523	16.198
CAR	2.9475	0.834	3.536	0.000	1.314	4.581
WORKTIME	2.0321	0.417	4.871	0.000	1.214	2.850
CREDIT	1.6029	0.253	6.336	0.000	1.107	2.099
PURPOSE_其他借款	14.7556	1.769	8.341	0.000	11.288	18.223
INTEREST	1.4143	0.165	8.566	0.000	1.091	1.738

Omnibus:	11480.291	**Durbin-Watson:**	1.774
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1253186.560
Skew:	6.014	**Prob(JB):**	0.00
Kurtosis:	56.507	**Cond. No.**	298.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [348]:

```
x = np.linspace(0,1000,len(Y))
y_fitted = result_ols.fittedvalues
res = Y - y_fitted
res = (res-res.mean())/res.std()
fig, ax = plt.subplots(figsize=(8,6))
ax.plot(x, Y, 'o', label='data')
ax.plot(x, res, 'r--.',label='OLS')
ax.legend(loc='best')
```

Out[348]:

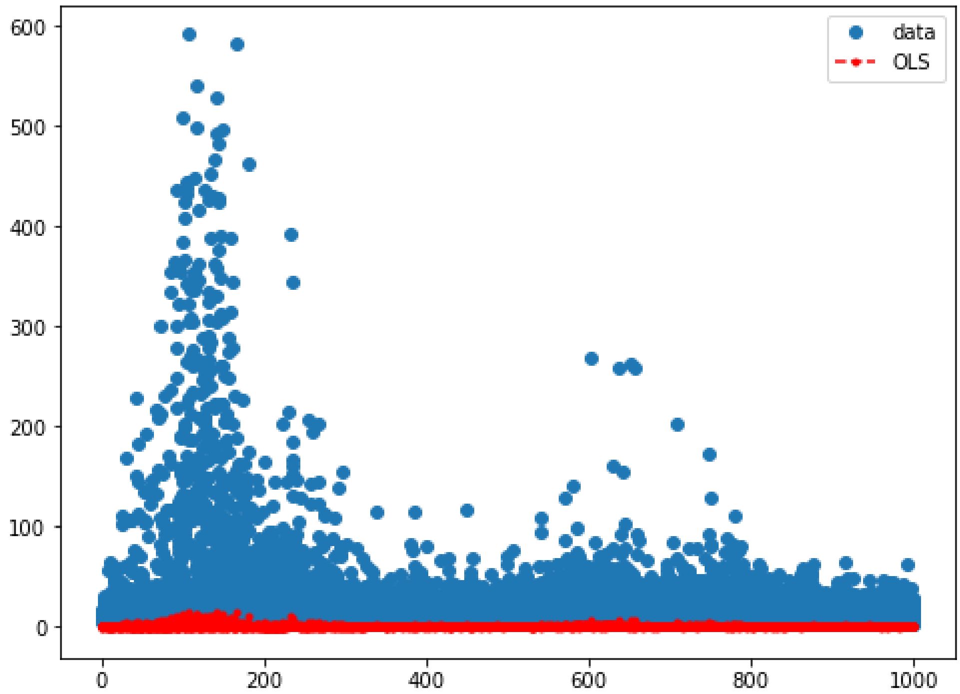
```
[<matplotlib.lines.Line2D at 0x1de84c15400>]
```

Out[348]:

```
[<matplotlib.lines.Line2D at 0x1de84c15820>]
```

Out[348]:

```
<matplotlib.legend.Legend at 0x1de84c15640>
```



(5) The Fifth Model

In these two models I drop insignificant feature Intereset.
After that I plot a residual graph of the final model. Compared to the model earlier, the line is much more smooth

In [350]:

```
bidsIndex = bidsIndex_0
bidsIndex = bidsIndex.drop(['AMOUNT',"loanId","MARRY_已婚","INTEREST"])
bidsIndex
```

Out[350]:

```
Index(['INCOME', 'AGE', 'IND_制造业', 'CAR', 'WORKTIME', 'CREDIT',
       'PURPOSE_其他借款'],
      dtype='object')
```

In [351]:

```
X = data_2[bidsIndex]
Y = data_2["BIDS"]
X = sm.add_constant(X)
model = sm.OLS(Y,X)
result_ols = model.fit()
result_ols.summary()
```

Out[351]:

OLS Regression Results

Dep. Variable:	BIDS	**R-squared:**	0.190
Model:	OLS	**Adj. R-squared:**	0.189
Method:	Least Squares	**F-statistic:**	334.2
Date:	Fri, 24 Sep 2021	**Prob (F-statistic):**	0.00
Time:	17:35:44	**Log-Likelihood:**	-50356.
No. Observations:	10000	**AIC:**	1.007e+05
Df Residuals:	9992	**BIC:**	1.008e+05
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-55.6554	2.180	-25.527	0.000	-59.929	-51.382
INCOME	8.8782	0.304	29.178	0.000	8.282	9.475
AGE	0.8132	0.064	12.647	0.000	0.687	0.939
IND_制造业	14.8213	0.939	15.782	0.000	12.980	16.662
CAR	2.6880	0.836	3.215	0.001	1.049	4.327
WORKTIME	1.9524	0.419	4.664	0.000	1.132	2.773
CREDIT	1.4124	0.253	5.585	0.000	0.917	1.908
PURPOSE_其他借款	14.8417	1.775	8.360	0.000	11.362	18.322

Omnibus:	11562.235	**Durbin-Watson:**	1.756
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1281987.443
Skew:	6.087	**Prob(JB):**	0.00
Kurtosis:	57.116	**Cond. No.**	211.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [352]:

```
x = np.linspace(0,1000,len(Y))
y_fitted = result_ols.fittedvalues
res = Y - y_fitted
res = (res-res.mean())/res.std()
fig, ax = plt.subplots(figsize=(8,6))
ax.plot(x, Y, 'o', label='data')
ax.plot(x, res, 'r--.',label='OLS')
ax.legend(loc='best')
```

Out[352]:

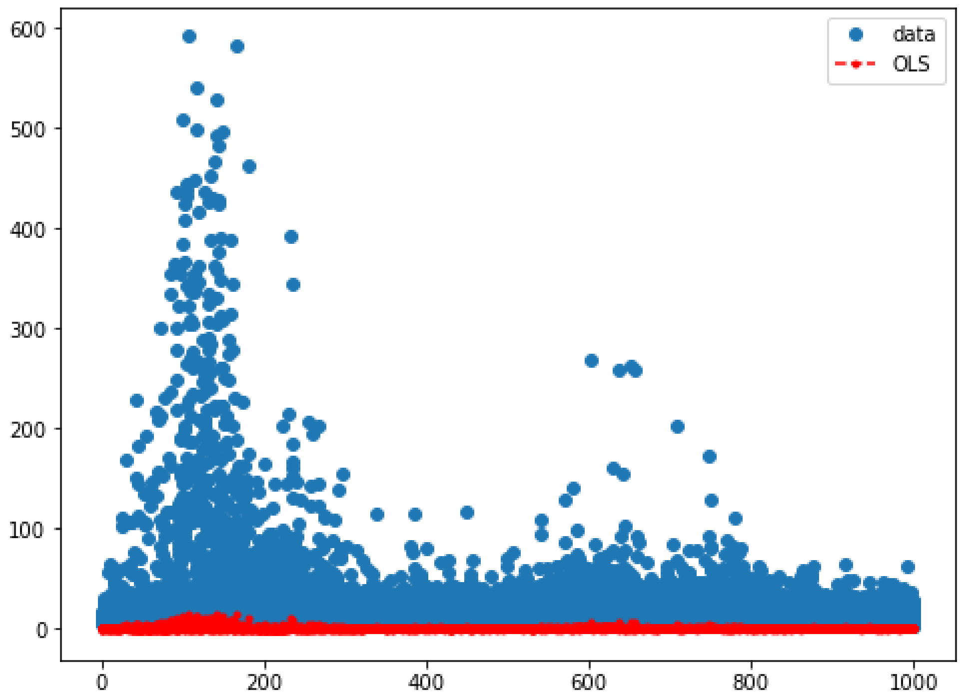
```
[<matplotlib.lines.Line2D at 0x1de84c8fb20>]
```

Out[352]:

```
[<matplotlib.lines.Line2D at 0x1de84c8ff40>]
```

Out[352]:

```
<matplotlib.legend.Legend at 0x1de84c8fd30>
```



2.P2P Lending Platform

2.1 P2P Lending Platform Data Summary

Data description: 1000 records X 17 columns

Data operation

(1) Genereate Duation feature
It is generated based on Open-time and Bankrupt-time, using integer to represent the result.
For example Open time 2014/05/19 - Bankrupt-time Year 2017, we get Duration (20170000 - 201405190)

(2) Generate dummy variable
I generate dummy variable for Background including 4 types of background.

(3) Correlation test
Based on heat map, find if there is high correlation among features and it may lead to multicollinearity. As a result I just kick one of the backgroud variable out of the table sicne they are highly related.

(4)Null value handle
There are some missing records in the features. In the statistic table I found the missing records exist in label feature, and the number is limited. So I simply fill these null values with its own median value.

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In [357]:

```
data_p2p = pd.read_csv(r"..\Week 2 Assignment\p2p.csv",encoding="gbk")
data_p2p.head()
```

Out[357]:

	fullname	OnlineTime_YMD	Bankrupt_WDZJ	Province	City	Collapse	Benign	Fraud	RegCa
0	123便利贷	20140519	2.017e+07	上海	上海	1	0.0	0.0	
1	17聚财	20151231	2.017e+07	上海	上海	1	0.0	0.0	
2	360易贷	20150504	2.016e+07	辽宁	沈阳	1	0.0	0.0	
3	365储蓄家	20180310	2.018e+07	浙江	杭州	1	0.0	0.0	
4	51丰收宝	20180320	2.018e+07	广东	深圳	1	0.0	1.0	

In [358]:

```
data_p2p.shape
```

Out[358]:

(1000, 17)

In [360]:

```
data_p2p.describe()
```

Out[360]:

	OnlineTime_YMD	Bankrupt_WDZJ	Collapse	Benign	Fraud	RegCapital	Capitaldeposi
count	1.000e+03	7.820e+02	1000.000	782.000	782.000	1000.000	1000.00
mean	2.015e+07	2.016e+07	0.782	0.098	0.247	596.064	0.19
std	1.135e+04	1.304e+04	0.413	0.298	0.431	2328.222	0.39
min	2.009e+07	2.012e+07	0.000	0.000	0.000	2.000	0.00
25%	2.014e+07	2.015e+07	1.000	0.000	0.000	100.000	0.00
50%	2.015e+07	2.016e+07	1.000	0.000	0.000	300.000	0.00
75%	2.015e+07	2.017e+07	1.000	0.000	0.000	500.000	0.00
max	2.018e+07	2.019e+07	1.000	1.000	1.000	50000.000	1.00

Generate Duration feature baed on OnlineTime and bankrupt time

In [366]:

```
data_p2p["endtime"] = data_p2p["Bankrupt_WDZJ"]
data_p2p["endtime"][data_p2p["endtime"].isnull()] = 20210000
data_p2p["Duration"] = data_p2p["endtime"] - data_p2p["OnlineTime_YMD"]
data_p2p.describe()["Duration"]
```

```
<ipython-input-366-d566a584de42>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  data_p2p["endtime"][data_p2p["endtime"].isnull()] = 20210000
```

Out[366]:

```
count      1000.000
mean      24984.026
std       22517.608
min           0.000
25%        9604.750
50%       19517.500
75%       39737.250
max      108987.000
Name: Duration, dtype: float64
```

Generate Dummy variabel for Background

In [372]:

```
data_p2p = pd.get_dummies(data_p2p,columns=["Background"])
```

Correlationship test

In [376]:

```
abs(data_p2p.corr()["Collapse"]).sort_values(ascending=False)
collapse_index_0 = abs(data_p2p.corr()["Collapse"]).sort_values(ascending=False).index[3:16
collapse_index_0
```

Out[376]:

```
Collapse          1.000
endtime           0.858
Duration          0.821
Capitaldeposit    0.477
Joinasso          0.231
Background_民营系     0.214
Transright        0.174
Background_上市公司    0.164
Background_国企背景    0.138
Obtaininvest      0.092
Autobid           0.078
Thirdguarantee    0.077
OnlineTime_YMD    0.070
Background_风投系     0.061
Riskdeposit       0.032
RegCapital        0.028
Bankrupt_WDZJ       NaN
Benign              NaN
Fraud               NaN
Name: Collapse, dtype: float64
```

Out[376]:

```
Index(['Capitaldeposit', 'Joinasso', 'Background_民营系', 'Transright',
       'Background_上市公司', 'Background_国企背景', 'Obtaininvest', 'Autobi
d',
       'Thirdguarantee', 'OnlineTime_YMD', 'Background_风投系', 'Riskdeposi
t',
       'RegCapital'],
      dtype='object')
```

(3) Correlation test

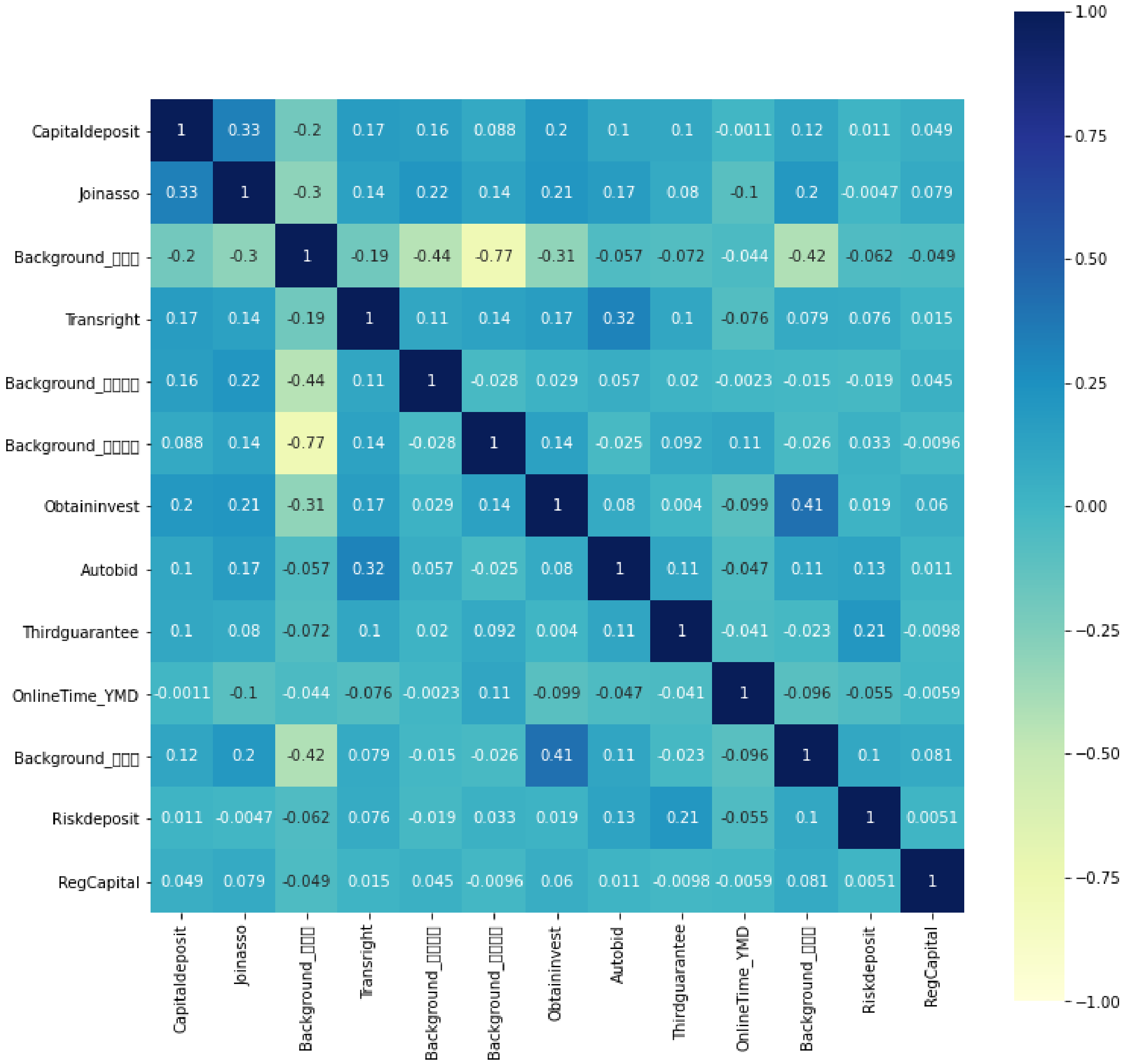
Based on heat map, find if there is high correlation among features and it may lead to multicollinearity. As a result I just kick one of the backgroud variable out of the table sicne they are highly related.

In [378]:

```
fig, ax = plt.subplots(figsize = (12,12))
sns.heatmap(data_p2p[collapse_index_0].corr(),annot=True, vmax=1, vmin=-1,square=True,cmap=
```

Out[378]:

<AxesSubplot:>



In [379]:

```
collapse_index_0 = collapse_index_0.drop("Background_上市公司")
collapse_index_0
```

Out[379]:

```
Index(['Capitaldeposit', 'Joinasso', 'Background_民营系', 'Transright',
       'Background_国企背景', 'Obtaininvest', 'Autobid', 'Thirdguarantee',
       'OnlineTime_YMD', 'Background_风投系', 'Riskdeposit', 'RegCapital'],
      dtype='object')
```

In [380]:

```
data_p2p.describe()[collapse_index_0]
```

Out[380]:

	Capitaldeposit	Joinasso	Background_民营系	Transright	Background_国企背景	Obtaininvest	Autobid
count	1000.000	968.000	1000.000	1000.000	1000.000	968.000	1000.000
mean	0.191	0.055	0.924	0.177	0.046	0.027	0.244
std	0.393	0.228	0.265	0.382	0.210	0.162	0.430
min	0.000	0.000	0.000	0.000	0.000	0.000	0.000
25%	0.000	0.000	1.000	0.000	0.000	0.000	0.000
50%	0.000	0.000	1.000	0.000	0.000	0.000	0.000
75%	0.000	0.000	1.000	0.000	0.000	0.000	0.000
max	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Fill numm value with median

In [382]:

```
for index in collapse_index_0:
    data_p2p[index][data_p2p[index].isnull()] = data_p2p[index].median()
data_p2p.describe()[collapse_index_0]
```

```
:aveats in the documentation: https://pandas.pydata.org/pandas-doc
'user_guide/indexing.html#returning-a-view-versus-a-copy (https://
/data.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
;us-a-copy)
?p[index][data_p2p[index].isnull()] = data_p2p[index].median()
```

pitaldeposit	Joinasso	Background_民营系	Transright	Background_国企背景	Obtaininvest	Autobid	Thirdguarantee	OnlineT
1000.000	1000.000	1000.000	1000.000	1000.000	1000.000	1000.000	1000.000	
0.191	0.053	0.924	0.177	0.046	0.026	0.244	0.033	
0.393	0.224	0.265	0.382	0.210	0.159	0.430	0.179	
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	

2.2 Cox model

features are significant(p<=0.5): Joinasso, Background_民营, Transright,Autobid
(1) When a commpany has joined the associate, it is 0.63 times to collapse
(2) When a company is private it is 3.08 times more likely to collapse
(3) If a company provides bonds transfering, it is 0.62 times as same as those not to collapse
(4) If a firm provides auto-bid it is 0.83 times as same as those not to collapse

Back to content

In [386]:

```
from lifelines import CoxPHFitter
```

In [392]:

```
collapse_index_0
```

Out[392]:

```
Index(['Capitaldeposit', 'Joinasso', 'Background_民营系', 'Transright',
       'Background_国企背景', 'Obtaininvest', 'Autobid', 'Thirdguarantee',
       'OnlineTime_YMD', 'Background_风投系', 'Riskdeposit', 'RegCapital'],
      dtype='object')
```

In [395]:

```
data_cox = data_p2p[['Capitaldeposit', 'Joinasso', 'Background_民营系', 'Transright',
       'Background_国企背景', 'Obtaininvest', 'Autobid', 'Thirdguarantee',
        'Background_风投系', 'Riskdeposit', 'RegCapital',"Duration","Collapse"]]
```

In [396]:

```
cph = CoxPHFitter()
cph.fit(data_cox, 'Duration', event_col='Collapse')
cph.print_summary()
```

Out[396]:

```
<lifelines.CoxPHFitter: fitted with 1000 total observations, 218 right-censo
red observations>
```

model	lifelines.CoxPHFitter
duration col	'Duration'
event col	'Collapse'
baseline estimation	breslow
number of observations	1000
number of events observed	782
partial log-likelihood	-4770.93
time fit was run	2021-09-24 12:14:45 UTC

	coef	exp(coef)	se(coef)	coef lower 95%	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%	z	p	lo
Capitaldeposit	-1.51	0.22	0.13	-1.76	-1.26	0.17	0.28	-11.77	<0.005	1
Joinasso	-0.46	0.63	0.23	-0.91	-0.01	0.40	0.99	-2.00	0.05	
Background_民营系	1.12	3.08	0.51	0.13	2.12	1.14	8.32	2.22	0.03	
Transright	-0.47	0.62	0.11	-0.68	-0.26	0.50	0.77	-4.38	<0.005	
Background_国企背景	0.59	1.80	0.54	-0.48	1.65	0.62	5.21	1.08	0.28	
Obtaininvest	0.08	1.09	0.28	-0.47	0.64	0.62	1.90	0.29	0.77	
Autobid	-0.19	0.83	0.09	-0.37	-0.01	0.69	0.99	-2.09	0.04	
Thirdguarantee	-0.17	0.85	0.23	-0.61	0.28	0.54	1.32	-0.74	0.46	
Background_风投系	0.80	2.23	0.62	-0.41	2.02	0.66	7.53	1.29	0.20	
Riskdeposit	-0.10	0.90	0.27	-0.63	0.42	0.53	1.52	-0.39	0.70	
RegCapital	0.00	1.00	0.00	-0.00	0.00	1.00	1.00	0.31	0.75	

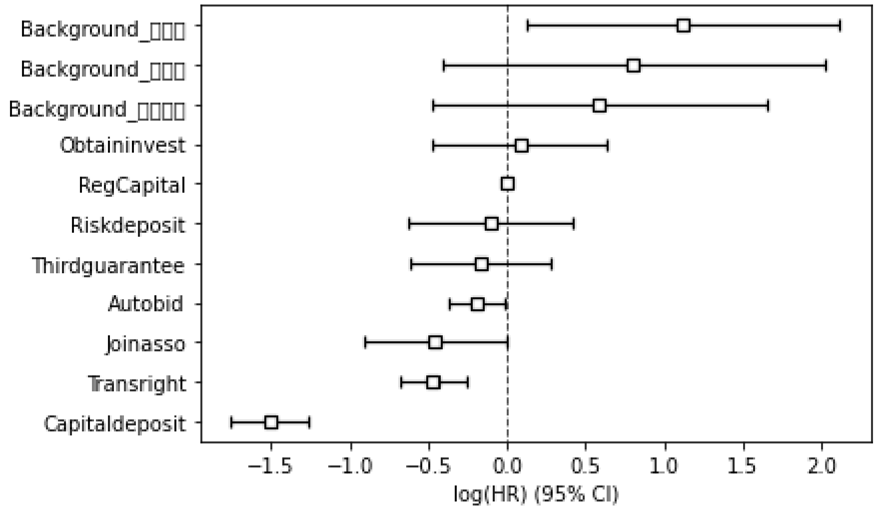
Concordance	0.68
Partial AIC	9563.85
log-likelihood ratio test	327.07 on 11 df
-log2(p) of ll-ratio test	208.51

In [399]:

```
cph.plot()
```

Out[399]:

<AxesSubplot:xlabel='log(HR) (95% CI)'>



In [ ]:

```

```