Credit Risk Modelling - IFRS9 and CECL: Developing Scorecards (Generalized Linear Models)

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[1]:
```
## Uncomment to install it
#! pip uninstall scorecardpy
#or for the latest version via
#! pip install git+git://github.com/shichenxie/scorecardpy.git
```

[128]:
```
# Import libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from datetime import datetime
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
import statsmodels.api as sm
import scorecardpy as sc
#from scorecardpy import woebin, scorecard, scorecard_ply, woebin_ply, woebin_adj
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.model_selection import KFold
```

1 Import data

[259]:
```
# Import data (data will be provided with this code)
df0 = pd.read_csv('data/Chap2/chap2oneypdcsv.csv', header=0,␣
↪sep='"","",|,"|,|",|"""|,""|"",|",""',\
                  engine='python').replace('"', '', regex=True).iloc[:, 1:45]

# Data overview: data content and format
print(df0.info())
```

```
df0.head(5)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25906 entries, 0 to 25905
Data columns (total 44 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   id                          25906 non-null  int64
 1   vintage_year                25906 non-null  int64
 2   monthly_installment         25906 non-null  float64
 3   loan_balance                25906 non-null  float64
 4   bureau_score                25473 non-null  float64
 5   num_bankrupt_iva            25473 non-null  float64
 6   time_since_bankrupt         25473 non-null  float64
 7   num_ccj                     25473 non-null  float64
 8   time_since_ccj              25473 non-null  float64
 9   ccj_amount                  25473 non-null  float64
 10  num_bankrupt                25473 non-null  float64
 11  num_iva                     25473 non-null  float64
 12  min_months_since_bankrupt   25473 non-null  float64
 13  pl_flag                     25906 non-null  int64
 14  region                      25905 non-null  object
 15  ltv                         25906 non-null  float64
 16  arrears_months              25906 non-null  float64
 17  origination_date            25906 non-null  object
 18  maturity_date               25906 non-null  object
 19  repayment_type              25906 non-null  object
 20  arrears_status              25906 non-null  int64
 21  arrears_segment             25906 non-null  int64
 22  mob                         25906 non-null  int64
 23  remaining_mat               25906 non-null  int64
 24  loan_term                   25906 non-null  int64
 25  live_status                 25906 non-null  int64
 26  repaid_status               25906 non-null  int64
 27  month                       25906 non-null  int64
 28  arrears_event               25906 non-null  int64
 29  bankrupt_event              25906 non-null  int64
 30  term_expiry_event           25906 non-null  int64
 31  worst_arrears_status        25906 non-null  int64
 32  max_arrears_12m             25906 non-null  float64
 33  recent_arrears_date         814 non-null    object
 34  months_since_2mia           814 non-null    float64
 35  avg_mia_6m                  25902 non-null  float64
 36  max_arrears_bal_6m          25902 non-null  float64
 37  max_mia_6m                  25902 non-null  float64
 38  avg_bal_6m                  25902 non-null  float64
 39  avg_bureau_score_6m         25515 non-null  float64
 40  cc_util                     25906 non-null  float64
```

```
 41  annual_income                25906 non-null  int64
 42  emp_length                   25906 non-null  int64
 43  months_since_recent_cc_delinq  25906 non-null  object
dtypes: float64(21), int64(17), object(6)
memory usage: 8.7+ MB
None
```

[259]:

```
        id  vintage_year  monthly_installment  loan_balance  bureau_score  \
0  6670001          2005               746.70     131304.44         541.0
1  9131199          2006               887.40     115486.51         441.0
2  4963167          2004              1008.50     128381.73         282.0
3  3918582          2005               458.23      35482.96         461.0
4  5949777          2006               431.20      77086.31         466.0

   num_bankrupt_iva  time_since_bankrupt  num_ccj  time_since_ccj  ccj_amount  \
0               0.0                  0.0      0.0             0.0         0.0
1               0.0                  0.0      0.0             0.0         0.0
2               0.0                  0.0      1.0            36.0       459.0
3               0.0                  0.0      0.0             0.0         0.0
4               0.0                  0.0      0.0             0.0         0.0

   ...  months_since_2mia  avg_mia_6m  max_arrears_bal_6m  max_mia_6m  \
0  ...                NaN         0.0               -42.0         0.0
1  ...                NaN         0.0                 0.0         0.0
2  ...                0.0         0.0              1198.0         2.0
3  ...                NaN         0.0              -114.0         0.0
4  ...                NaN         0.0                 0.0         0.0

  avg_bal_6m  avg_bureau_score_6m  cc_util annual_income emp_length  \
0   132080.0                542.0   0.4578         76749          3
1   116972.0                494.0   0.6299         78451         10
2   128500.0                290.0   0.6331         31038          3
3    36610.0                460.0   0.4990         56663          8
4    77518.0                468.0   0.9568         77014         10

  months_since_recent_cc_delinq
0                            11
1                             7
2                             6
3                             6
4                             3

[5 rows x 44 columns]
```

2 Make EDA on the imported data

[281]:
```
# check/count for missing / NAN data
NAN = (df0.isna().sum()/len(df0)).sort_values(ascending=False)*100
NA[NA>0]
```

[281]:
```
recent_arrears_date          96.857871
months_since_2mia            96.857871
num_ccj                       1.671427
min_months_since_bankrupt     1.671427
num_bankrupt                  1.671427
ccj_amount                    1.671427
time_since_ccj                1.671427
num_iva                       1.671427
time_since_bankrupt           1.671427
num_bankrupt_iva              1.671427
bureau_score                  1.671427
avg_bureau_score_6m           1.509303
avg_bal_6m                    0.015440
max_mia_6m                    0.015440
max_arrears_bal_6m            0.015440
avg_mia_6m                    0.015440
region                        0.003860
dtype: float64
```

Note: 'recent_arrears_date', and 'months_since_2mia' columns each contain about 96.85% of NaN/missing enteries, Thus the two colomns will be dropped. Also, given that we have suficient amount of data, we will drop all rows containing NaNs.

[282]:
```
## drop recent_arrears_date', and 'months_since_2mia' columns columns and store␣
↪in new dataframe
df = df0.drop(['recent_arrears_date', 'months_since_2mia'], axis=1)

# drop NaNs and duplicates
df.dropna(inplace=True)

# Date format for relevant date type columns: "origination_date", "maturity_date"
df[["origination_date", "maturity_date"]] = \
                        df[["origination_date", "maturity_date"]].apply(pd.
↪to_datetime)

# change dtype for columns
df[["months_since_recent_cc_delinq"]] = df[["months_since_recent_cc_delinq"]].
↪astype('int')
```

[283]:
```
# Have a look at unique values from object type columns
for col in df.select_dtypes(include=['object']):
```

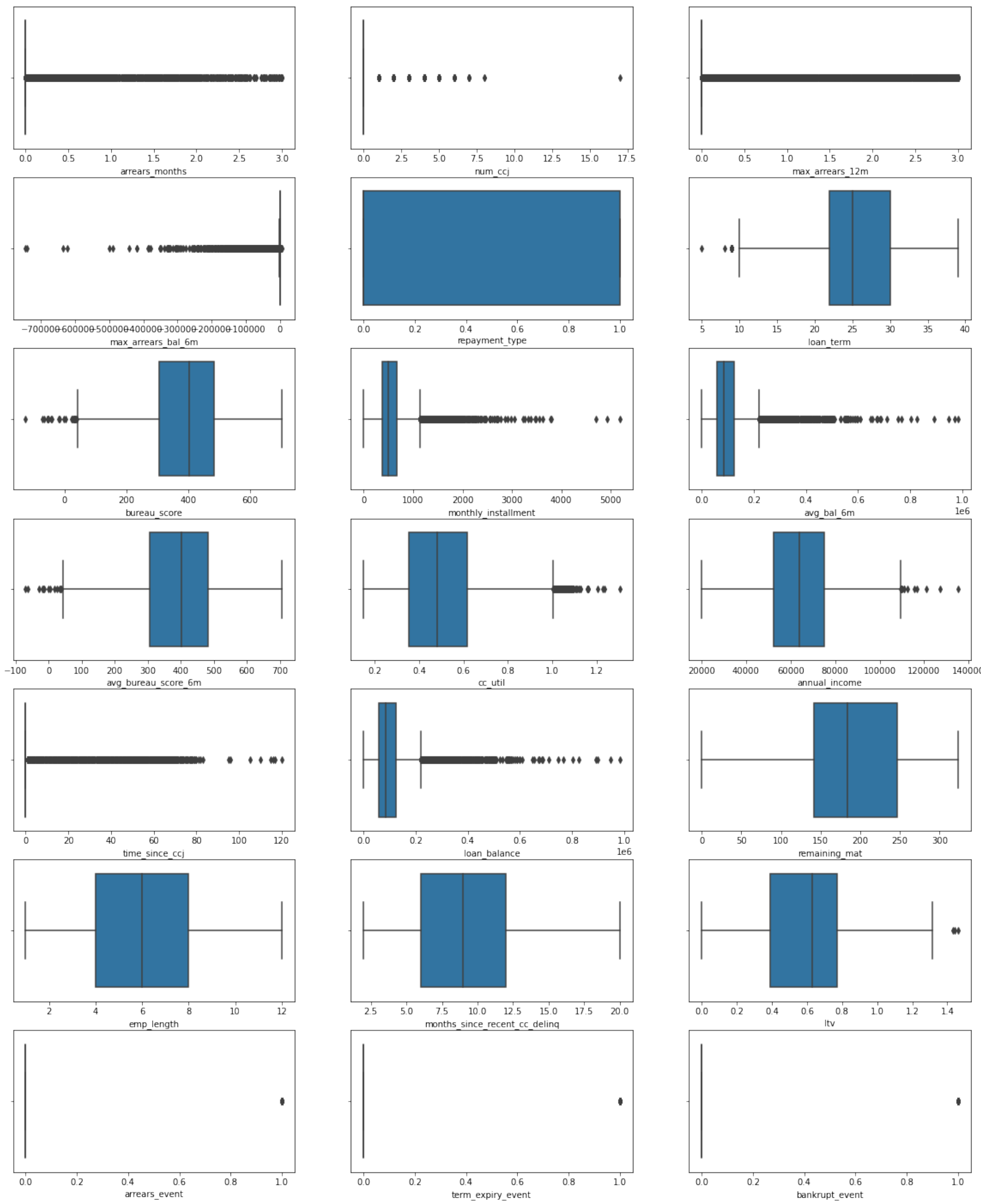
```
    print(col, ":" , df[col].unique())
```

```
region : ['r_a' 'r_b' 'r_c' 'r_d' 'r_e' 'r_f' 'r_h' 'r_i' 'r_g' 'r_l' 'r_m']
repayment_type : ['Non-IO' 'IO']
```

[284]:
```
# For later purpose, we replace 'Non-IO' by 0, and 'IO'by 1 in the␣
↪'repayment_type' column
df = df.drop_duplicates().replace({'Non-IO': 0, 'IO':1})
df.head(5)
```

[284]:
```
        id  vintage_year  monthly_installment  loan_balance  bureau_score  \
0  6670001          2005               746.70     131304.44         541.0
1  9131199          2006               887.40     115486.51         441.0
2  4963167          2004              1008.50     128381.73         282.0
3  3918582          2005               458.23      35482.96         461.0
4  5949777          2006               431.20      77086.31         466.0

   num_bankrupt_iva  time_since_bankrupt  num_ccj  time_since_ccj  ccj_amount  \
0               0.0                  0.0      0.0             0.0         0.0
1               0.0                  0.0      0.0             0.0         0.0
2               0.0                  0.0      1.0            36.0       459.0
3               0.0                  0.0      0.0             0.0         0.0
4               0.0                  0.0      0.0             0.0         0.0

   ...  max_arrears_12m  avg_mia_6m  max_arrears_bal_6m  max_mia_6m  \
0  ...          0.00000         0.0               -42.0         0.0
1  ...          0.00000         0.0                 0.0         0.0
2  ...          2.18823         0.0              1198.0         2.0
3  ...          0.00000         0.0              -114.0         0.0
4  ...          0.00000         0.0                 0.0         0.0

  avg_bal_6m  avg_bureau_score_6m  cc_util annual_income emp_length  \
0   132080.0                542.0   0.4578         76749          3
1   116972.0                494.0   0.6299         78451         10
2   128500.0                290.0   0.6331         31038          3
3    36610.0                460.0   0.4990         56663          8
4    77518.0                468.0   0.9568         77014         10

   months_since_recent_cc_delinq
0                             11
1                              7
2                              6
3                              6
4                              3

[5 rows x 42 columns]
```

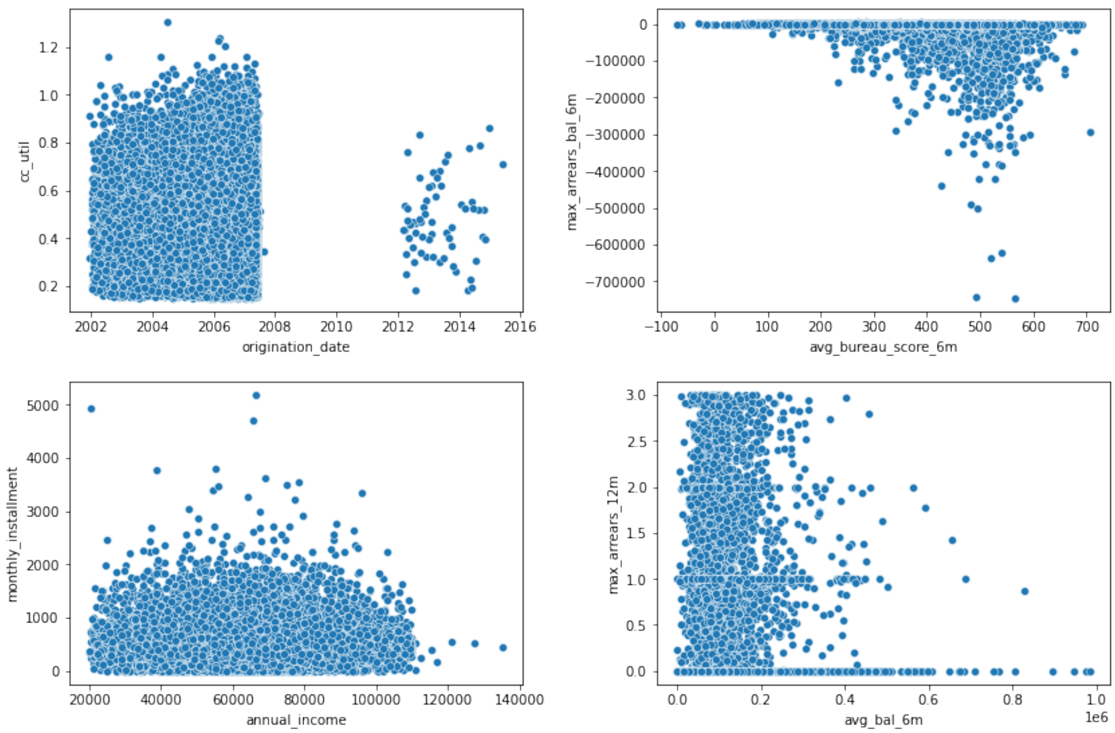
[285]:
```
# Plots: search for potential outliers
# In this work, we will make our analysis besed on the following features␣
↪(columns)
colssel = ['arrears_months', 'num_ccj', 'max_arrears_12m', 'max_arrears_bal_6m',␣
↪'repayment_type', 'loan_term',
       'bureau_score', 'monthly_installment', 'avg_bal_6m',␣
↪'avg_bureau_score_6m', 'cc_util', 'annual_income',
       'time_since_ccj', 'loan_balance', 'remaining_mat', 'emp_length',␣
↪'months_since_recent_cc_delinq','ltv',
       'arrears_event', 'term_expiry_event', 'bankrupt_event']

# Visualizing data
fig, ax = plt.subplots(int(len(colssel)/3), 3, figsize=(20, 25))
key = 0
ix = 0
for val in colssel:
    if (key/3 == int(key/3)):
        ix = 0

    # plot
    sns.boxplot(x=df[val], ax= ax[int(key/3), ix])
    ix += 1
    key += 1
```



[286]:

```
fig, ax = plt.subplots(2, 2, figsize=(12,8))
ypd = df[df["origination_date"] <= '2018-12-31']
sns.scatterplot(data=ypd, x ="origination_date", y ='cc_util', ax=ax[0,0])
sns.scatterplot(data=ypd, x="avg_bureau_score_6m", y='max_arrears_bal_6m', ax=ax[0,1])
sns.scatterplot(data=ypd, x="annual_income", y='monthly_installment', ax=ax[1,0])
```

```
sns.scatterplot(data=ypd, x="avg_bal_6m", y='max_arrears_12m', ax=ax[1,1])
plt.tight_layout(pad=2)
plt.show()
```



Note: After a close look, it is worth remarking that there is less significant data availabe from, roughly, the year 2008, representing only about 0.25% of the total data. Thus, one would be reasonable to consider only the data before 2008, precisely before 2007-08-17.

[287]:
```
### Remove outliers
df2 = df.loc[(df["origination_date"] <= '2017-08-17')].copy()

# Round arrears count fields
df2.loc[:,'max_arrears_12m'] = df2['max_arrears_12m'].round(4)
df2.loc[:,'arrears_months'] = df2['arrears_months'].round(4)

# Select columns of interest
colssel = ['arrears_months', 'num_ccj', 'max_arrears_12m', 'max_arrears_bal_6m',␣
 ↪'repayment_type', 'loan_term',
       'bureau_score', 'monthly_installment', 'avg_bal_6m',␣
 ↪'avg_bureau_score_6m', 'cc_util', 'annual_income',
       'time_since_ccj', 'loan_balance', 'remaining_mat', 'emp_length',␣
 ↪'months_since_recent_cc_delinq','ltv',
       'arrears_event', 'term_expiry_event', 'bankrupt_event']
```

```python
oneypd = df2[colssel].copy()
print(oneypd.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25465 entries, 0 to 25905
Data columns (total 21 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   arrears_months                  25465 non-null  float64
 1   num_ccj                         25465 non-null  float64
 2   max_arrears_12m                 25465 non-null  float64
 3   max_arrears_bal_6m              25465 non-null  float64
 4   repayment_type                  25465 non-null  int64  
 5   loan_term                       25465 non-null  int64  
 6   bureau_score                    25465 non-null  float64
 7   monthly_installment             25465 non-null  float64
 8   avg_bal_6m                      25465 non-null  float64
 9   avg_bureau_score_6m             25465 non-null  float64
 10  cc_util                         25465 non-null  float64
 11  annual_income                   25465 non-null  int64  
 12  time_since_ccj                  25465 non-null  float64
 13  loan_balance                    25465 non-null  float64
 14  remaining_mat                   25465 non-null  int64  
 15  emp_length                      25465 non-null  int64  
 16  months_since_recent_cc_delinq   25465 non-null  int32  
 17  ltv                             25465 non-null  float64
 18  arrears_event                   25465 non-null  int64  
 19  term_expiry_event               25465 non-null  int64  
 20  bankrupt_event                  25465 non-null  int64  
dtypes: float64(12), int32(1), int64(8)
memory usage: 4.2 MB
None
```

3 Default flag definition

This step allows to define criteria or conditions for default. From a modelling perspective, a default flag is defined as binary variable. It conventionally assumes the value 0 if no default occurs, and 1 in the case of default. Following Basel II principles "A default is considered to have occurred when: the banking institution considers that an obligor is unlikely to repay in full its credit obligations to the banking group, without recourse by the banking institution to actions such as realising security; or the obligor has breached its contractual repayment schedule and is past due for more than 90 days on any material credit obligation to the banking group". From an IFRS9 perspective, it does not directly define default, but requires entities to align with internal credit risk management. A rebuttable presumption holds: default does not occur later than a financial asset is 90 days past due.

In the following, the default flag relies on: arrears, bankruptcy and term expiry. Default is caused when arrears exceed 3 months (that is, 3 months in arrears (MIA) or 90 days past due). Also, a default flag is triggered when bankruptcy takes place. Moreover, term expiry indicates that a facility passed its original maturity with a positive residual debt.

[288]:
```
# Default flag definition
oneypd.loc[:, 'default_event'] = oneypd.apply(lambda row: 1 if␣
↪row['arrears_event'] == 1 \
                                               or row['term_expiry_event'] == 1 \
                                               or row['bankrupt_event'] == 1 else␣
↪0, axis=1)

# Database split in train and test samples
# Recode default event variables for more convenient use: 0-default,␣
↪1-non-default
oneypd.loc[:, 'default_flag'] = oneypd['default_event'].apply(lambda x: 0 if x␣
↪== 1 else 1)
```

4 Splitting data into train and test sets

[289]:
```
## Splitting data into train and test sets
#train, test = train_test_split(oneypd, test_size=0.3, random_state=42)

# Perform a stratified sampling: 70% train and 30% test
train, test = train_test_split(oneypd, test_size=0.3,␣
↪stratify=oneypd['default_event'], random_state=2122)
```

5 Univariate analysis: Information Value (IV) assessment

[303]:
```
# Binning and assignment of Weight of Evidence (WOE) values

woe_vars_train = pd.DataFrame()
woe_vars_test = pd.DataFrame()

# Bureau score
woe_vars_train['woe_bureau_score'] = pd.cut(train['bureau_score'],
                                    bins=[-np.inf, 308, 404, 483, np.inf],
                                    labels=[-0.7994, -0.0545, 0.7722, 1.0375],
                                    right=False, include_lowest=True).replace(np.
↪nan, -0.0910)

woe_vars_test['woe_bureau_score'] = pd.cut(test['bureau_score'],
                                   bins=[float('-inf'), 308, 404, 483,␣
↪float('inf')],
                                   labels=[-0.7994, -0.0545, 0.7722, 1.0375],
```

```
                                        right=False, include_lowest=True).replace(np.
↪nan, -0.0910)

# CC utilization
woe_vars_train['woe_cc_util'] = pd.cut(train['cc_util'],
                                    bins=[float('-inf'), 0.55, 0.70, 0.85,␣
↪float('inf')],
                                    labels=[1.8323, -0.4867, -1.1623, -2.3562],
                                    right=False, include_lowest=True).replace(np.nan,␣
↪0)

woe_vars_test['woe_cc_util'] = pd.cut(test['cc_util'],
                                   bins=[float('-inf'), 0.55, 0.70, 0.85,␣
↪float('inf')],
                                   labels=[1.8323, -0.4867, -1.1623, -2.3562],
                                   right=False, include_lowest=True).replace(np.nan,␣
↪0)

# Number of CCJ events
woe_vars_train['woe_num_ccj'] = pd.cut(train['num_ccj'],
                                    bins=[float('-inf'), 0, 1, float('inf')],
                                    labels=[0.1877, -0.9166, -1.1322],
                                    right=False, include_lowest=True).replace(np.nan,␣
↪-0.0910)

woe_vars_test['woe_num_ccj'] = pd.cut(test['num_ccj'],
                                   bins=[float('-inf'), 0, 1, float('inf')],
                                   labels=[0.1877, -0.9166, -1.1322],
                                   right=False, include_lowest=True).replace(np.nan,␣
↪-0.0910)

# Maximum arrears in previous 12 months
woe_vars_train['woe_max_arrears_12m'] = pd.cut(train['max_arrears_12m'],
                                            bins=[float('-inf'), 0, 1, 1.4,␣
↪float('inf')],
                                            labels=[0.7027, -0.8291, -1.1908, -2.
↪2223],
                                            right=False, include_lowest=True).
↪replace(np.nan, 0)

woe_vars_test['woe_max_arrears_12m'] = pd.cut(test['max_arrears_12m'],
                                           bins=[float('-inf'), 0, 1, 1.4,␣
↪float('inf')],
                                           labels=[0.7027, -0.8291, -1.1908, -2.2223],
                                           right=False, include_lowest=True).
↪replace(np.nan, 0)
```

```python
# Maximum arrears balance in previous 6 months
woe_vars_train['woe_max_arrears_bal_6m'] = pd.cut(train['max_arrears_bal_6m'],
                                           bins=[float('-inf'), 0, 300, 600, 900,␣
 ↪float('inf')],
                                           labels=[0.5771, -0.7818, -1.2958, -1.
 ↪5753, -2.2110],
                                           right=False, include_lowest=True).
 ↪replace(np.nan, 0)

woe_vars_test['woe_max_arrears_bal_6m'] = pd.cut(test['max_arrears_bal_6m'],
                                          bins=[float('-inf'), 0, 300, 600, 900,␣
 ↪float('inf')],
                                          labels=[0.5771, -0.7818, -1.2958, -1.
 ↪5753, -2.2110],
                                          right=False, include_lowest=True).
 ↪replace(np.nan, 0)

# Employment length (years)
woe_vars_train['woe_emp_length'] = pd.cut(train['emp_length'],
                                  bins=[float('-inf'), 2, 4, 7, float('inf')],
                                  labels=[-0.7514, -0.3695, 0.1783, 0.5827],
                                  right=False, include_lowest=True).replace(np.
 ↪nan, 0)

woe_vars_test['woe_emp_length'] = pd.cut(test['emp_length'],
                                 bins=[float('-inf'), 2, 4, 7, float('inf')],
                                 labels=[-0.7514, -0.3695, 0.1783, 0.5827],
                                 right=False, include_lowest=True).replace(np.
 ↪nan, 0)

# Months since recent CC delinquency
woe_vars_train['woe_months_since_recent_cc_delinq'] = pd.
 ↪cut(train['months_since_recent_cc_delinq'],
                                                      bins=[float('-inf'), 6, 11,␣
 ↪float('inf')],
                                                      labels=[-0.4176, -0.1942, 1.
 ↪3166],
                                                      right=False,␣
 ↪include_lowest=True).replace(np.nan, 0)

woe_vars_test['woe_months_since_recent_cc_delinq'] = pd.
 ↪cut(test['months_since_recent_cc_delinq'],
                                                     bins=[float('-inf'), 6, 11,␣
 ↪float('inf')],
```

```
                                                    labels=[-0.4176, -0.1942, 1.
↪3166],
                                                    right=False,␣
↪include_lowest=True).replace(np.nan, 0)

# Annual income
woe_vars_train['woe_annual_income'] = pd.cut(train['annual_income'],
                                     bins=[float('-inf'), 35064, 41999, 50111,␣
↪65050, float('inf')],
                                     labels=[-1.8243, -0.8272, -0.3294, 0.2379,␣
↪0.6234],
                                     right=False, include_lowest=True).
↪replace(np.nan, 0)

woe_vars_test['woe_annual_income'] = pd.cut(test['annual_income'],
                                    bins=[float('-inf'), 35064, 41999, 50111,␣
↪65050, float('inf')],
                                    labels=[-1.8243, -0.8272, -0.3294, 0.2379, 0.
↪6234],
                                    right=False, include_lowest=True).replace(np.
↪nan, 0)
#woe_vars_train
```

[303]:

```
       woe_bureau_score woe_cc_util woe_num_ccj woe_max_arrears_12m  \
2876             1.0375      1.8323     -0.9166             -0.8291
25771            0.7722     -0.4867     -0.9166             -0.8291
6507            -0.7994     -2.3562     -0.9166             -0.8291
4274             1.0375      1.8323     -0.9166             -0.8291
16262           -0.0545     -0.4867     -0.9166             -0.8291
...                 ...         ...         ...                 ...
24601            0.7722     -0.4867     -0.9166             -0.8291
21580            0.7722      1.8323     -0.9166             -0.8291
2613            -0.0545      1.8323     -0.9166             -0.8291
6053             1.0375      1.8323     -0.9166             -0.8291
4019            -0.7994      1.8323     -1.1322             -0.8291

       woe_max_arrears_bal_6m woe_emp_length woe_months_since_recent_cc_delinq  \
2876                  -0.7818         0.1783                            -0.1942
25771                 -0.7818         0.5827                            -0.1942
6507                   0.5771         0.5827                            -0.4176
4274                   0.5771         0.1783                             1.3166
16262                  0.5771         0.1783                            -0.4176
...                       ...            ...                                ...
24601                 -0.7818         0.1783                            -0.1942
21580                  0.5771         0.1783                             1.3166
2613                  -0.7818         0.1783                            -0.1942
```

```
6053                    0.5771          0.5827                              1.3166
4019                    0.5771          0.1783                              1.3166

      woe_annual_income
2876               0.2379
25771              0.6234
6507               0.2379
4274               0.6234
16262              0.2379
...                   ...
24601              0.6234
21580              0.6234
2613               0.6234
6053               0.6234
4019               0.2379

[17825 rows x 8 columns]
```

[304]:
```python
woe_vars_train = woe_vars_train.astype(float)
woe_vars_test = woe_vars_test.astype(float)
woe_vars_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7640 entries, 21948 to 19744
Data columns (total 8 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
 0   woe_bureau_score                   7640 non-null   float64
 1   woe_cc_util                        7640 non-null   float64
 2   woe_num_ccj                        7640 non-null   float64
 3   woe_max_arrears_12m                7640 non-null   float64
 4   woe_max_arrears_bal_6m             7640 non-null   float64
 5   woe_emp_length                     7640 non-null   float64
 6   woe_months_since_recent_cc_delinq  7640 non-null   float64
 7   woe_annual_income                  7640 non-null   float64
dtypes: float64(8)
memory usage: 537.2 KB
```

[305]:
```python
# Combine all training and test data
woe_train_data = pd.concat([train, woe_vars_train], axis=1)
woe_test_data = pd.concat([test, woe_vars_test], axis=1)
```

[306]:
```python
# Compute Information Value (IV) from scorecardpy

# Select interested columns
woecolsiv = ['arrears_months', 'num_ccj', 'max_arrears_12m',␣
 ↪'max_arrears_bal_6m',
             'loan_term', 'bureau_score', 'monthly_installment', 'avg_bal_6m',
```

```
              'avg_bureau_score_6m', 'annual_income', 'time_since_ccj', 'cc_util',
              'loan_balance', 'ltv', 'remaining_mat',␣
 ↪'emp_length','repayment_type',
              'months_since_recent_cc_delinq', 'default_flag']

bins = sc.woebin(woe_train_data[woecolsiv], \
                 y="default_flag", positive="default_flag|1")
var_IV = pd.concat(bins).drop_duplicates(subset='variable').
 ↪reset_index(drop=True)
IV = var_IV.sort_values(by='total_iv', ascending=False)[['variable', 'total_iv']]
IV
```

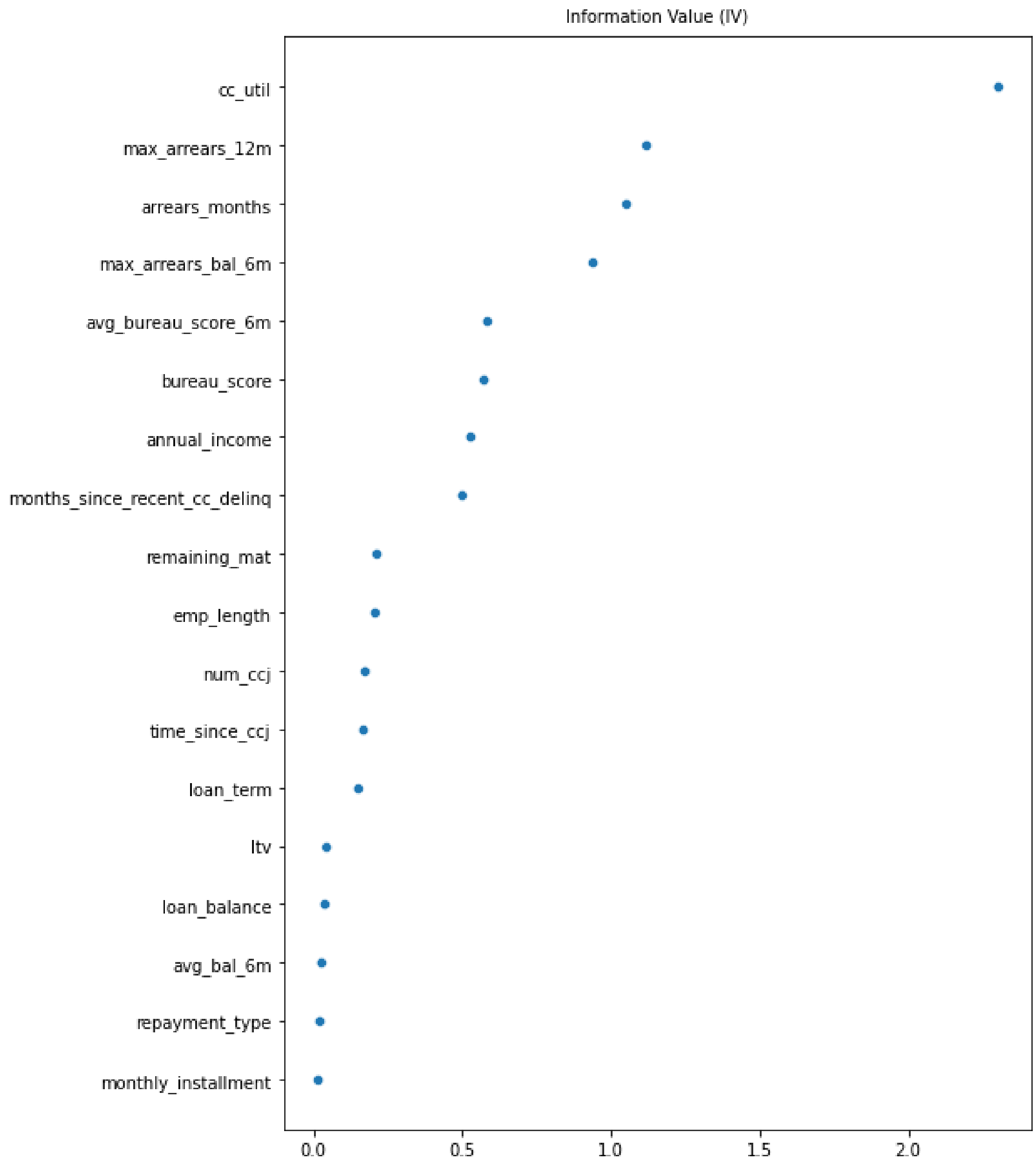
```
[INFO] creating woe binning ...
Binning on 17825 rows and 19 columns in 00:00:36
```

[306]:

	variable	total_iv
12	cc_util	2.299992
4	max_arrears_12m	1.118560
15	arrears_months	1.047456
9	max_arrears_bal_6m	0.939263
2	avg_bureau_score_6m	0.580160
1	bureau_score	0.569292
7	annual_income	0.524548
11	months_since_recent_cc_delinq	0.497799
0	remaining_mat	0.210437
10	emp_length	0.205538
5	num_ccj	0.171339
16	time_since_ccj	0.165837
8	loan_term	0.146300
17	ltv	0.042551
6	loan_balance	0.033045
3	avg_bal_6m	0.022092
13	repayment_type	0.019044
14	monthly_installment	0.012765

[294]:

```
# Plot IV summary table
fig, ax = plt.subplots(figsize=(8,12))
#sns.scatterplot(data=iv_analysis, y="variable", x="info_value")
sns.scatterplot(data=IV, y="variable", x="total_iv")
plt.xlabel("Information Value (IV)", labelpad=10)
ax.xaxis.set_label_position('top')
plt.ylabel("")
plt.show()
```



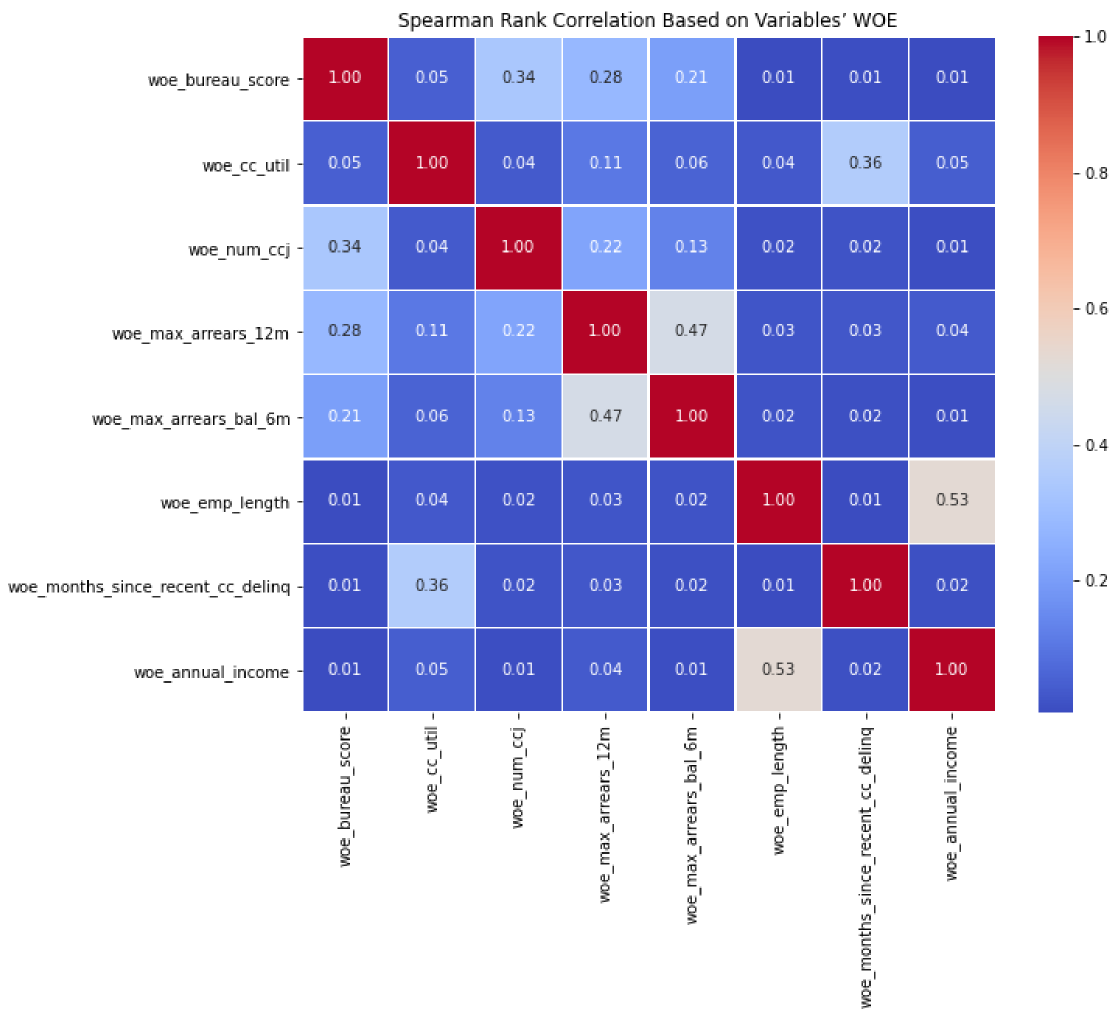
Note According to this Figure showing the Information value (IV), a part from ‘cc_util’, a set of 7 variables shows a strong power in predicting default (IV > 0.5). Other 6 variables have a medium IV, and 5 variables show weak discriminatory power (IV < 0.1). A business check highlights that some variables encompass similar information. In particular ‘arrears_months’ shares a similar content with ‘max_arrears_12m’ (that is, maximum number months in arrears during the last 12 months). Likewise, ‘avg_bureau_score_6m’ (that is, average bureau score over the previous 6-month period) is pretty close to ‘bureau_score’. For this reason they are not considered in the next step of the process. As part of an expert judgement evaluation, ‘emp_length’ (that is, the length of employment), ‘num_ccj’ (number of County Court Judgements), and 'months_since_recent_cc_delinq' (number of months since the most recent delinquent status) are chosen among the variables with medium IV. All these variables constitute the long list to examine through a multivariate assessment

[295]:
```
### Calculate weight of evidence (WOE) for target columns
```

6 Multivariate analysis

Spearman rank correlation based on variables' weight of evidence (WOE)

[296]:
```
# Compute Spearman rank correlation based on variables' weight of evidence (WOE)
# based on Table 2.2 binning scheme
woe_vars = woe_vars_train.filter(like="woe")
woe_corr = woe_vars.corr(method='spearman')

# Graphical inspection
plt.figure(figsize=(10, 8))
sns.heatmap(woe_corr, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Spearman Rank Correlation Based on Variables' WOE')
plt.show()
```



Stepwise regression

[297]:
```
# Stepwise regression
# Discard highly correlated variable

# Select the concerned features (as noted above)
colswoe = ['woe_bureau_score', 'woe_cc_util', 'woe_max_arrears_12m', \
           'woe_months_since_recent_cc_delinq', 'woe_annual_income']
woe_vars_clean = woe_vars[colswoe]


# Stepwise model fitting
# Full data/featurea
logit_full = sm.GLM(train['default_event'], sm.add_constant(woe_vars),
                    family=sm.families.Binomial()).fit()
```

```
# Selected data/featurea
logit_stepwise = sm.GLM(train['default_event'], sm.add_constant(woe_vars_clean),
                        family=sm.families.Binomial()).fit()

#print(logit_full.summary())
print(logit_stepwise.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:          default_event   No. Observations:                17825
Model:                            GLM   Df Residuals:                    17819
Model Family:                Binomial   Df Model:                            5
Link Function:                  logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -2298.7
Date:                Thu, 04 Apr 2024   Deviance:                       4597.4
Time:                        00:35:40   Pearson chi2:                 1.71e+04
No. Iterations:                     8
Covariance Type:            nonrobust
================================================================================
=====================
                                       coef    std err          z      P>|z|
[0.025      0.975]
--------------------------------------------------------------------------------
---------------------
const                               -4.5605      0.099    -45.952      0.000
-4.755      -4.366
woe_bureau_score                    -0.6443      0.060    -10.801      0.000
-0.761      -0.527
woe_cc_util                         -0.9138      0.034    -27.173      0.000
-0.980      -0.848
woe_max_arrears_12m                 -1.6231      0.076    -21.434      0.000
-1.772      -1.475
woe_months_since_recent_cc_delinq   -0.2213      0.067     -3.280      0.001
-0.354      -0.089
woe_annual_income                   -0.9613      0.050    -19.319      0.000
-1.059      -0.864
================================================================================
=====================
```

7 Calibration

[298]:
```
# CALIBRATION
# Define a scaling function
def scaled_score(logit, odds, offset=500, pdo=20):
    '''
    scores scaling function
    '''
```

```
    b = pdo / np.log(2)
    a = offset - b * np.log(odds)

    return np.round(a + b * np.log((1 - logit) / logit))

# Score the entire dataset
# Use fitted model to score both test and train datasets
predict_logit_test = logit_stepwise.predict(sm.
 ↪add_constant(woe_test_data[woe_vars_clean.columns]), transform=False)
predict_logit_train = logit_stepwise.predict(sm.
 ↪add_constant(woe_train_data[woe_vars_clean.columns]), transform=False)

# Merge predictions with train/test data
woe_test_data.loc[:,'predict_logit'] = predict_logit_test
woe_train_data.loc[:,'predict_logit'] = predict_logit_train
woe_train_data.loc[:,'sample'] = 'train'
woe_test_data.loc[:,'sample'] = 'test'
data_whole = pd.concat([woe_train_data, woe_test_data])

# Define scoring parameters in line with objectives
data_whole.loc[:,'score'] = scaled_score(data_whole['predict_logit'], 72, 660,␣
 ↪40)
#data_whole.head(5)
data_whole[['score']]
```

[298]:

```
       score
2876   745.0
25771  634.0
6507   453.0
4274   785.0
16262  579.0
...      ...
8155   612.0
24624  489.0
11482  640.0
4161   565.0
19744  745.0

[25465 rows x 1 columns]
```

[299]:

```
# Upload data
data_score = data_whole.copy()  # Assuming data_whole is already defined

# Fit logistic regression
X = data_score[['score']]
y = data_score['default_event']
pd_model = sm.GLM(y, sm.add_constant(X), family=sm.families.Binomial()).fit()
```

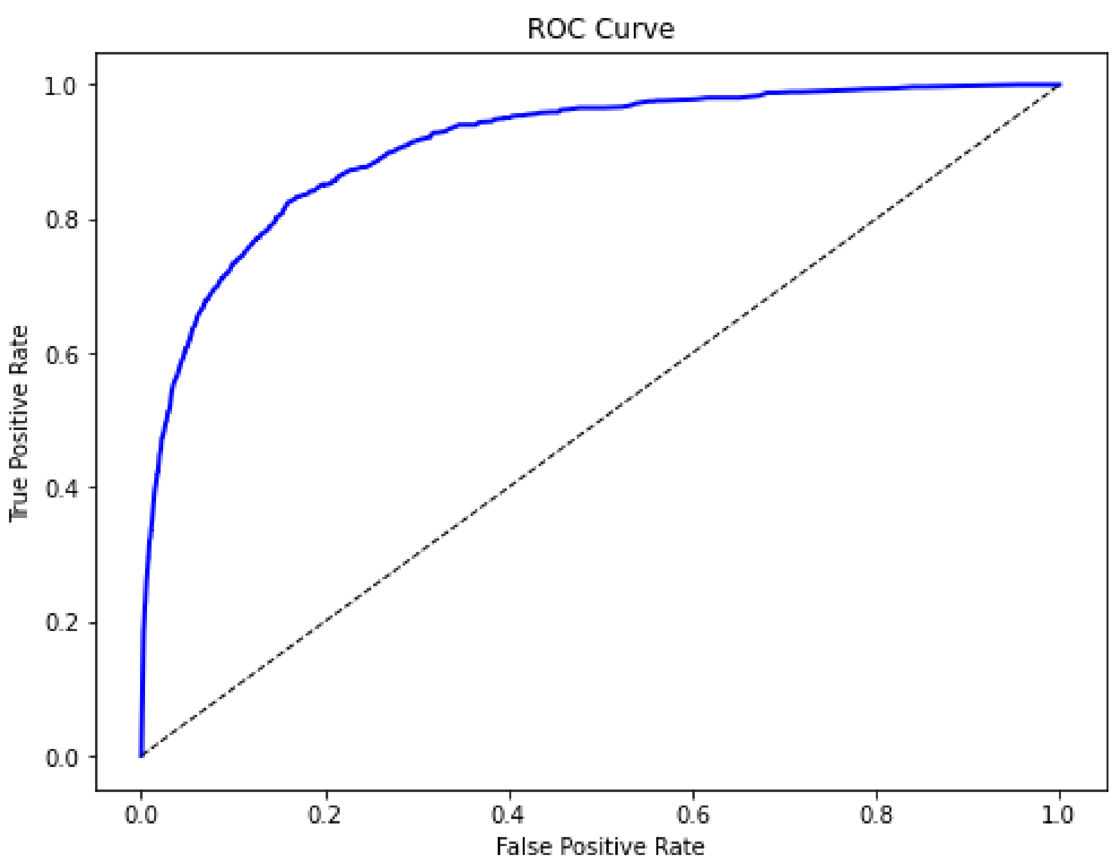
```python
# Print summary
print(pd_model.summary())

# Use model coefficients to obtain PDs
data_score['pd'] = pd_model.predict(sm.add_constant(X))
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:          default_event   No. Observations:                25465
Model:                            GLM   Df Residuals:                    25463
Model Family:                Binomial   Df Model:                            1
Link Function:                  logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -3256.6
Date:                Thu, 04 Apr 2024   Deviance:                       6513.2
Time:                        00:35:41   Pearson chi2:                 2.36e+04
No. Iterations:                     8
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          7.3442      0.194     37.841      0.000       6.964       7.725
score         -0.0177      0.000    -48.366      0.000      -0.018      -0.017
==============================================================================
```

[300]:
```python
def gini_coefficient(y_true, y_pred):
    '''
    This fucntion returns the Gini coefficient
    '''
    # Sort actual and predicted values by predicted values
    sorted_indices = np.argsort(y_pred)
    y_true_sorted = y_true.iloc[sorted_indices]
    n = len(y_true)

    # Compute the Gini coefficient
    cum_true = np.cumsum(y_true_sorted)
    sum_true = np.sum(y_true_sorted)
    gini_sum = np.sum((cum_true / sum_true) * (1 - cum_true / sum_true))

    return 1 - 2 * gini_sum / n


# Gini index
gini_train = gini_coefficient(woe_train_data['predict_logit'],␣
 ↪woe_train_data['default_event'])
print('Training Gini coefficient = {}'.format(gini_train))
# 0.8335868
```

```
# ROC curve
fpr, tpr, thresholds = roc_curve(woe_train_data['default_event'],␣
 ↪woe_train_data['predict_logit'])
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2)
plt.plot([0, 1], [0, 1], '--', color='black', lw=1.)
plt.title('ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```

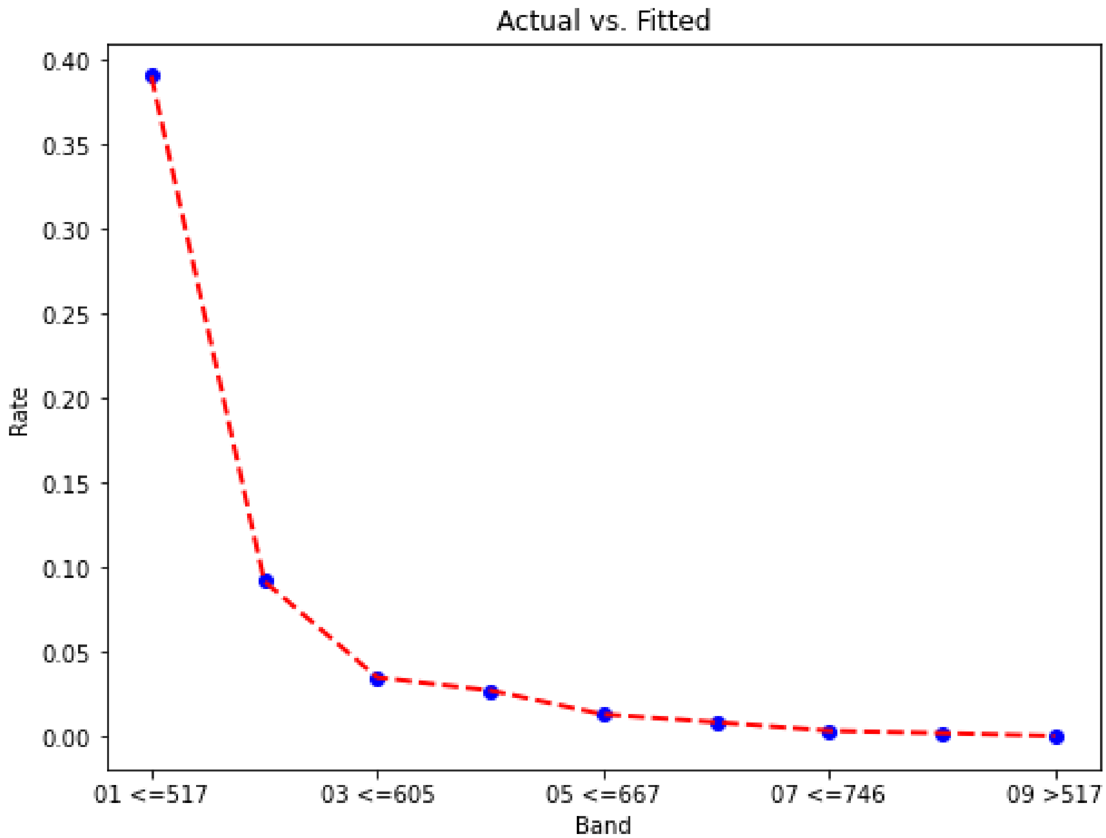
```
Training Gini coefficient = 0.6381317315510084
```



Note: The Gini coefficient is a measure of the inequality of a distribution, and it's often used in the context of binary classification models to measure their predictive power. In this case, a training Gini coefficient of 0.638 suggests that the model has a relatively high discriminatory power in separating the positive and negative classes in the training dataset.

A Gini coefficient closer to 1 indicates better discrimination, meaning the model is better at distinguishing between the positive and negative classes. In our case, a value of 0.638 suggests that the model is reasonably effective at this task. However, it could be essential to also evaluate the model on unseen data (e.g., a validation or test set) to ensure that it generalizes well beyond the training data.

[301]:
```
# COMPARISON OF ACTUAL VERSUS FITTED PDS (BY SCORE BAND)

# Create score bands
cuts = [-np.inf, 517, 576, 605, 632, 667, 716, 746, 773, np.inf]
labels = ['01 <=517', '02 <=576', '03 <=605', '04 <=632', '05 <=667',\
          '06 <=716', '07 <=746', '09 <=773', '09 >517']

# Bin the 'score' variable based on the specified cuts
data_score['score_woe'] = pd.cut(data_score['score'], bins=cuts, labels=labels)

# Group by bands, and compare actual against fitted PDs
# Compute mean values
data_pd = data_score.groupby('score_woe').agg(mean_dr=('default_event', 'mean'),␣
 ↪mean_pd=('pd', 'mean')).round(4).reset_index()

plt.figure(figsize=(8, 6))
plt.plot(data_pd['score_woe'], data_pd['mean_dr'], 'o', color='blue', lw=2)
plt.plot(data_pd['score_woe'], data_pd['mean_dr'], '--', color='red', lw=2)
plt.xticks(['01 <=517',  '03 <=605', '05 <=667',\
            '07 <=746', '09 >517'])
plt.title('Actual vs. Fitted')
plt.xlabel('Band')
plt.ylabel('Rate')
plt.show()

# Compute rmse
rmse = np.sqrt(((data_pd['mean_dr'] - data_pd['mean_pd'])**2).mean())
print('rmse = {}'.format(rmse))
# 0.002732317
```




```
rmse = 0.0039574121735183355
```

Note The RMSE (Root Mean Square Error) is a measure of the differences between values predicted by a model and the actual observed values. In the context of model evaluation, a lower RMSE indicates better accuracy of the model's predictions.

In this case, an RMSE of approximately 0.00396 suggests that the model's predictions are, on average, around 0.00396 units away from the actual values. This indicates that the model's predictions are quite close to the actual values, indicating good predictive performance.

[302]:
```
# Prepare the cross-validation dataset
data_subset = data_whole[['default_event', 'woe_bureau_score',␣
↪'woe_annual_income', \
                           'woe_max_arrears_12m',␣
↪'woe_months_since_recent_cc_delinq', \
                           'woe_cc_util']].copy()

# Perform the cross-validation loop
# Initialise loop arguments and vectors
m = 20  # number of folds
kf = KFold(n_splits=m)
```

```
auc_vector = np.zeros(m)
gini_vector = np.zeros(m)

# Run the loop
j = 0
for train_index, test_index in kf.split(data_subset):
    train_set, test_set = data_subset.iloc[train_index], data_subset.
 ↪iloc[test_index]

    # Model Fitting
    X_train = train_set[['woe_bureau_score', 'woe_annual_income',␣
 ↪'woe_max_arrears_12m', \
                         'woe_months_since_recent_cc_delinq', 'woe_cc_util']]
    y_train = train_set['default_event']

    # Fit model with GLM
    model = sm.GLM(y_train, sm.add_constant(X_train), family=sm.families.
 ↪Binomial()).fit()

    # Predict results
    X_test = test_set[['woe_bureau_score', 'woe_annual_income',␣
 ↪'woe_max_arrears_12m',\
                       'woe_months_since_recent_cc_delinq', 'woe_cc_util']]
    predict_cv = model.predict(sm.add_constant(X_test))

    # Calculate performance metrics for each fold/run
    auc_vector[j] = roc_auc_score(test_set['default_event'], predict_cv)
    gini_vector[j] = 2 * auc_vector[j] - 1

    j += 1

# Print performance metrics
print("Mean AUC = ", np.mean(auc_vector))
print("Mean Gini = ", np.mean(gini_vector))
```

```
Mean AUC =  0.9124702260162412
Mean Gini =  0.824940452032482
```

Note After performing the cross-validation loop:

- The mean AUC of approximately 0.912 indicates that, on average, the model has very good discriminatory power across different cross-validation folds. An AUC close to 1 suggests that the model is highly effective at distinguishing between the positive and negative classes.
- The mean Gini coefficient of approximately 0.825 suggests that the model's discriminatory power is also quite high. The Gini coefficient is often considered a normalized version of the AUC, with values ranging from 0 to 1, where higher values indicate better discrimination.

Overall, these results indicate that the model performs very well in terms of discrimination in the cross-validation process. However, keep in mind that it's important to validate the model's performance on unseen data to ensure that it generalizes well beyond the training dataset.

[258]:
```
# Plot / visualize AUC and Gini distributions
#fig, ax = plt.subplots(1,2, figsize=(18, 5))
#ax[0].hist(auc_vector, bins=7, color='blue', edgecolor='black')
#ax[0].set_xlabel('AUC distribution: {} folds'.format(m))
#ax[0].set_ylabel('Frequency')
#ax[1].hist(gini_vector, bins=7, color='purple', edgecolor='black')
#ax[1].set_xlabel('Gini distribution: {} folds'.format(m))
#ax[1].set_ylabel('Frequency')
#plt.show()
```