Loan Default Analysis of Lending Club

Description

Environment: OS: macOS Big Sur 11.1; Language: python 3.7**:** Editor: jupyter notebook

Motivation

Lending Club is the largest online loan marketplace, facilitating personal loans, and financing of medical procedures. Borrowers can easily access lower interest rate loans through a fast online interface.Like most other lending companies, lending loans to 'risky' applicants is the largest source of financial loss (called credit loss). The credit loss is the amount of money lost by the lender when the borrower refuses to pay or runs away with the money owed. Therefore, using Data Science, Exploratory Data Analysis and public data from Lending Club, we will be exploring and crunching out the driving factors that exists behind the loan default, i.e. the variables which are strong indicators of default. That's why we think this topic is suitable for us to show what we learn in the class.

Dataset

The dataset contains complete loan data for all loans issued through four seasons in 2018, including the current loan status (Current, Charged-off, Fully Paid) and latest payment information. Additional features include credit scores, number of finance inquiries, and collections among others. The file is a matrix of about 495,242 observations and 102 variables.

Analyzing Tool

Linear regression, random forest, XGBoost, GBDT and LightGBM.

Implementation

Feature Distribution: First of all, "Loan Characteristics" such as loan amount, term, purpose which shows the information about the loan that will help us in finding loan default. Second, "Demographic Variables" such as age, employment status, relationship status which shows the information about the borrower profile which is not useful for us. Last but not least, "Behavioural Variables" such as next payment date, EMI, delinquency which shows the information which is updated after providing the loan which in our case is not useful as we need to decide whether we should approve the loan or not by default analysis.

I. Data Preprocessing

- Read Data and Delete Loss Data

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
plt.style.use('ggplot')
import seaborn as sns
sns.set_style('whitegrid')
from sklearn.metrics import roc_curve, auc
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

pd.set_option('display.float_format', lambda x: '%.5f' % x)
```

```python
data1 = pd.read_csv('LoanStats_2018Q1.csv' , encoding='latin-1')
data2 = pd.read_csv('LoanStats_2018Q2.csv' , encoding='latin-1')
data3 = pd.read_csv('LoanStats_2018Q3.csv' , encoding='latin-1')
data4 = pd.read_csv('LoanStats_2018Q4.csv' , encoding='latin-1')
loans = pd.concat([data1, data2, data3, data4])
```

```python
thresh_count = len(loans)*0.4
```

```python
loans = loans .dropna(thresh=thresh_count, axis=1 ) # 若某一列數據缺失的數量超過閥值就會被刪除
loans
```

	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	...	pct_tl_nvr_dlq	percent_bc_gt
0	25000	25000	25000.00000	60 months	21.85%	688.35000	D	D5	Asphalt Supervisor	10+ years	...	75.00000	100.00000
1	10000	10000	10000.00000	60 months	12.61%	225.54000	C	C1	Supervisor	4 years	...	91.30000	40.00000
2	11200	11200	11200.00000	60 months	30.79%	367.82000	G	G1	Client services	< 1 year	...	71.40000	0.00000
3	6500	6500	6500.00000	36 months	6.07%	197.95000	A	A2	dental assistant	10+ years	...	93.80000	20.00000
4	6000	6000	6000.00000	36 months	10.41%	194.77000	B	B3	Dental Hygienist	1 year	...	100.00000	50.00000
...	...	...	...	...	...	...	...	...	...	...	...	...	...
128407	23000	23000	23000.00000	36 months	15.02%	797.53000	C	C3	Tax Consultant	10+ years	...	96.40000	14.30000
128408	10000	10000	10000.00000	36 months	15.02%	346.76000	C	C3	security guard	5 years	...	73.30000	40.00000
128409	5000	5000	5000.00000	36 months	13.56%	169.83000	C	C1	Payoff Clerk	10+ years	...	92.90000	50.00000
128410	10000	10000	9750.00000	36 months	11.06%	327.68000	B	B3	NaN	NaN	...	92.00000	0.00000
128411	10000	10000	10000.00000	36 months	16.91%	356.08000	C	C5	Key Accounts Manager	2 years	...	74.20000	0.00000

495242 rows × 102 columns

- Loss Value Preprocessing

```python
# 缺失值處理—分類型變量
objectColumns = loans.select_dtypes(include=["object"]).columns # 篩選數據類型為 object 的數據
loans[objectColumns] = loans[objectColumns].fillna("Unknown") # 以分類 "Unknown" 填充缺失值
```

```python
# 缺失值處理—數值型變量
numColumns = loans.select_dtypes(include=[np.number]).columns
from sklearn.impute import SimpleImputer
imr = SimpleImputer(strategy='mean')
imr = imr.fit(loans[numColumns])
loans[numColumns] = imr.transform(loans[numColumns])
```

- Feature Derivation

```python
# 特徵衍生
loans['installment_feat'] = loans['installment'] / (loans['annual_inc'] / 12)
loans['installment_feat'] = loans['installment_feat'].replace([np.inf], 0)
```

- Data Filtering

```python
# 數據過濾
pred_list = ['term', 'grade', 'emp_length', 'home_ownership', 'verification_status', 'loan_status', 'purpose', 'delinq_2yrs',
'revol_bal', 'total_acc', 'application_type', 'installment_feat']
loans = loans[pred_list]
```

- Data Dummy Code

```python
# 特徵抽象
# 使用 Pandas replace 函數定義新函數
def coding(col, codeDict):
    colCoded = pd.Series(col, copy=True)
    for key, value in codeDict.items():
        colCoded.replace(key, value, inplace=True)
    return colCoded

# 把貸款狀態 LoanStatus 編碼為：違約=1, 正常=0
pd.value_counts(loans["loan_status"])
loans["loan_status"] = coding(loans["loan_status"], {'Current':0,
                                                      'Fully Paid':0,
                                                      'In Grace Period':1,
                                                      'Late (31-120 days)':1,
                                                      'Late (16-30 days)':1,
                                                      'Charged Off':1,
                                                      'Default':1})
```

- Double Check Data

```python
loans.select_dtypes(include=["object"]).describe().T # 再次檢查數據
```

	count	unique	top	freq
term	495242	2	36 months	344671
grade	495242	7	B	141365
emp_length	495242	12	10+ years	160382
home_ownership	495242	4	MORTGAGE	239220
verification_status	495242	3	Not Verified	199934
purpose	495242	13	debt_consolidation	259642
application_type	495242	2	Individual	426257

- Ordered Feature Mapping

```python
# 有序特徵的映射
# 對有序變量 “emp_length”、“grade” 進行轉換
loans["emp_length"] = coding(loans["emp_length"], {"10+ years": 10,
                                                    "9 years": 9,
                                                    "8 years": 8,
                                                    "7 years": 7,
                                                    "6 years": 6,
                                                    "5 years": 5,
                                                    "4 years": 4,
                                                    "3 years": 3,
                                                    "2 years": 2,
                                                    "1 year": 1,
                                                    "< 1 year": 0,
                                                    "n/a": 0,
                                                    "Unknown": 0})
loans["grade"] = coding(loans["grade"], {"A": 1,
                                          "B": 2,
                                          "C": 3,
                                          "D": 4,
                                          "E": 5,
                                          "F": 6,
                                          "G": 7})
```

```
loans
```

	term	grade	emp_length	home_ownership	verification_status	loan_status	purpose	delinq_2yrs	revol_bal	total_acc	application_ty
0	60 months	4	10	MORTGAGE	Source Verified	0	debt_consolidation	1.00000	8657.00000	16.00000	Individual
1	60 months	3	4	MORTGAGE	Source Verified	0	home_improvement	0.00000	10710.00000	23.00000	Individual
2	60 months	7	0	RENT	Not Verified	0	medical	1.00000	1526.00000	14.00000	Joint App
3	36 months	1	10	MORTGAGE	Not Verified	0	debt_consolidation	0.00000	7871.00000	16.00000	Individual
4	36 months	2	1	RENT	Not Verified	0	credit_card	0.00000	5566.00000	12.00000	Individual
...	...	...	...	...	...	...	...	...	...	...	...
128407	36 months	3	10	MORTGAGE	Source Verified	1	debt_consolidation	1.00000	22465.00000	28.00000	Individual
128408	36 months	3	5	MORTGAGE	Not Verified	0	debt_consolidation	3.00000	5634.00000	16.00000	Individual
128409	36 months	3	10	MORTGAGE	Not Verified	0	debt_consolidation	1.00000	2597.00000	15.00000	Individual
128410	36 months	2	0	RENT	Source Verified	0	credit_card	0.00000	6269.00000	25.00000	Individual
128411	36 months	3	2	RENT	Not Verified	0	other	1.00000	1942.00000	31.00000	Individual

495242 rows × 12 columns

II. Exploratory Data Analysis (EDA)

- Describe

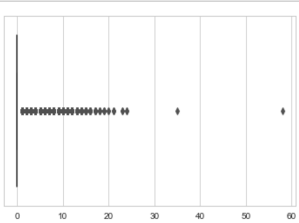
```
# 類別型 column: term, grade, emp_length, home_ownership, verification_status, purpose, application_type
# 數值型 column: delinq_2yrs, revol_bal, total_acc, installment_feat
```

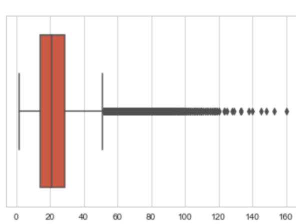
```
loans.describe()
```

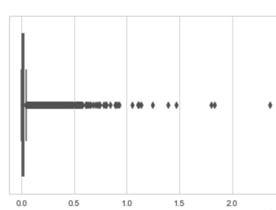
	grade	emp_length	loan_status	delinq_2yrs	revol_bal	total_acc	installment_feat
count	495242.00000	495242.00000	495242.00000	495242.00000	495242.00000	495242.00000	495242.00000
mean	2.40928	5.30466	0.04325	0.22925	16270.82999	22.62415	0.32890
std	1.18331	3.93569	0.20342	0.74367	22832.36428	12.10400	39.92818
min	1.00000	0.00000	0.00000	0.00000	0.00000	2.00000	0.00000
25%	1.00000	2.00000	0.00000	0.00000	5304.00000	14.00000	0.04466
50%	2.00000	5.00000	0.00000	0.00000	10832.00000	21.00000	0.07129
75%	3.00000	10.00000	0.00000	0.00000	19867.00000	29.00000	0.10871
max	7.00000	10.00000	1.00000	58.00000	2358150.00000	160.00000	12053.40000

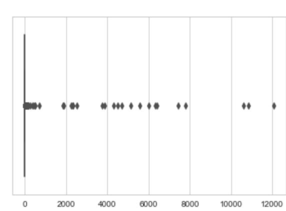
- Numerical Type

```
for col in numberic_col:
    sns.boxplot(loans[col],data=loans)
    plt.show()
```

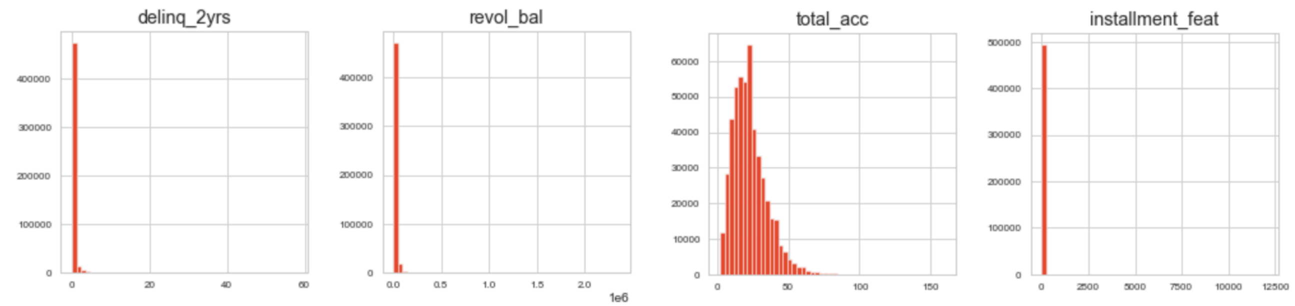






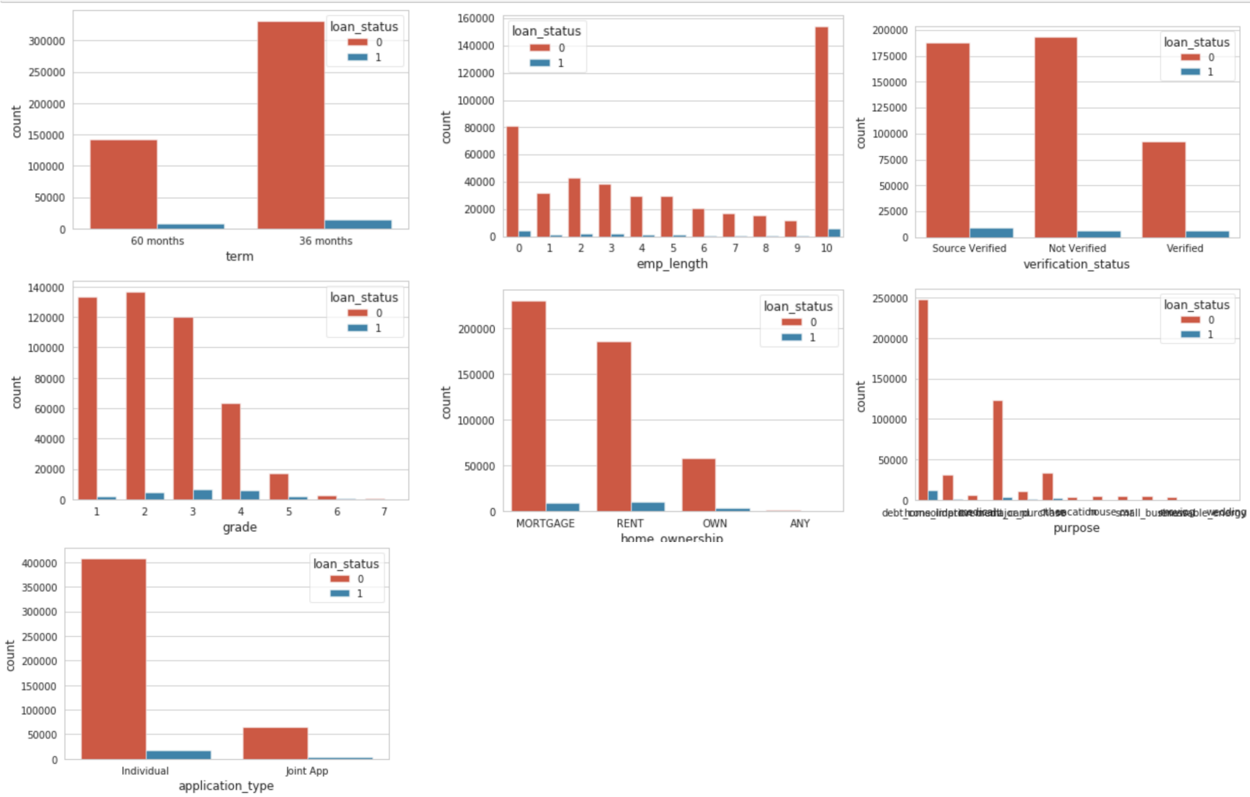



```
loans[numberic_col].hist(figsize=(8, 8), bins=50, xlabelsize=8, ylabelsize=8);
```



- Category Type

```
qua_col = ['term','grade','emp_length','home_ownership','verification_status','purpose','application_type']
numberic_col = ['delinq_2yrs','revol_bal','total_acc','installment_feat']
for col in qua_col :
    sns.countplot(loans[value],hue=loans["loan_status"])
    plt.show()
```




```
for col in qua_col :
    plt.pie(loans[col].value_counts().values.tolist(),labels=loans[col].value_counts().index.tolist())
    plt.title(col)
    plt.show()
```

```
corr = loans.drop(["home_ownership", "verification_status", "application_type","purpose", "term"], axis=1).corr() # We alread
y examined non-number
plt.figure(figsize=(12, 10))

sns.heatmap(corr, cmap='viridis', vmax=1.0, vmin=-1.0, linewidths=0.1,
            annot=True, annot_kws={"size": 8}, square=True);
```

- One-Hot Encoding

```
# one-hot coding
n_columns = ["home_ownership", "verification_status", "application_type","purpose", "term"]
dummy_df = pd.get_dummies(loans[n_columns]) # 用 get_dummies 進行 one-hot 編碼
loans = pd.concat([loans, dummy_df], axis=1) # 當 axis = 1的時候，concat 就是行對齊，然後將不同列名稱的兩張表合併
loans = loans.drop(n_columns, axis=1)  # 清除原來的分類變量
```

```
loans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 495242 entries, 0 to 128411
Data columns (total 31 columns):
 #   Column                              Non-Null Count   Dtype  
---  ------                              --------------   -----  
 0   grade                               495242 non-null  int64  
 1   emp_length                          495242 non-null  int64  
 2   loan_status                         495242 non-null  int64  
 3   delinq_2yrs                         495242 non-null  float64
 4   revol_bal                           495242 non-null  float64
 5   total_acc                           495242 non-null  float64
 6   installment_feat                    495242 non-null  float64
 7   home_ownership_ANY                  495242 non-null  uint8  
 8   home_ownership_MORTGAGE             495242 non-null  uint8  
 9   home_ownership_OWN                  495242 non-null  uint8  
 10  home_ownership_RENT                 495242 non-null  uint8  
 11  verification_status_Not Verified    495242 non-null  uint8  
 12  verification_status_Source Verified 495242 non-null  uint8  
 13  verification_status_Verified        495242 non-null  uint8  
 14  application_type_Individual         495242 non-null  uint8  
 15  application_type_Joint App          495242 non-null  uint8  
 16  purpose_car                         495242 non-null  uint8  
 17  purpose_credit_card                 495242 non-null  uint8  
 18  purpose_debt_consolidation          495242 non-null  uint8  
 19  purpose_home_improvement            495242 non-null  uint8  
 20  purpose_house                       495242 non-null  uint8  
 21  purpose_major_purchase              495242 non-null  uint8  
 22  purpose_medical                     495242 non-null  uint8  
 23  purpose_moving                      495242 non-null  uint8  
 24  purpose_other                       495242 non-null  uint8  
 25  purpose_renewable_energy            495242 non-null  uint8  
 26  purpose_small_business              495242 non-null  uint8  
 27  purpose_vacation                    495242 non-null  uint8  
 28  purpose_wedding                     495242 non-null  uint8  
 29  term_ 36 months                     495242 non-null  uint8  
 30  term_ 60 months                     495242 non-null  uint8  
dtypes: float64(4), int64(3), uint8(24)
memory usage: 51.6 MB
```

- Feature Scaling

```
# 特徵縮放
col = loans.select_dtypes(include=['int64','float64']).columns
col = col.drop('loan_status') # 剔除目標變量
loans_ml_df = loans # 複製數據至變量 loans_ml_df
from sklearn.preprocessing import StandardScaler # 導入模塊
sc = StandardScaler() # 初始化縮放器
loans_ml_df[col] = sc.fit_transform(loans_ml_df[col]) # 對數據進行標準化
loans_ml_df.head() # 查看經標準化後的數據
```

	grade	emp_length	loan_status	delinq_2yrs	revol_bal	total_acc	installment_feat	home_ownership_ANY	home_ownership_MORTGAGE	home_owner
0	1.34429	1.19302	0	1.03642	-0.33347	-0.54727	-0.00505	0	1	0
1	0.49921	-0.33149	0	-0.30827	-0.24355	0.03105	-0.00739	0	1	0
2	3.87956	-1.34783	0	1.03642	-0.64579	-0.71250	-0.00573	0	0	0
3	-1.19097	1.19302	0	-0.30827	-0.36789	-0.54727	-0.00705	0	1	0
4	-0.34588	-1.09375	0	-0.30827	-0.46885	-0.87774	-0.00696	0	0	0

5 rows × 31 columns

- Dealing with Unbalanced Data

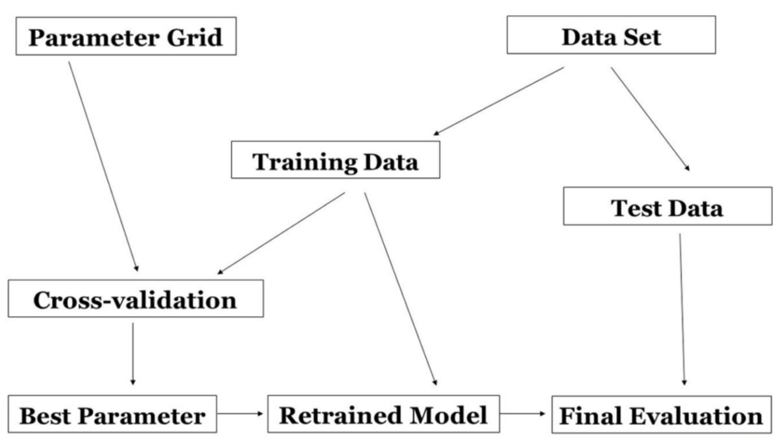
```
# 處理不平衡數據
from imblearn.over_sampling import SMOTE # 導入 SMOTE 算法模塊
sm = SMOTE(random_state=42)     # 處理過採樣的方法
X, y = sm.fit_sample(x_val, y_val)
print('通過 SMOTE 方法平衡正負樣本後')
n_sample = y.shape[0]
n_pos_sample = y[y == 0].shape[0]
n_neg_sample = y[y == 1].shape[0]
print('樣本個數：{}; 正樣本佔{:.2%}; 負樣本佔{:.2%}'.format(n_sample, n_pos_sample / n_sample, n_neg_sample / n_sample))
print('特徵維數：', X.shape[1])
```

```
通過 SMOTE 方法平衡正負樣本後
樣本個數：947646; 正樣本佔50.00%; 負樣本佔50.00%
特徵維數： 30
```

Evaluation Method

- Method

In the previous test, we found that our model training and testing are performed on the same dataset, which will cause following two problems. First of all, it is likely that the learner will learn the training sample "too well", and regard the characteristics of the training sample itself as the general nature of all potential samples. Second, the model is trained and tested on the same data set, so that the sample attributes of the test set are leaked to the model in advance.



The above two problems will cause the generalization ability of the model to decrease. This phenomenon is called "overfitting". Therefore, we need to divide the dataset into the test data and the training data, make the model learn on the training data, and test the discriminative ability of the model on the test data.That’s the reason why we use cross-validation for dividing a data set into a training set and a test set.
In this project, we used cross-validation to divide the data set, dividing the data into three parts, training set, validation set, and test set. Let the model learn on the training set, perform parameter

tuning on the validation set, and finally use the test set data to evaluate the performance of the model. And this make our model better.

```
# cross-validation
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 = 0) # random_state = 0 每次切分的數據都一樣
```

```
import sklearn.metrics as metrics

# Evaluation Function
def Evaluation(y_test, preds):
    print("Confusion Matrix:")
    print(metrics.confusion_matrix(y_test, preds))
    print(metrics.classification_report(y_test, preds))
    print("Area under the ROC curve : %f" % metrics.roc_auc_score(y_test, preds))
```

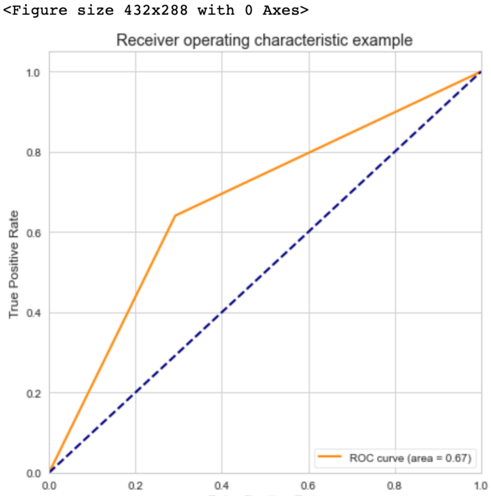
- Linear Regression

```
from sklearn.linear_model import LogisticRegression
clf1 = LogisticRegression() # 構建邏輯回歸分類器
clf1.fit(X_train, y_train)
pred1 = clf1.predict(X_test)
Evaluation(y_test, pred1)
```

```
Confusion Matrix:
[[100846  41629]
 [ 50940  90879]]
              precision    recall  f1-score   support

           0       0.66      0.71      0.69    142475
           1       0.69      0.64      0.66    141819

    accuracy                           0.67    284294
   macro avg       0.68      0.67      0.67    284294
weighted avg       0.68      0.67      0.67    284294

Area under the ROC curve : 0.674313
```

```
# Compute ROC curve and ROC area for each class
fpr,tpr,threshold = roc_curve(y_test, pred1) ###計算真正率和假正率
roc_auc = auc(fpr,tpr) ### 計算auc的值
plt.figure()
lw = 2
plt.figure(figsize=(7,7))
plt.plot(fpr, tpr, color='darkorange',
lw=lw, label='ROC curve (area = %0.2f)' % roc_auc) ### 假正率為橫座標，真正率為縱座標做曲線
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



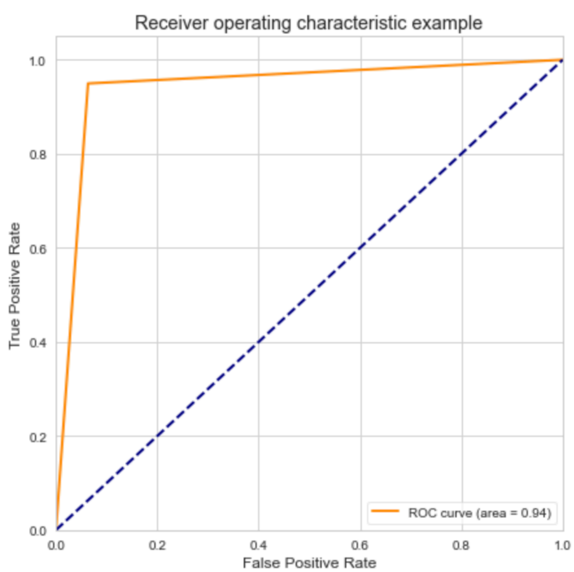
- Random Forest

```
from sklearn.ensemble import RandomForestClassifier
clf2 = RandomForestClassifier() # 構建分類隨機森林分類器
clf2.fit(X_train, y_train)
pred2 = clf2.predict(X_test)
Evaluation(y_test, pred2)
```

```
Confusion Matrix:
[[133450   9025]
 [  7141 134678]]
              precision    recall  f1-score   support

           0       0.95      0.94      0.94    142475
           1       0.94      0.95      0.94    141819

    accuracy                           0.94    284294
   macro avg       0.94      0.94      0.94    284294
weighted avg       0.94      0.94      0.94    284294

Area under the ROC curve : 0.943151
```

```
# Compute ROC curve and ROC area for each class
fpr,tpr,threshold = roc_curve(y_test, pred2) ### 計算真正率和假正率
roc_auc = auc(fpr,tpr) ### 計算auc的值
plt.figure()
lw = 2
plt.figure(figsize=(7,7))
plt.plot(fpr, tpr, color='darkorange',
lw=lw, label='ROC curve (area = %0.2f)' % roc_auc) ### 假正率為橫座標，真正率為縱座標做曲線
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

<Figure size 432x288 with 0 Axes>



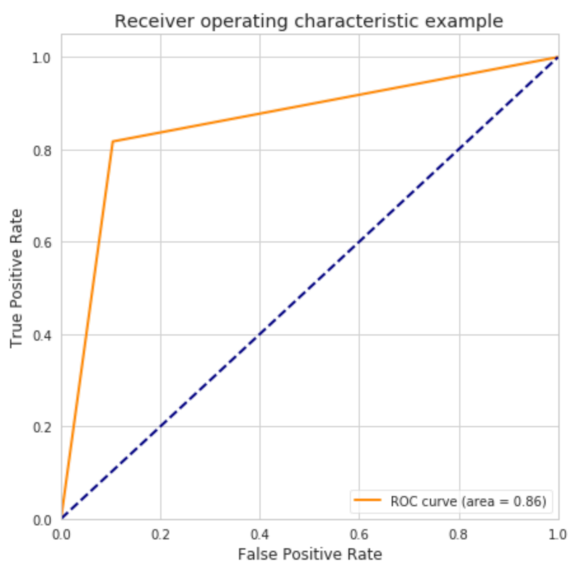
- XGBoost

```
# XGBoost
from sklearn.ensemble import XGBClassifier
XGBoost_model = XGBClassifier(n_estimators = 100, max_features = 100, max_depth = 5, learning_rate = 0.1)
XGBoost_model.fit(X_train, y_train)
pred3 = XGBoost_model.predict(X_test)
Evaluation(y_test, pred3)
```

```
Confusion Matrix:
[[127645  14830]
 [ 25922 115897]]
              precision    recall  f1-score   support

           0       0.83      0.90      0.86    142475
           1       0.89      0.82      0.85    141819

    accuracy                           0.86    284294
   macro avg       0.86      0.86      0.86    284294
weighted avg       0.86      0.86      0.86    284294

Area under the ROC curve : 0.856565
```

```python
# Compute ROC curve and ROC area for each class
fpr,tpr,threshold = roc_curve(y_test, pred3) ### 計算真正率和假正率
roc_auc = auc(fpr,tpr) ### 計算auc的值
plt.figure()
lw = 2
plt.figure(figsize=(7,7))
plt.plot(fpr, tpr, color='darkorange',
lw=lw, label='ROC curve (area = %0.2f)' % roc_auc) ### 假正率為橫座標，真正率為縱座標做曲線
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



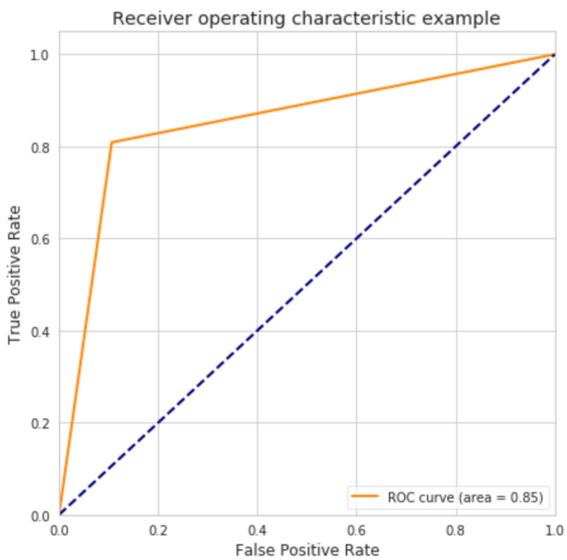
- GBDT

```python
# GBDT
from sklearn.ensemble import GradientBoostingClassifier
GBDT_model = GradientBoostingClassifier(n_estimators = 100, max_features = 100, max_depth = 5, learning_rate = 0.1)
GBDT_model.fit(X_train, y_train)
pred4 = GBDT_model.predict(X_test)
Evaluation(y_test, pred4)
```

```
Confusion Matrix:
[[127327  15148]
 [ 27121 114698]]
              precision    recall  f1-score   support

           0       0.82      0.89      0.86    142475
           1       0.88      0.81      0.84    141819

    accuracy                           0.85    284294
   macro avg       0.85      0.85      0.85    284294
weighted avg       0.85      0.85      0.85    284294

Area under the ROC curve : 0.851221
```

```
# Compute ROC curve and ROC area for each class
fpr,tpr,threshold = roc_curve(y_test, pred4) ### 計算真正率和假正率
roc_auc = auc(fpr,tpr) ### 計算auc的值
plt.figure()
lw = 2
plt.figure(figsize=(7,7))
plt.plot(fpr, tpr, color='darkorange',
lw=lw, label='ROC curve (area = %0.2f)' % roc_auc) ### 假正率為橫座標，真正率為縱座標做曲線
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



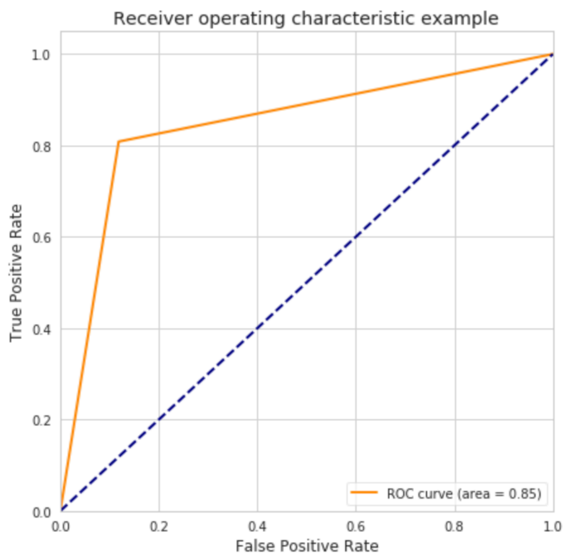
- LightGBM

```
# LightGBM
from sklearn.ensemble import LGBMClassifier
LightGBM_model = LGBMClassifier(n_estimators = 100, num_leaves = 100, max_depth = 5, learning_rate = 0.1)
LightGBM_model.fit(X_train, y_train)
pred5 = LightGBM_model.predict(X_test)
Evaluation(y_test, pred5)
```

```
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set num_leaves OR 2^max_depth > num_leaves. (num_leaves=3
1).
Confusion Matrix:
[[125603  16872]
 [ 27168 114651]]
              precision    recall  f1-score   support

           0       0.82      0.88      0.85    142475
           1       0.87      0.81      0.84    141819

    accuracy                           0.85    284294
   macro avg       0.85      0.85      0.84    284294
weighted avg       0.85      0.85      0.84    284294

Area under the ROC curve : 0.845006
```

```
# Compute ROC curve and ROC area for each class
fpr,tpr,threshold = roc_curve(y_test, pred5) ### 計算真正率和假正率
roc_auc = auc(fpr,tpr) ### 計算auc的值
plt.figure()
lw = 2
plt.figure(figsize=(7,7))
plt.plot(fpr, tpr, color='darkorange',
lw=lw, label='ROC curve (area = %0.2f)' % roc_auc) ### 假正率為橫座標，真正率為縱座標做曲線
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



Analysis Results

- **Revenue**

The revenue of Lending Club is more dependent on the scale of loan transactions. The operating income of Lending Club is mainly loan transaction fees, investment service fees and account management fees. According to the 2018 financial report, loan transaction fees are US$449 million, accounting for 78.08%, and investment service fees are US$87 million, accounting for 15.16% , Lending Club's revenue is dominated by loan transaction fees, and is more dependent on the scale of loan transactions.

- **Internal Risk Control Mechanism**

The mechanism of internal risk control of Lending Club is relatively mature. In the personal loan approval process, the Lending Club risk control mechanism is based on FICO credit score data. After the loan applicant submits an application, the platform will review it according to the standards. The applicant's access conditions are as follows:

FICO credit score is not less than 660 points;

The debt-to-income ratio is less than 40%;

In the credit report, at least two accounts are in normal use;

No more than 5 times of credit inquiry in the last 6 months;

Provide a credit history of at least 36 months.

- **Credit Rating Model**

LendingClub implements a differentiated risk pricing strategy, and its credit rating model is relatively mature. For standard personal loan business, Lending Club comprehensively evaluates the loan applicant’s FICO scores, credit records and credit risk indicator information in the loan application, verifies the applicant’s assets and income, and uses a proprietary credit rating model to risk the applicant Evaluation, combined with the amount and duration of the loan applied for, determines the loan credit rating and loan interest rate. Loan credit rating is divided into seven grades, A-G, and five sub-grades are set up under each grade. LendingClub comprehensively considers market benchmarks and credit risks when setting interest rates, and implements a differentiated risk pricing strategy. The lower the loan credit rating, the higher the loan interest rate. The lower the credit rating of a loan, the higher the loan default rate, and the Lending Club credit rating model is more mature.

Opinion

- **Risk Identification**

From the perspective of risk identification, the risk control model online of Lending Club relies more on quantitative indicators such as credit scores or annual income. For risk assessment, it should also consider the influence of American consumers' concepts of early consumption and overconsumption and seasonal factors. The higher the income, the greater the personal consumption expenditure, and may be more likely to fall into the dilemma of insolvency. Individuals applying for loans are mainly used for debt consolidation and credit card repayment, and loan customers have greater financial risks. In the fourth quarter, consumers' financial pressure on holiday spending has increased the possibility of overdue loans and bad debts.

- **Credit Rating Standard**

From the perspective of credit rating standards, according to the 2018 financial report, Lending Club's loan transaction scale and operating income grew slowly from 2015 to 2018. The platform adjusted credit rating standards and pricing strategies to maintain transaction scale development. Since 2015, the loan overdue rate has exceeded the average level of US bank consumer loans. While maintaining business growth, Lending Club should also implement risk control mechanisms to ensure loan quality, control default risks, and pay attention to operating efficiency.

- **High-Risk Market**

From the perspective of high-risk customers, under normal circumstances, P2P loan customers are mainly high-risk groups who cannot meet the traditional bank credit standards. The return of credit funds depends on the customer's repayment ability and willingness to repay. Lending Club should strengthen the screening and monitoring of customer segments with high default risk based on the customer characteristics of different loan credit ratings, promptly warn of the risk of overdue loans, and actively carry out collection work to reduce the risk of bad debts.