1_Modeling on imbalanced dataset

0.0.1 Overview

Lending Club loan dataset is an imbalanced dataset with good and bad loan ratio around 8:2. The purpose of this task is to distinguish bad loans from good loans. There are several approaches to deal with this imbalanced probelm:

```
1. Change the evaluation metric from accuracy to F1 score, since F1 score is a balanced mesaure
2. Under, over or SMOTE sampling the training dataset to make classes balance, then train the mo
3. Put more weight on the minority class.
```

Since imbalance ratio at 8:2 is not very severe, this notebook is modeled on the original imbalanced dataset and see what best approach it can get. The modeling steps are:

```
1. Check correlation between description features and target feature
2. Select best model from a list of candidates
3. Model parameter tuning
4. Threshold selection
```

After all these steps, the final model is Logistic Regression with L1(Lasso) penalty C=1 and threshold 0.3. The best training performance are: F1: 69.04, Precision: 76.61, Recall: 62.83, AUC: 78.78, Accuracy: 87.84. The testing performance are: F1: 68.43, Precision: 75.75, Recall: 62.39, AUC: 78.46, Accuracy: 87.63. There is no big disparency between training and testing performance, which means overfitting is prohibited.

According to feature importance, people with high last_fico_range_high and annual_inc are less likely to default on loans, applicatnts with debt_settlement_flag Y are more likely to default on loans.

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

def warn(*args, **kwargs): pass
import warnings
warnings.warn = warn

from sklearn import model_selection
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
#from sklearn.svm import SVC
```

```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

from sklearn.metrics import confusion_matrix
```

[2]:
```python
df = pd.read_csv("LendingClub_2011_2014_cleanedData.csv")
df.head()
```

[2]:
```
   loan_amnt  int_rate  installment  emp_length  annual_inc  loan_status  \
0      10400      6.99       321.08           8     58000.0            1
1      15000     12.39       336.64          10     78000.0            0
2       9600     13.66       326.53          10     69000.0            0
3      12800     17.14       319.08          10    125000.0            0
4      21425     15.59       516.36           6     63800.0            0

     dti  delinq_2yrs  fico_range_low  fico_range_high  ...  purpose_moving  \
0  14.92            0             710              714  ...               0
1  12.03            0             750              754  ...               0
2  25.81            0             680              684  ...               0
3   8.31            1             665              669  ...               0
4  18.49            0             685              689  ...               0

   purpose_other  purpose_renewable_energy  purpose_small_business  \
0              0                         0                       0
1              0                         0                       0
2              0                         0                       0
3              0                         0                       0
4              0                         0                       0

   purpose_vacation  purpose_wedding  initial_list_status_f  \
0                 0                0                      0
1                 0                0                      0
2                 0                0                      1
3                 0                0                      0
4                 0                0                      0

   initial_list_status_w  debt_settlement_flag_N  debt_settlement_flag_Y
0                      1                       1                       0
1                      1                       1                       0
2                      0                       1                       0
3                      1                       1                       0
4                      1                       1                       0

[5 rows x 83 columns]
```

0.0.2 1. check correlation between target feature and description features then rank absolute value from high to low

[3]:
```
df[df.columns[:]].corr()['loan_status'][:].abs().nlargest(n=10, keep='first')
```

[3]:
```
loan_status                 1.000000
last_fico_range_high        0.566410
last_fico_range_low         0.494946
debt_settlement_flag_N      0.303142
debt_settlement_flag_Y      0.303142
int_rate                    0.234969
term_ 36 months             0.156282
term_ 60 months             0.156282
fico_range_low              0.110235
fico_range_high             0.110234
Name: loan_status, dtype: float64
```

No feature has high correlation with loan_status

0.0.3 read splitted training and testing set

[4]:
```
X_train = pd.read_csv('x_train.csv')
y_train = pd.read_csv('y_train.csv')
X_test = pd.read_csv('x_test.csv')
y_test = pd.read_csv('y_test.csv')
```

[5]:
```
y_train.value_counts()
```

[5]:
```
loan_status
0              127625
1               27453
dtype: int64
```

[6]:
```
y_test.value_counts()
```

[6]:
```
loan_status
0              63813
1              13726
dtype: int64
```

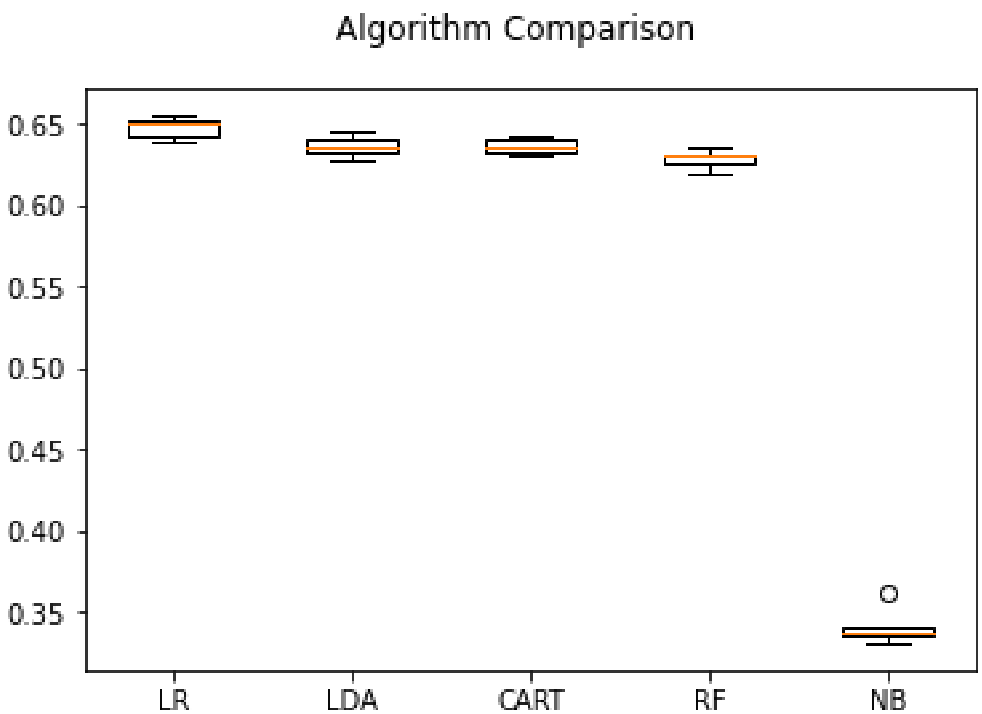
0.0.4 2. Select model with highest F1 score using 5-fold Cross Validation

[7]:
```
seed = 7
# prepare models
models = []
models.append(('LR', LogisticRegression()))
models.append(('LDA', LinearDiscriminantAnalysis()))
```

```python
models.append(('CART', DecisionTreeClassifier(max_depth=10)))
models.append(('RF', RandomForestClassifier(max_depth=10)))#slow
models.append(('NB', GaussianNB()))
#models.append(('SVM', SVC())) slow

# evaluate each model in turn
results = []
names = []
for name, model in models:
    kfold = model_selection.KFold(n_splits=5, random_state=seed)
    cv_results = model_selection.cross_val_score(model, X_train, y_train,␣
↪cv=kfold, scoring='f1')
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
LR: 0.647674 (0.006004)
LDA: 0.635764 (0.006295)
CART: 0.635839 (0.004437)
RF: 0.628152 (0.005667)
NB: 0.341344 (0.010628)
```

[8]:
```python
# boxplot algorithm comparison
fig = plt.figure()
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```



===> Logistic Regression performed better than other models.

check the detailed performance of the logistic regression on trainining dataset

- define a function which could return confusion matrix and other measurements.

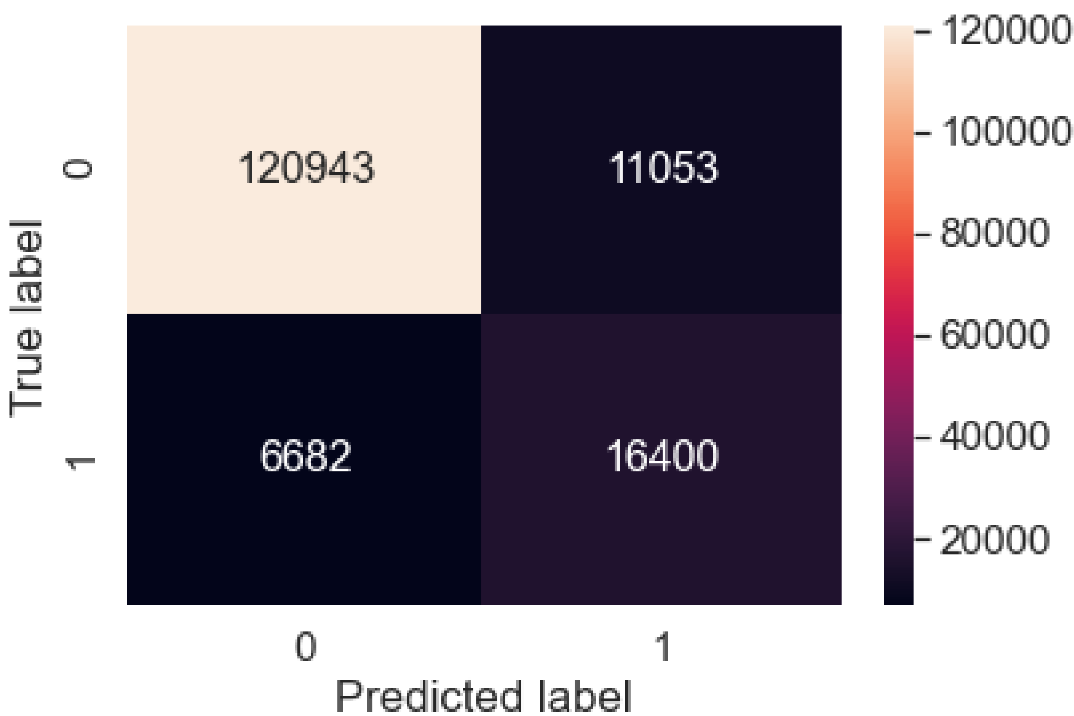
[9]:
```
def plot_confusion_matrix(pred, act, title):
    import seaborn as sns

    cnf_matrix = confusion_matrix(pred, act, labels=[0, 1])
    precision = cnf_matrix[1,1]/(cnf_matrix[0,1]+cnf_matrix[1,1])
    recall = cnf_matrix[1,1]/(cnf_matrix[1,0]+cnf_matrix[1,1])
    f1 = 2*precision*recall/(precision+recall)
    aucRoc = roc_auc_score(pred, act)
    acc = (cnf_matrix[0,0] + cnf_matrix[1,1])/cnf_matrix.sum()
    print('')
    print(title)

    sns.set(font_scale=1.4) # for label size
    sns.heatmap(cnf_matrix, annot=True, annot_kws={"size": 16},fmt='g') # font␣
 ↪size
    #plt.title(title)
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

```
    plt.show()

    print('Mesurements:')
    method_dict = {'F1': '{:.2f}'.format(f1*100),
                   'Precision': '{:.2f}'.format(precision*100),
                   'Recall': '{:.2f}'.format(recall*100),
                   'AUC': '{:.2f}'.format(aucRoc*100),
                   'Accuracy': '{:.2f}'.format(acc*100)
                  }
    return pd.DataFrame(method_dict,index=['values'])
```

[10]:
```
lr = LogisticRegression()
lr.fit(X_train, y_train)
y_pred = lr.predict(X_train)
```

[11]:
```
plot_confusion_matrix(y_pred, y_train, 'Logistic Regression: Train Performance')
```

Logistic Regression: Train Performance



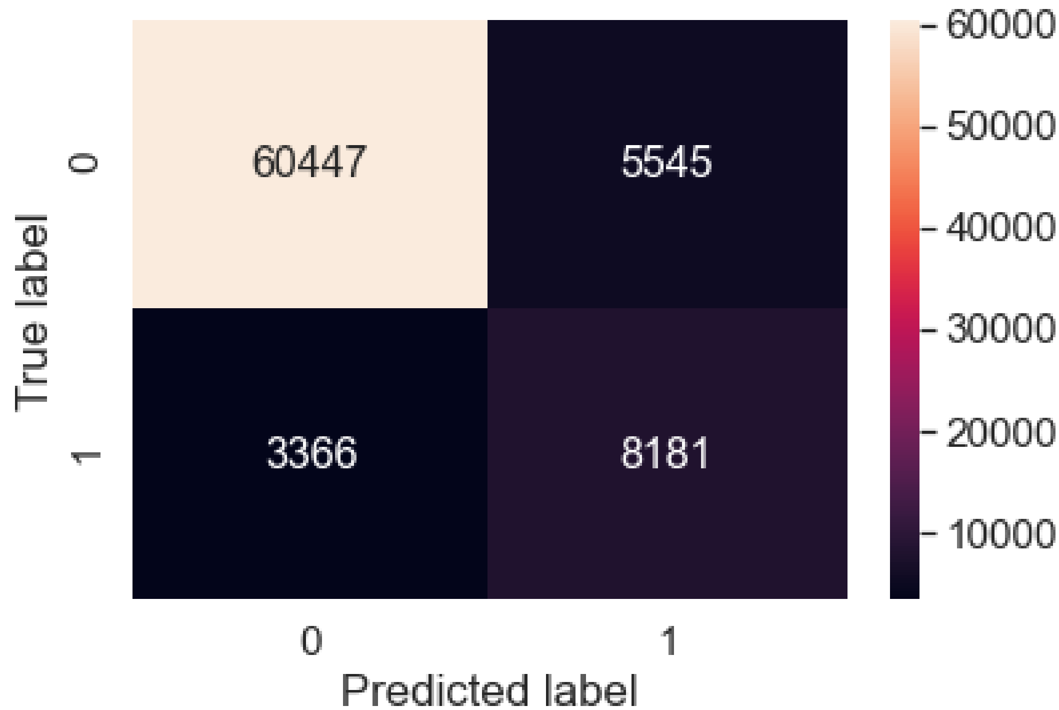
Mesurements:

[11]:

	F1	Precision	Recall	AUC	Accuracy
values	64.91	59.74	71.05	81.34	88.56

[12]:
```
y_test_pred = lr.predict(X_test)

plot_confusion_matrix(y_test_pred, y_test,
                      'Logistic Regression: Test Performance')
```

```
Logistic Regression: Test Performance
```




```
Mesurements:
```

[12]:

	F1	Precision	Recall	AUC	Accuracy
values	64.74	59.60	70.85	81.22	88.51

===> performance on logistic regression:

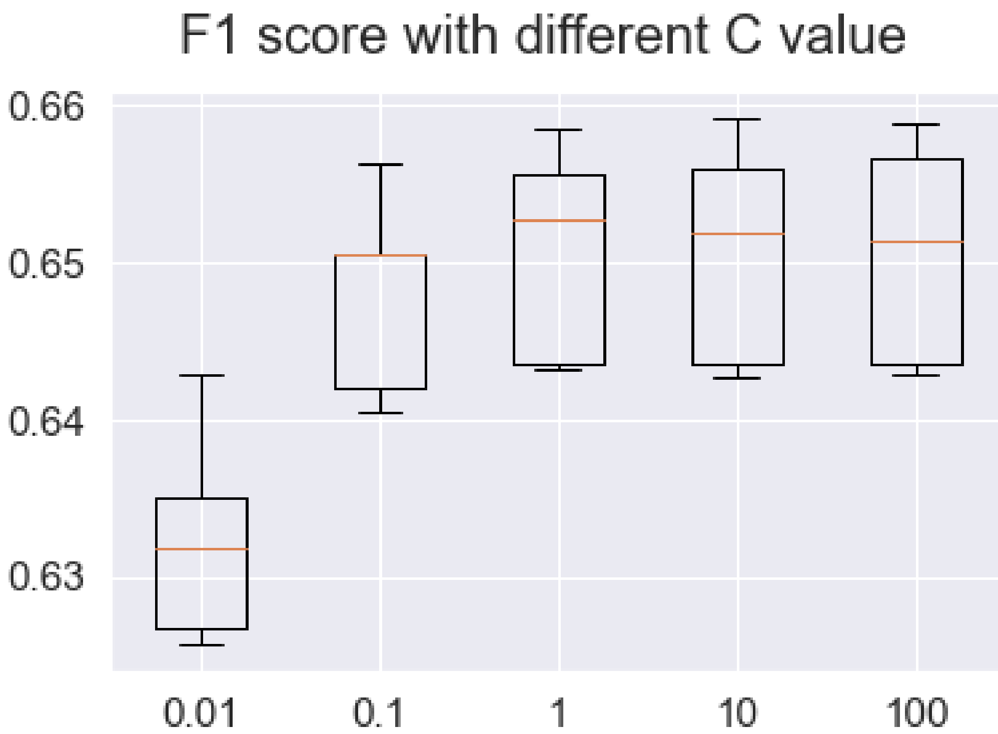
- training F1 score 64.91
- testing F1 score 64.74

0.0.5 2. tune parameter

penalty L1 regularization may not be better than L2 in principle, but in practice one good reason to prefer L1 is that it can save you time and money. L1 regularization typically leaves you with a smaller set of predictors, while L2 might just leave you with smaller coefficients on most if not all of your potential predictors.

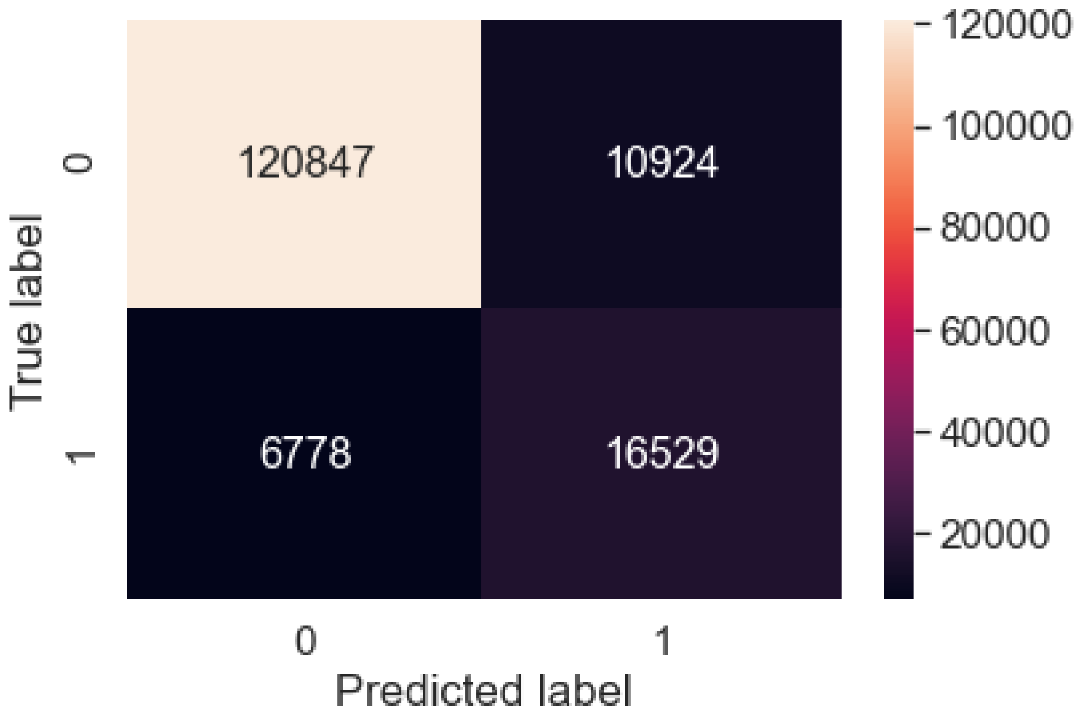
[13]:
```
def c_scores(X_train, y_train):
    #penalty range
    c_param_range = [0.01, 0.1, 1, 10, 100]

    regularization = []
    results = []
    for c_param in c_param_range:

        lr = LogisticRegression(C = c_param, penalty='l1',solver='saga')
        kfold = model_selection.KFold(n_splits=5, random_state=seed)
        cv_results = model_selection.cross_val_score(lr, X_train, y_train,␣
↪cv=kfold, scoring='f1')

        results.append(cv_results)
        regularization.append(c_param)
        print('regularization:', c_param, 'f1: ', cv_results.mean(), 'std: ',␣
↪cv_results.std())

    fig = plt.figure()
    fig.suptitle('F1 score with different C value')
    ax = fig.add_subplot(111)
    plt.boxplot(results)
    ax.set_xticklabels(regularization)
    plt.show()

c_scores(X_train, y_train)
```

```
regularization: 0.01 f1:  0.6324151640158046 std:  0.006268871332884192
regularization: 0.1 f1:  0.6480196747679133 std:  0.005893072488315733
regularization: 1 f1:  0.6507568243991375 std:  0.006305248739651821
regularization: 10 f1:  0.6507088854301633 std:  0.0065946206080626756
regularization: 100 f1:  0.6506745759702948 std:  0.0065273436661144124
```



[14]:
```
lr = LogisticRegression(C = 1, penalty='l1',solver='saga')
lr.fit(X_train, y_train)
y_pred = lr.predict(X_train)
plot_confusion_matrix(y_pred, y_train, 'Logistic Regression(C=1,L1): Train␣
↪Performance')
```

```
Logistic Regression(C=1,L1): Train Performance
```



Mesurements:

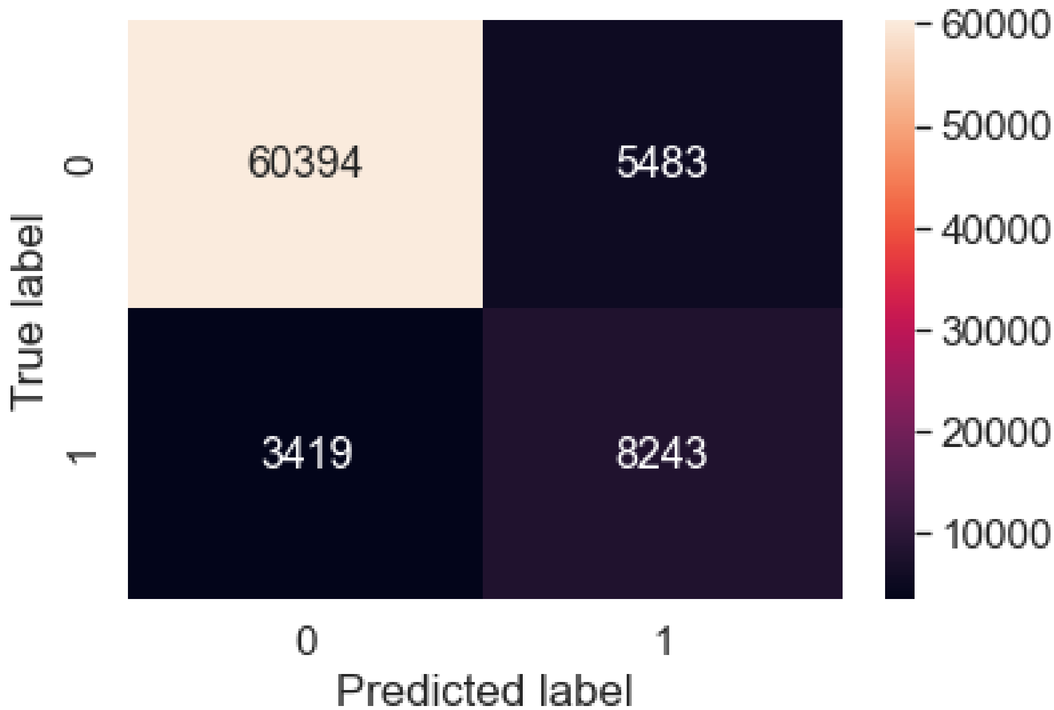
[14]:

	F1	Precision	Recall	AUC	Accuracy
values	65.13	60.21	70.92	81.31	88.59

[15]:

```
y_test_pred = lr.predict(X_test)

plot_confusion_matrix(y_test_pred, y_test,
                      'Logistic Regression(C=1,L1): Test Performance')
```

Logistic Regression(C=1,L1): Test Performance



Mesurements:

[15]:

	F1	Precision	Recall	AUC	Accuracy
values	64.94	60.05	70.68	81.18	88.52

===> after tuning parameter c1:

- training F1 score increased from 64.91 to 65.12
- testing F1 score increased from 64.74 to 64.94

0.0.6 3. threshold

[16]:
```
def best_threshod(y_pred_proba, y_train, threshold_range):
    Precision = []
    Recall = []
    F1 = []
    AUC = []
    Accuracy = []
    for i  in threshold_range:
        y_pred = y_pred_proba[:,1] > i
        cnf_matrix = confusion_matrix(y_pred, y_train)

        precision = cnf_matrix[1,1]/(cnf_matrix[1,0]+cnf_matrix[1,1])
        recall = cnf_matrix[1,1]/(cnf_matrix[0,1]+cnf_matrix[1,1])
```

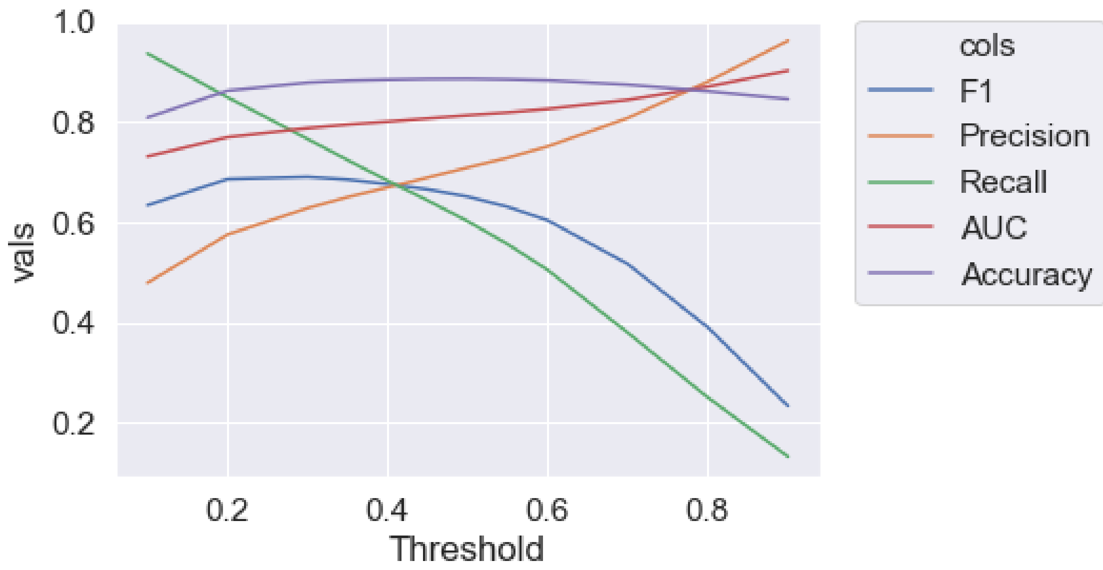
```python
        f1 = 2*precision*recall/(precision+recall)
        aucRoc = roc_auc_score(y_pred, y_train)
        acc = (cnf_matrix[0,0] + cnf_matrix[1,1])/cnf_matrix.sum()

        F1.append(f1)
        Precision.append(precision)
        Recall.append(recall)
        AUC.append(aucRoc)
        Accuracy.append(acc)

    method_dict = {'Threshold':threshold_range,
                   'F1': F1,
                   'Precision': Precision,
                   'Recall': Recall,
                   'AUC': AUC,
                   'Accuracy':Accuracy
                  }
    df = pd.DataFrame(method_dict)
    df2 = df.melt('Threshold', var_name='cols',  value_name='vals')

    sns.lineplot(x="Threshold", y="vals", hue='cols',data=df2)
    plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
    print('Best threshold based on highest F1 score:')
    return df[df.F1 == df.F1.max()]
```

[17]:
```python
threshold_range = [0.1, 0.2, 0.3, 0.35, 0.4, 0.45, 0.5, 0.55, 0.6, 0.7, 0.8, 0.9]
y_pred_proba = lr.predict_proba(X_train)

best_threshod(y_pred_proba, y_train, threshold_range)
```

```
Best threshold based on highest F1 score:
```

[17]:

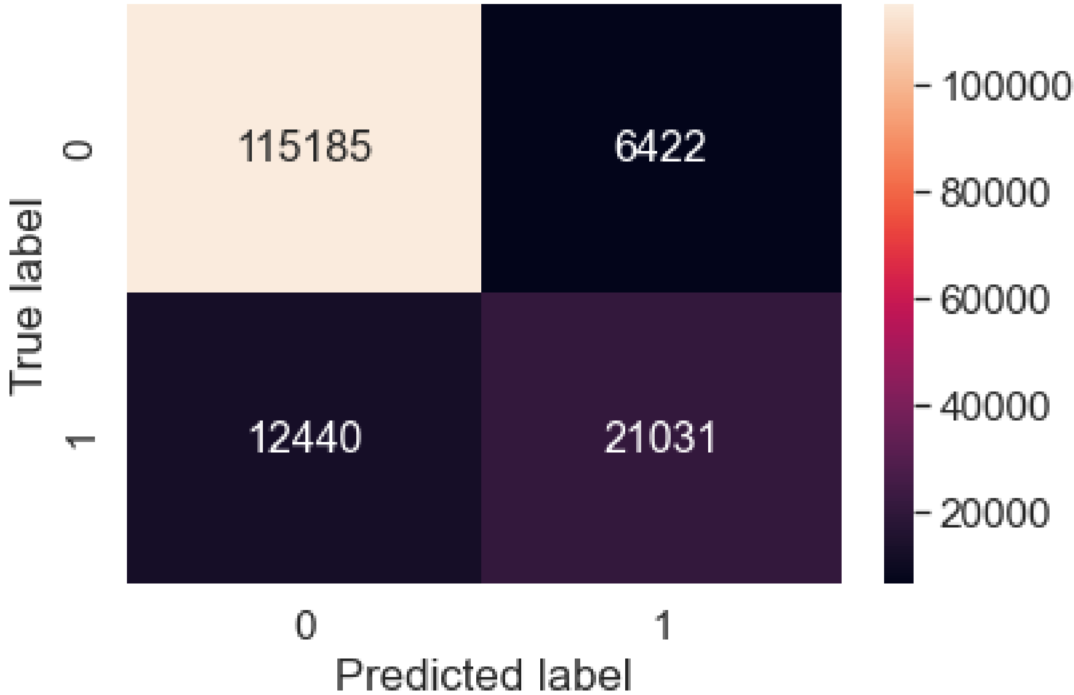
	Threshold	F1	Precision	Recall	AUC	Accuracy
2	0.3	0.690401	0.628335	0.766073	0.787763	0.878371



====> When threshold = 0.3, training model has the highest F1 score

[18]:
```
threshold = 0.3
y_proba = lr.predict_proba(X_train)
y_pred = y_proba[:,1] > threshold

plot_confusion_matrix(y_pred, y_train, 'Logistic Regression(C=1, L1, Threshold=0.
↪3): Train Performance')
```

```
Logistic Regression(C=1, L1, Threshold=0.3): Train Performance
```




```
Mesurements:
```

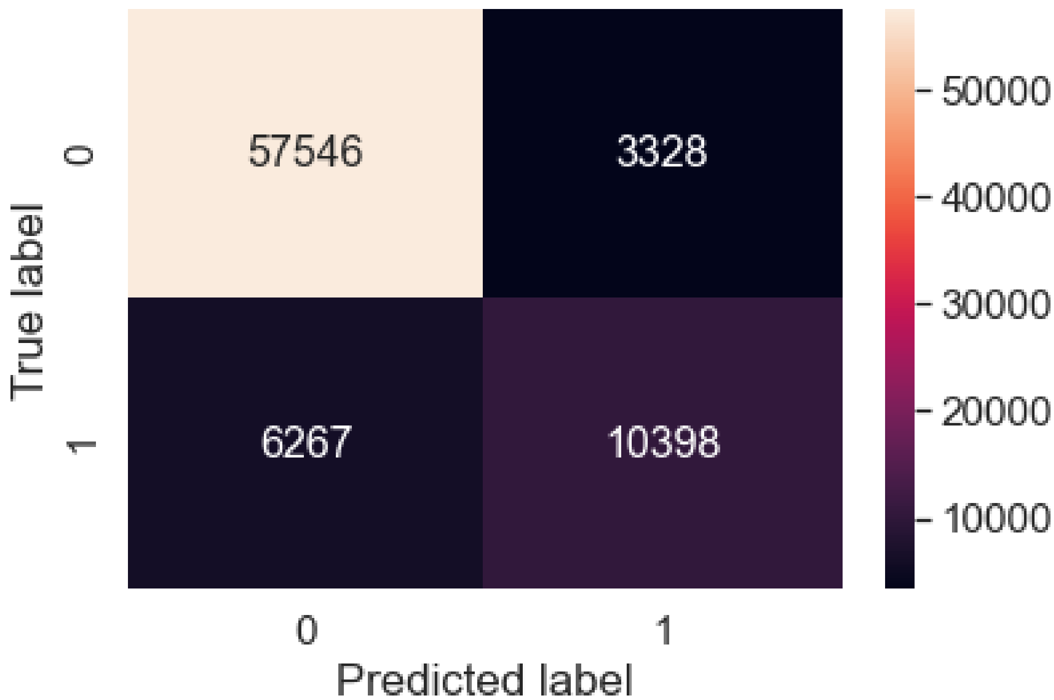
[18]:

	F1	Precision	Recall	AUC	Accuracy
values	69.04	76.61	62.83	78.78	87.84

[19]:

```
y_test_proba = lr.predict_proba(X_test)
y_test_pred = y_test_proba[:,1] > threshold

plot_confusion_matrix(y_test_pred, y_test, 'Logistic Regression(C=1, Threshold=0.
↪3): Test Performance')
```

```
Logistic Regression(C=100, Threshold=0.3): Test Performance
```




```
Mesurements:
```

[19]:

	F1	Precision	Recall	AUC	Accuracy
values	68.43	75.75	62.39	78.46	87.63

===> after adjust threshold:

- training F1 score increased from 65.12 to 69.04
- testing F1 score increased from 64.94 to 68.43

The logistic regression model built on imbalanced dataset has testing performance f1 = 68.43, precision = 75.75 and recall = 62.39 with area under ROC curve 78.46% which is a acceptable outcome.

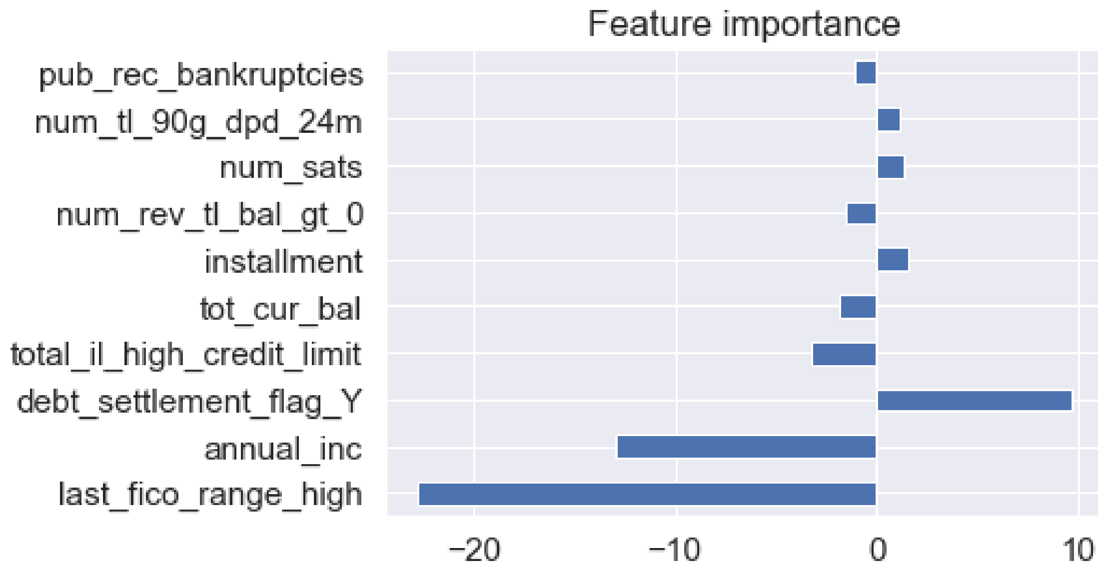
0.0.7 Feature importance

[20]:

```
model = LogisticRegression(C = 1, penalty='l1',solver='saga')
model.fit(X_train, y_train)
feat_importances = pd.Series(model.coef_[0], index=X_train.columns)
important = list(feat_importances.abs().nlargest(10).index)
feat_importances[important].plot(kind='barh', title = 'Feature importance')
```

[20]:

```
<AxesSubplot:title={'center':'Feature importance'}>
```



People with high last_fico_range_high and annual_inc are less likely to default on loans, applicants with debt_settlement_flag Y are more likely to default on loans.

```
[ ]:
```