Examining Predictions for Credit Card Defaults_EmmaSun

December 7, 2023

1 1.read in dataset

[1]:
```
import pandas as pd
import numpy as np

df = pd.read_csv('/Users/emmasun/Desktop/final/data/American Express credit␣
 ↪card default dataset.csv')

df.head(10)
```

[1]:
```
  customer_id             name  age gender owns_car owns_house  no_of_children  \
0  CST_115179         ita Bose   46      F        N          Y             0.0
1  CST_121920  Alper Jonathan   29      M        N          Y             0.0
2  CST_109330     Umesh Desai   37      M        N          Y             0.0
3  CST_128288             Rie   39      F        N          Y             0.0
4  CST_151355          McCool   46      M        Y          Y             0.0
5  CST_123268     Sarah Marsh   46      F        Y          N             0.0
6  CST_127502           Mason   38      M        N          Y             1.0
7  CST_151722            Saba   46      F        Y          Y             1.0
8  CST_133768        Ashutosh   40      F      NaN          Y             0.0
9  CST_111670  David Milliken   39      F        Y          Y             2.0

   net_yearly_income  no_of_days_employed        occupation_type  \
0          107934.04                612.0                Unknown
1          109862.62               2771.0               Laborers
2          230153.17                204.0               Laborers
3          122325.82              11941.0             Core staff
4          387286.00               1459.0             Core staff
5          252765.91               2898.0            Accountants
6          262389.20               5541.0  High skill tech staff
7          241211.39               1448.0             Core staff
8          210091.43              11551.0               Laborers
9          207109.13               2791.0  High skill tech staff

   total_family_members  migrant_worker  yearly_debt_payments  credit_limit  \
0                   1.0             1.0              33070.28      18690.93
1                   2.0             0.0              15329.53      37745.19
```

```
2                 2.0             0.0              48416.60      41598.36
3                 2.0             0.0              22574.36      32627.76
4                 1.0             0.0              38282.95      52950.64
5                 2.0             1.0              37046.86      40245.64
6                 3.0             0.0              50839.39      41311.08
7                 3.0             0.0              30008.46      32209.22
8                 2.0             0.0              21521.89      65037.74
9                 4.0             0.0               9509.10      28425.52

   credit_limit_used(%)  credit_score  prev_defaults  default_in_last_6months  \
0                    73         544.0              2                        1
1                    52         857.0              0                        0
2                    43         650.0              0                        0
3                    20         754.0              0                        0
4                    75         927.0              0                        0
5                    19         937.0              0                        0
6                    42         733.0              0                        0
7                    91         906.0              0                        0
8                    14         783.0              0                        0
9                    14         666.0              0                        0

   credit_card_default
0                    1
1                    0
2                    0
3                    0
4                    0
5                    0
6                    0
7                    0
8                    0
9                    0
```

[2]:
```
df.shape
```

[2]:
```
(45528, 19)
```

[3]:
```
df.dtypes
```

[3]:
```
customer_id                 object
name                        object
age                          int64
gender                      object
owns_car                    object
owns_house                  object
no_of_children             float64
net_yearly_income          float64
```

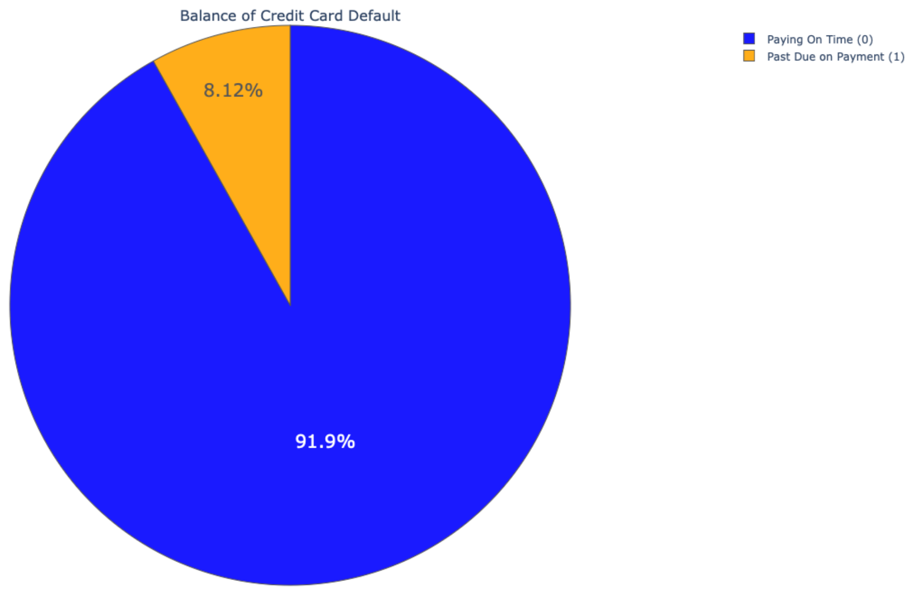
```
no_of_days_employed        float64
occupation_type             object
total_family_members       float64
migrant_worker             float64
yearly_debt_payments       float64
credit_limit               float64
credit_limit_used(%)         int64
credit_score               float64
prev_defaults                int64
default_in_last_6months      int64
credit_card_default          int64
dtype: object
```

2 2.EDA_target variable

[4]:
```
print(df['credit_card_default'].value_counts())
```

```
0    41831
1     3697
Name: credit_card_default, dtype: int64
```

[5]:
```
import matplotlib
from matplotlib import pylab as plt
import plotly.graph_objs as go
import plotly.offline as py
import plotly.io as pio
from plotly.subplots import make_subplots

labels = ['Paying On Time (0)', 'Past Due on Payment (1)']
values = df['credit_card_default'].value_counts()

trace = go.Pie(labels=labels, values=values,
               textfont=dict(size=20), opacity=0.9,
               marker=dict(colors=['blue', 'orange'], line=dict(width=1)))

layout = dict(title='Balance of Credit Card Default')
fig = dict(data=[trace], layout=layout)

fig = make_subplots(rows=1, cols=1, subplot_titles=('Balance of Credit Card␣
 ↪Default',))
fig.add_trace(trace)
#dpi=350
fig.update_layout(width=800, height=800)
fig.show()
fig.write_image('credit_card_default_pie_plot.png')
```



3 2.EDA_features

[6]:
```
print(df['occupation_type'].value_counts())
```

```
Unknown                  14299
Laborers                  8134
Sales staff               4725
Core staff                4062
Managers                  3168
Drivers                   2747
High skill tech staff     1682
Accountants               1474
Medicine staff            1275
Security staff            1025
Cooking staff              902
Cleaning staff             665
Private service staff      387
Low-skill Laborers         336
Waiters/barmen staff       203
Secretaries                199
Realty agents              101
HR staff                    78
IT staff                    66
Name: occupation_type, dtype: int64
```

[7]:
```
print(df['gender'].value_counts())
```

```
F      29957
M      15570
XNA        1
Name: gender, dtype: int64
```

[8]:
```
print(df['owns_car'].value_counts())
```

```
N    29743
Y    15238
Name: owns_car, dtype: int64
```

[9]:
```
print(df['owns_house'].value_counts())
```

```
Y    31642
N    13886
Name: owns_house, dtype: int64
```

[10]:
```
print(df['migrant_worker'].value_counts())
```

```
0.0    37302
1.0     8139
Name: migrant_worker, dtype: int64
```

[11]:
```
print(df['no_of_children'].value_counts())
```

```
0.0    31241
1.0     8985
2.0     3862
3.0      584
4.0       60
5.0       13
6.0        6
7.0        1
8.0        1
9.0        1
Name: no_of_children, dtype: int64
```

[12]:
```
print(df['total_family_members'].value_counts())
```

```
2.0     23455
1.0      9913
3.0      7812
4.0      3623
5.0       564
6.0        57
7.0        12
8.0         6
10.0        2
```

```
9.0          1
Name: total_family_members, dtype: int64
```

[13]:
```
df.describe()
```

[13]:

	age	no_of_children	net_yearly_income	no_of_days_employed
count	45528.000000	44754.000000	4.552800e+04	45065.000000
mean	38.993411	0.420655	2.006556e+05	67609.289293
std	9.543990	0.724097	6.690740e+05	139323.524434
min	23.000000	0.000000	2.717061e+04	2.000000
25%	31.000000	0.000000	1.263458e+05	936.000000
50%	39.000000	0.000000	1.717149e+05	2224.000000
75%	47.000000	1.000000	2.406038e+05	5817.000000
max	55.000000	9.000000	1.407590e+08	365252.000000

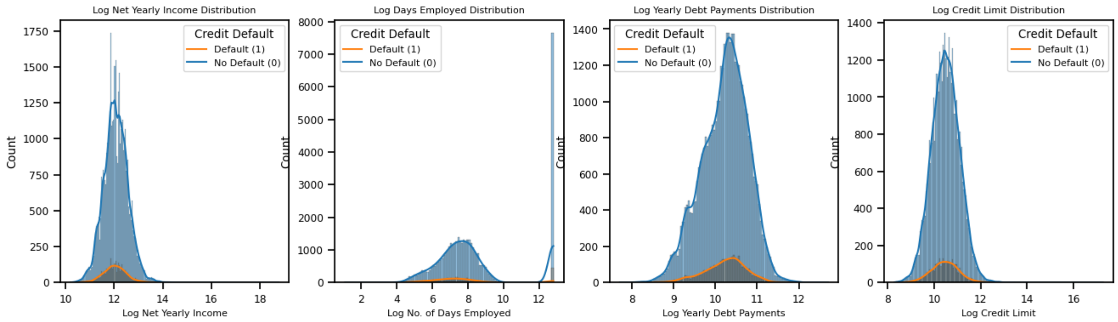
	total_family_members	migrant_worker	yearly_debt_payments
count	45445.000000	45441.000000	45433.000000
mean	2.158081	0.179111	31796.965311
std	0.911572	0.383450	17269.727234
min	1.000000	0.000000	2237.470000
25%	2.000000	0.000000	19231.140000
50%	2.000000	0.000000	29081.650000
75%	3.000000	0.000000	40561.150000
max	10.000000	1.000000	328112.860000

	credit_limit	credit_limit_used(%)	credit_score	prev_defaults
count	4.552800e+04	45528.00000	45520.000000	45528.000000
mean	4.354842e+04	52.23502	782.791257	0.060710
std	1.487847e+05	29.37691	100.619746	0.264629
min	4.003140e+03	0.00000	500.000000	0.000000
25%	2.397381e+04	27.00000	704.000000	0.000000
50%	3.568804e+04	54.00000	786.000000	0.000000
75%	5.343576e+04	78.00000	867.000000	0.000000
max	3.112997e+07	99.00000	949.000000	2.000000

	default_in_last_6months	credit_card_default
count	45528.000000	45528.000000
mean	0.050540	0.081203
std	0.219059	0.273149
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	1.000000	1.000000

4 2.EDA_correlation_categorical vs continuous

[14]:
```
import seaborn as sns

sns.set_context("notebook", font_scale=0.8)

fig, axes = plt.subplots(nrows=1, ncols=4, figsize=(16, 4))  # Update nrows and␣
↪ncols

# Set DPI to 350
plt.figure(dpi=350)

df['log_net_yearly_income'] = np.log1p(df['net_yearly_income'])
df['log_no_of_days_employed'] = np.log1p(df['no_of_days_employed'])
df['log_yearly_debt_payments'] = np.log1p(df['yearly_debt_payments'])
df['log_credit_limit'] = np.log1p(df['credit_limit'])

sns.histplot(data=df, x="log_net_yearly_income", hue="credit_card_default",␣
↪kde=True, ax=axes[0])
sns.histplot(data=df, x="log_no_of_days_employed", hue="credit_card_default",␣
↪kde=True, ax=axes[1])
sns.histplot(data=df, x="log_yearly_debt_payments", hue="credit_card_default",␣
↪kde=True, ax=axes[2])
sns.histplot(data=df, x="log_credit_limit", hue="credit_card_default",␣
↪kde=True, ax=axes[3])

axes[0].set_xlabel("Log Net Yearly Income", fontsize=8)
axes[1].set_xlabel("Log No. of Days Employed", fontsize=8)
axes[2].set_xlabel("Log Yearly Debt Payments", fontsize=8)
axes[3].set_xlabel("Log Credit Limit", fontsize=8)

for ax in axes:
    ax.legend(title="Credit Default", labels=["Default (1)", "No Default (0)"],␣
↪fontsize=8)

axes[0].set_title("Log Net Yearly Income Distribution", fontsize=8)
axes[1].set_title("Log Days Employed Distribution", fontsize=8)
axes[2].set_title("Log Yearly Debt Payments Distribution", fontsize=8)
axes[3].set_title("Log Credit Limit Distribution", fontsize=8)

plt.tight_layout()

plt.savefig('histogram_distribution_with_log.png')

plt.show()
```

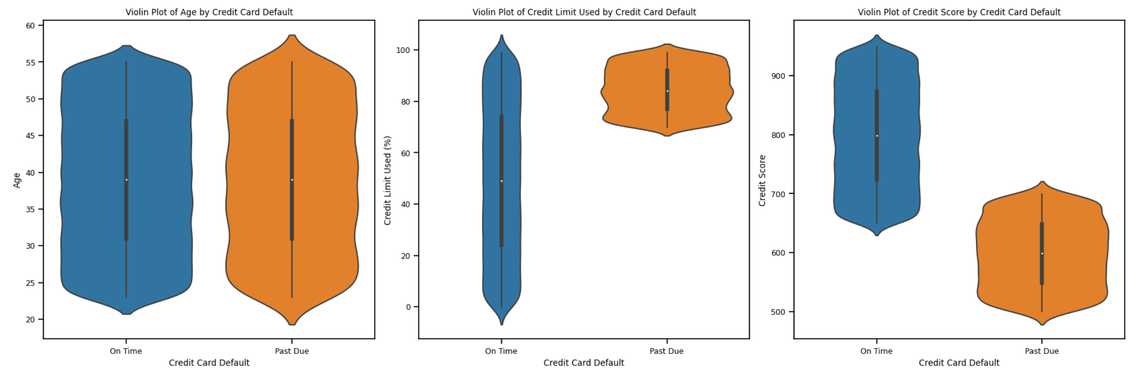



```
<Figure size 2240x1680 with 0 Axes>
```

[15]:

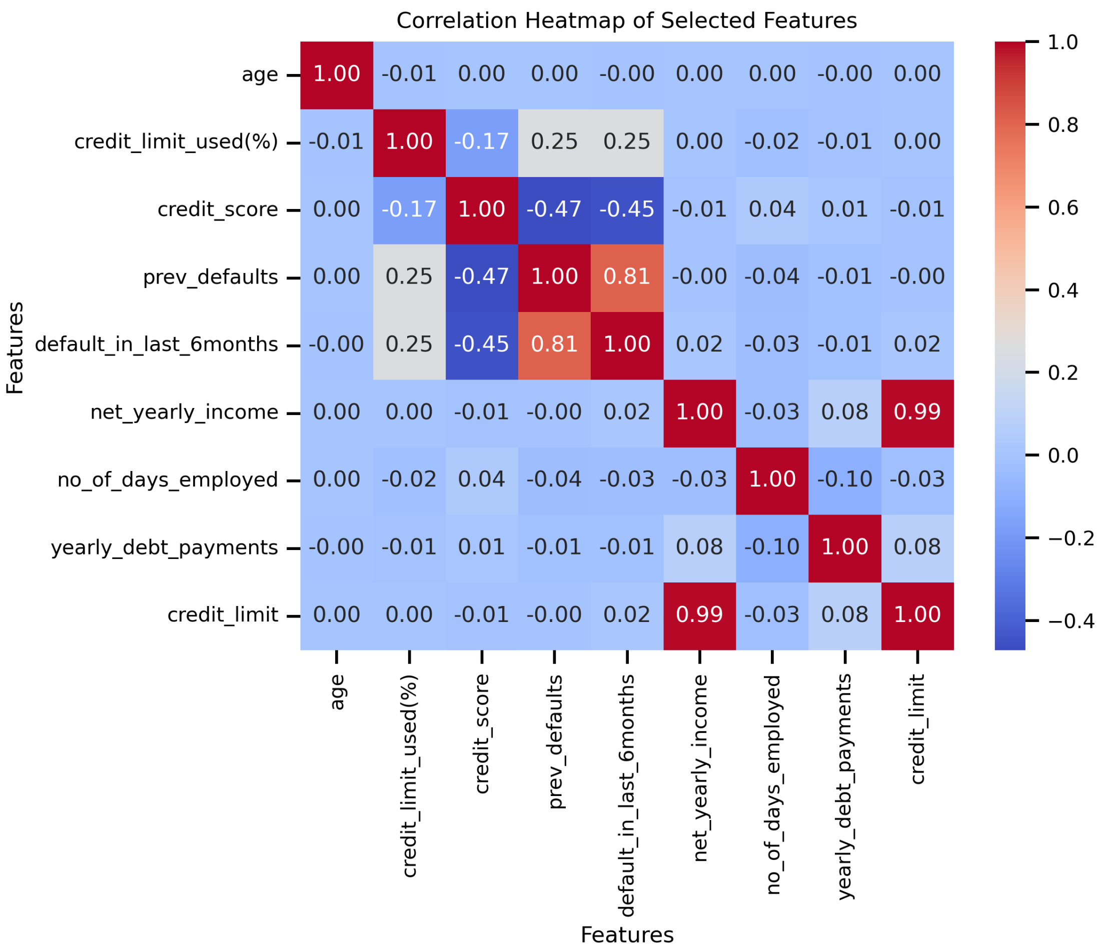
```python
plt.figure(dpi=350)

fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 6))

sns.violinplot(x="credit_card_default", y="age", data=df, ax=axes[0])
sns.violinplot(x="credit_card_default", y="credit_limit_used(%)", data=df,␣
    ↪ax=axes[1])
sns.violinplot(x="credit_card_default", y="credit_score", data=df, ax=axes[2])

axes[0].set_xlabel("Credit Card Default")
axes[0].set_ylabel("Age")
axes[0].set_title("Violin Plot of Age by Credit Card Default")
axes[0].set_xticklabels(['On Time', 'Past Due'])

axes[1].set_xlabel("Credit Card Default")
axes[1].set_ylabel("Credit Limit Used (%)")
axes[1].set_title("Violin Plot of Credit Limit Used by Credit Card Default")
axes[1].set_xticklabels(['On Time', 'Past Due'])

axes[2].set_xlabel("Credit Card Default")
axes[2].set_ylabel("Credit Score")
axes[2].set_title("Violin Plot of Credit Score by Credit Card Default")
axes[2].set_xticklabels(['On Time', 'Past Due'])

plt.tight_layout()
plt.savefig('violin_plots.png')
plt.show()
```

```
<Figure size 2240x1680 with 0 Axes>
```



5 2.EDA_correlation_continuous vs continuous

[16]:
```
selected_features = [
    'age', 'credit_limit_used(%)', 'credit_score', 'prev_defaults',
    'default_in_last_6months', 'net_yearly_income', 'no_of_days_employed',
    'yearly_debt_payments', 'credit_limit'
]

correlation_matrix = df[selected_features].corr()

# Set DPI to 350
plt.figure(dpi=350)

sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")

plt.xlabel("Features")
plt.ylabel("Features")
plt.title("Correlation Heatmap of Selected Features")

plt.savefig('heatmap.png')

plt.show()
```

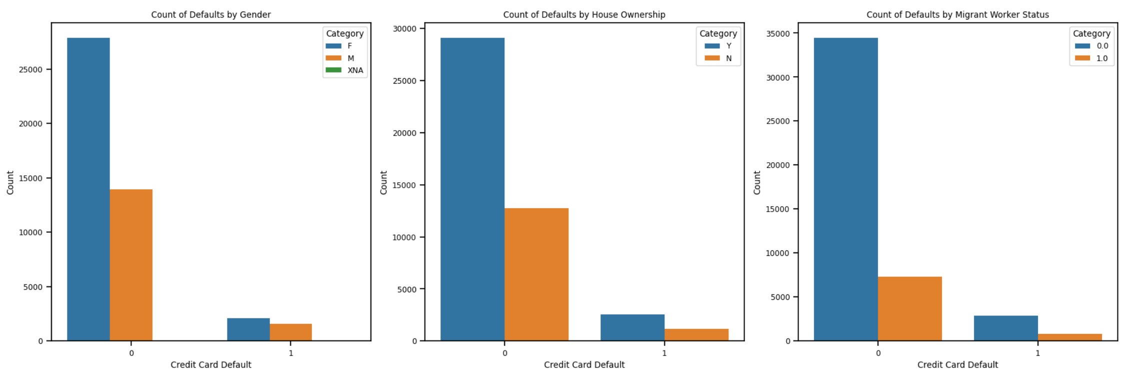


6 2.EDA_correlation_categorical vs categorical

[17]:
```
plt.figure(dpi=350)

fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 6))

sns.countplot(x="credit_card_default", hue="gender", data=df, ax=axes[0])
sns.countplot(x="credit_card_default", hue="owns_house", data=df, ax=axes[1])
sns.countplot(x="credit_card_default", hue="migrant_worker", data=df,␣
↪ax=axes[2])

axes[0].set_xlabel("Credit Card Default")
axes[0].set_ylabel("Count")
axes[0].set_title("Count of Defaults by Gender")

axes[1].set_xlabel("Credit Card Default")
```

```
axes[1].set_ylabel("Count")
axes[1].set_title("Count of Defaults by House Ownership")

axes[2].set_xlabel("Credit Card Default")
axes[2].set_ylabel("Count")
axes[2].set_title("Count of Defaults by Migrant Worker Status")

for ax in axes:
    ax.legend(title="Category", loc="upper right")

plt.tight_layout()

plt.savefig('countplots.png')

plt.show()
```

```
<Figure size 2240x1680 with 0 Axes>
```



7 3.Methods_Handle Missing Value

[18]:
```
print('data dimensions:',df.shape)
perc_missing_per_ftr = df.isnull().sum(axis=0)/df.shape[0]
print('fraction of missing values in features:')
print(perc_missing_per_ftr[perc_missing_per_ftr >0])
print('data types of the features with missing values:')
print(df[perc_missing_per_ftr[perc_missing_per_ftr > 0].index].dtypes)
frac_missing = sum(df.isnull().sum(axis=1)!=0)/df.shape[0]
print('fraction of points with missing values:',frac_missing)
```

```
data dimensions: (45528, 23)
fraction of missing values in features:
owns_car                    0.012015
no_of_children              0.017001
no_of_days_employed         0.010170
```

```
total_family_members        0.001823
migrant_worker              0.001911
yearly_debt_payments        0.002087
credit_score                0.000176
log_no_of_days_employed     0.010170
log_yearly_debt_payments    0.002087
dtype: float64
data types of the features with missing values:
owns_car                     object
no_of_children              float64
no_of_days_employed         float64
total_family_members        float64
migrant_worker              float64
yearly_debt_payments        float64
credit_score                float64
log_no_of_days_employed     float64
log_yearly_debt_payments    float64
dtype: object
fraction of points with missing values: 0.04434633632050606
```

[19]:

```
y = df['credit_card_default']
customer_id = df['customer_id']
name = df['name']
# drop ID,name, and 4 features which are produced by log-transformation in EDA
X = df.
 ↪drop(columns=['credit_card_default','customer_id','name','log_net_yearly_income','log_no_of
classes, counts = np.unique(y,return_counts=True)
print(classes, counts)
print('balance:',np.max(counts/len(y)))
```

```
[0 1] [41831  3697]
balance: 0.9187972236865226
```

[20]:

```
#check whether dropped or not
X.describe()
```

[20]:

```
                age  no_of_children  net_yearly_income  no_of_days_employed  \
count  45528.000000    44754.000000       4.552800e+04         45065.000000
mean      38.993411        0.420655       2.006556e+05         67609.289293
std        9.543990        0.724097       6.690740e+05        139323.524434
min       23.000000        0.000000       2.717061e+04             2.000000
25%       31.000000        0.000000       1.263458e+05           936.000000
50%       39.000000        0.000000       1.717149e+05          2224.000000
75%       47.000000        1.000000       2.406038e+05          5817.000000
max       55.000000        9.000000       1.407590e+08        365252.000000

       total_family_members  migrant_worker  yearly_debt_payments  \
count          45445.000000    45441.000000          45433.000000
```

```
mean                2.158081         0.179111          31796.965311
std                 0.911572         0.383450          17269.727234
min                 1.000000         0.000000           2237.470000
25%                 2.000000         0.000000          19231.140000
50%                 2.000000         0.000000          29081.650000
75%                 3.000000         0.000000          40561.150000
max                10.000000         1.000000         328112.860000

       credit_limit  credit_limit_used(%)  credit_score  prev_defaults  \
count  4.552800e+04           45528.00000  45520.000000   45528.000000
mean   4.354842e+04              52.23502    782.791257       0.060710
std    1.487847e+05              29.37691    100.619746       0.264629
min    4.003140e+03               0.00000    500.000000       0.000000
25%    2.397381e+04              27.00000    704.000000       0.000000
50%    3.568804e+04              54.00000    786.000000       0.000000
75%    5.343576e+04              78.00000    867.000000       0.000000
max    3.112997e+07              99.00000    949.000000       2.000000

       default_in_last_6months
count             45528.000000
mean                  0.050540
std                   0.219059
min                   0.000000
25%                   0.000000
50%                   0.000000
75%                   0.000000
max                   1.000000
```

[21]:

```python
from sklearn.impute import SimpleImputer

continuous_features = ['credit_score','no_of_days_employed','yearly_debt_payments']

X_continuous = X[continuous_features]

imputer = SimpleImputer(strategy='mean')
X_continuous_imputed = pd.DataFrame(imputer.fit_transform(X_continuous), columns=continuous_features)

X[continuous_features] = X_continuous_imputed
```

[22]:

```python
#check whether imputed or not
print('data dimensions:',X.shape)
perc_missing_per_ftr = X.isnull().sum(axis=0)/X.shape[0]
print('fraction of missing values in features:')
print(perc_missing_per_ftr[perc_missing_per_ftr >0])
print('data types of the features with missing values:')
```

```
print(df[perc_missing_per_ftr[perc_missing_per_ftr > 0].index].dtypes)
frac_missing = sum(X.isnull().sum(axis=1)!=0)/df.shape[0]
print('fraction of points with missing values:',frac_missing)
```

```
data dimensions: (45528, 16)
fraction of missing values in features:
owns_car                0.012015
no_of_children          0.017001
total_family_members    0.001823
migrant_worker          0.001911
dtype: float64
data types of the features with missing values:
owns_car                 object
no_of_children          float64
total_family_members    float64
migrant_worker          float64
dtype: object
fraction of points with missing values: 0.03237568089966614
```

8 3.Methods_Write a Function

[23]:
```
import pandas as pd
import numpy as np
import random
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedKFold
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, fbeta_score


def MLpipe(X, y, preprocessor, ML_algo, param_grid):
    # lists to be returned
    scores = []
    best_models = []
    test_sets = []

    # loop through 10 different random states
    random.seed(42)
    random_state = random.sample(range(1, 101), 10)

    for i, rs in enumerate(random_state):
```

```
        # split the data to other and test (80-20)
        X_other, X_test, y_other, y_test = train_test_split(X, y, test_size=0.
↪2, random_state=rs, stratify=y)

        # print sets before preprocess
        print(f'\nSearch{i+1}, random_state = {rs}')
        print("X_other Shape before preprocessing:", X_other.shape)
        print("X_test Shape before preprocessing:", X_test.shape)

        # use StratifiedKFold with 4 folds
        kf = StratifiedKFold(n_splits=4, shuffle=True, random_state=rs)
        pipe = make_pipeline(preprocessor, ML_algo)
        fbeta_scorer = make_scorer(fbeta_score, beta=0.5)
        grid = GridSearchCV(pipe,
                            param_grid=param_grid,
                            scoring=fbeta_scorer,  # use F-beta score
                            cv=kf,
                            return_train_score=True,
                            n_jobs=-1,
                            verbose=True)

        # print sets after preprocess
        X_other_preprocessed = preprocessor.fit_transform(X_other)
        X_test_preprocessed = preprocessor.transform(X_test)
        print("X_other Shape after preprocessing:", X_other_preprocessed.shape)
        print("X_test Shape after preprocessing:", X_test_preprocessed.shape)

        # fit a model using GridSearchCV with StratifiedKFold and the␣
↪predefined Preprocessor
        grid.fit(X_other, y_other)

        # print the GridSearchCV results
        print("GridSearchCV Results:")
        print('Best Parameters:', grid.best_params_)
        print('Best Score:', grid.best_score_)

        # return a list of 10 best models
        best_model = grid.best_estimator_
        best_models.append(best_model)

        # calculate and print test scores
        # return a list of 10 test scores
        y_test_prob = best_model.predict_proba(X_test)[:, 1]  # the second␣
↪column is the positive class (credit_card_default=1)
        test_fbeta = fbeta_score(y_test, best_model.predict(X_test), beta=0.5)
        print("Test Score (F-beta):", test_fbeta)
        scores.append(test_fbeta)
```

```
        test_sets.append([X_test, y_test])

    return scores, best_models, test_sets
```

9 3.Methods_Logistic Regression

[24]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder,␣
 ↪OrdinalEncoder, MinMaxScaler
from sklearn.linear_model import LogisticRegression

#preprocessor
#ordinal_ftrs = []
#ordinal_cats = []
onehot_ftrs = ['gender', 'owns_car', 'owns_house', 'no_of_children',␣
 ↪'occupation_type', 'total_family_members', 'migrant_worker']
minmax_ftrs = ['age', 'credit_limit_used(%)', 'credit_score', 'prev_defaults',␣
 ↪'default_in_last_6months']
std_ftrs = ['net_yearly_income', 'no_of_days_employed', 'yearly_debt_payments',␣
 ↪'credit_limit']
preprocessor = ColumnTransformer(
    transformers=[
        ('onehot', OneHotEncoder(sparse_output=False, handle_unknown='ignore'),␣
 ↪onehot_ftrs),
        ('minmax', MinMaxScaler(), minmax_ftrs),
        ('std', StandardScaler(), std_ftrs)
    ]
)
#algorithms and parameters
ML_algo = LogisticRegression()
param_grid = {
    'logisticregression__C': [0.01, 0.1, 1, 10],
    'logisticregression__max_iter': [1000, 2000, 3000],  # Add one more␣
 ↪parameter
}

#use function
scores, best_models, test_sets = MLpipe(X, y, preprocessor, ML_algo, param_grid)
mean_scores = np.mean(scores)
std_score = np.std(scores)
print(f'Mean of Test Scores = {mean_scores}, Standard Deviation of Test Scores␣
 ↪= {std_score}')

# Save result and best model
scores_table1 = {}
scores_table1['Model'] = 'Logistic Regression'
```

```python
scores_table1['Mean of Test Score'] = mean_scores
scores_table1['Standard Deviation of Test Score'] = std_score
scores_table1['Coefficient of Variation'] = np.array(std_score) / np.
    ↪array(mean_scores)
scores_table1['Std Above Baseline'] = (np.array(mean_scores) - 0.
    ↪09754308570704885) / np.array(std_score)

#get best model
best_model_index = np.argmax(scores)
best_model1 = best_models[best_model_index]

#get X and y's test set
test_set1 = test_sets[best_model_index]
X_test1, y_test1 = test_set1
```

```
Search1, random_state = 82
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'logisticregression__C': 0.1, 'logisticregression__max_iter':
1000}
Best Score: 0.9359791572006294
Test Score (F-beta): 0.9472304162569649

Search2, random_state = 15
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'logisticregression__C': 0.1, 'logisticregression__max_iter':
1000}
Best Score: 0.9365661326228111
Test Score (F-beta): 0.9423909423909425

Search3, random_state = 4
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
```

```
Best Parameters: {'logisticregression__C': 0.1, 'logisticregression__max_iter':
1000}
Best Score: 0.9373595313028902
Test Score (F-beta): 0.9394957983193276

Search4, random_state = 95
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'logisticregression__C': 0.1, 'logisticregression__max_iter':
1000}
Best Score: 0.9376557080406291
Test Score (F-beta): 0.9390777515987883

Search5, random_state = 36
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'logisticregression__C': 0.1, 'logisticregression__max_iter':
1000}
Best Score: 0.9369680601544822
Test Score (F-beta): 0.939485122032765

Search6, random_state = 32
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'logisticregression__C': 0.1, 'logisticregression__max_iter':
1000}
Best Score: 0.9368065126384957
Test Score (F-beta): 0.9440211990725407

Search7, random_state = 29
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
```

```
Best Parameters: {'logisticregression__C': 0.1, 'logisticregression__max_iter':
1000}
Best Score: 0.93823224153883
Test Score (F-beta): 0.9373942470389172

Search8, random_state = 18
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'logisticregression__C': 0.1, 'logisticregression__max_iter':
1000}
Best Score: 0.9387519841498995
Test Score (F-beta): 0.9365456396335256

Search9, random_state = 14
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 58)
X_test Shape after preprocessing: (9106, 58)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'logisticregression__C': 0.1, 'logisticregression__max_iter':
1000}
Best Score: 0.938706281241672
Test Score (F-beta): 0.9373942470389172

Search10, random_state = 87
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'logisticregression__C': 0.1, 'logisticregression__max_iter':
1000}
Best Score: 0.9375459563859804
Test Score (F-beta): 0.9403285283271875
Mean of Test Scores = 0.9403363891709876, Standard Deviation of Test Scores =
0.0031626616032118453
```

10 3.Methods_Decision Tree

[25]:
```
from sklearn.tree import DecisionTreeClassifier

#preprocessor
onehot_ftrs = ['gender', 'owns_car', 'owns_house', 'no_of_children',␣
↪'occupation_type', 'total_family_members', 'migrant_worker']
minmax_ftrs = ['age', 'credit_limit_used(%)', 'credit_score', 'prev_defaults',␣
↪'default_in_last_6months']
std_ftrs = ['net_yearly_income', 'no_of_days_employed', 'yearly_debt_payments',␣
↪'credit_limit']
preprocessor = ColumnTransformer(
    transformers=[
        ('onehot', OneHotEncoder(sparse_output=False, handle_unknown='ignore'),␣
↪onehot_ftrs),
        ('minmax', MinMaxScaler(), minmax_ftrs),
        ('std', StandardScaler(), std_ftrs)
    ]
)

# algorithms and parameters
ML_algo = DecisionTreeClassifier()
param_grid = {
    'decisiontreeclassifier__max_depth': [5, 10, 15, None],
    'decisiontreeclassifier__min_samples_split': [2, 5, 10],  # Add one more␣
↪parameter
}

# use function
scores, best_models, test_sets = MLpipe(X, y, preprocessor, ML_algo, param_grid)
mean_scores = np.mean(scores)
std_score = np.std(scores)
print(f'Mean of Test Scores = {mean_scores}, Standard Deviation of Test Scores␣
↪= {std_score}')

# Save result and best model
scores_table2 = {}
scores_table2['Model'] = 'Decision Tree'
scores_table2['Mean of Test Score'] = mean_scores
scores_table2['Standard Deviation of Test Score'] = std_score
scores_table2['Coefficient of Variation'] = np.array(std_score) / np.
↪array(mean_scores)
scores_table2['Std Above Baseline'] = (np.array(mean_scores) - 0.
↪09754308570704885) / np.array(std_score)

#get best model
best_model_index = np.argmax(scores)
```

```python
best_model2 = best_models[best_model_index]

#get X and y's test set
test_set2 = test_sets[best_model_index]
X_test2, y_test2 = test_set2
```

```
Search1, random_state = 82
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'decisiontreeclassifier__max_depth': 5,
'decisiontreeclassifier__min_samples_split': 2}
Best Score: 0.9339490586251618
Test Score (F-beta): 0.9451518119490695

Search2, random_state = 15
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'decisiontreeclassifier__max_depth': 5,
'decisiontreeclassifier__min_samples_split': 2}
Best Score: 0.939327082428482
Test Score (F-beta): 0.9423650215303079

Search3, random_state = 4
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'decisiontreeclassifier__max_depth': 5,
'decisiontreeclassifier__min_samples_split': 2}
Best Score: 0.9405875894426018
Test Score (F-beta): 0.9394957983193276

Search4, random_state = 95
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
```

```
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'decisiontreeclassifier__max_depth': 5,
'decisiontreeclassifier__min_samples_split': 2}
Best Score: 0.9399679713983673
Test Score (F-beta): 0.9403285283271875

Search5, random_state = 36
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'decisiontreeclassifier__max_depth': 5,
'decisiontreeclassifier__min_samples_split': 2}
Best Score: 0.9384417084419139
Test Score (F-beta): 0.9398998330550918

Search6, random_state = 32
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'decisiontreeclassifier__max_depth': 5,
'decisiontreeclassifier__min_samples_split': 2}
Best Score: 0.9370419701080719
Test Score (F-beta): 0.9444260668210388

Search7, random_state = 29
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'decisiontreeclassifier__max_depth': 5,
'decisiontreeclassifier__min_samples_split': 2}
Best Score: 0.9397051770144842
Test Score (F-beta): 0.9361344537815127

Search8, random_state = 18
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
```

```
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'decisiontreeclassifier__max_depth': 5,
'decisiontreeclassifier__min_samples_split': 2}
Best Score: 0.9392686385002998
Test Score (F-beta): 0.9365456396335256

Search9, random_state = 14
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 58)
X_test Shape after preprocessing: (9106, 58)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'decisiontreeclassifier__max_depth': 5,
'decisiontreeclassifier__min_samples_split': 2}
Best Score: 0.9391148441966748
Test Score (F-beta): 0.9365558912386708

Search10, random_state = 87
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'decisiontreeclassifier__max_depth': 5,
'decisiontreeclassifier__min_samples_split': 2}
Best Score: 0.9393509322879166
Test Score (F-beta): 0.9398998330550918
Mean of Test Scores = 0.9400802877710823, Standard Deviation of Test Scores =
0.003012959587161753
```

11 3.Methods_Random Forest

[26]:
```
from sklearn.ensemble import RandomForestClassifier

#preprocessor
onehot_ftrs = ['gender', 'owns_car', 'owns_house', 'no_of_children',␣
 ↪'occupation_type', 'total_family_members', 'migrant_worker']
minmax_ftrs = ['age', 'credit_limit_used(%)', 'credit_score', 'prev_defaults',␣
 ↪'default_in_last_6months']
std_ftrs = ['net_yearly_income', 'no_of_days_employed', 'yearly_debt_payments',␣
 ↪'credit_limit']
preprocessor = ColumnTransformer(
    transformers=[
```

```
        ('onehot', OneHotEncoder(sparse_output=False, handle_unknown='ignore'),␣
 ↪onehot_ftrs),
        ('minmax', MinMaxScaler(), minmax_ftrs),
        ('std', StandardScaler(), std_ftrs)
    ]
)

# algorithms and parameters
ML_algo = RandomForestClassifier(random_state=42)
param_grid = {
    'randomforestclassifier__n_estimators': [50, 100, 150, 200],
    'randomforestclassifier__max_depth': [None, 10, 30],  #add one more␣
 ↪parameter
}

# use function
scores = MLpipe(X, y, preprocessor, ML_algo, param_grid)[0]
best_model = MLpipe(X, y, preprocessor, ML_algo, param_grid)[1]
test_sets = MLpipe(X, y, preprocessor, ML_algo, param_grid)[2]
mean_scores = np.mean(scores)
std_score = np.std(scores)
print(f'Mean of Test Scores = {mean_scores}, Standard Deviation of Test Scores␣
 ↪= {std_score}')

# Save result and best model
scores_table3 = {}
scores_table3['Model'] = 'Random Forest'
scores_table3['Mean of Test Score'] = mean_scores
scores_table3['Standard Deviation of Test Score'] = std_score
scores_table3['Coefficient of Variation'] = np.array(std_score) / np.
 ↪array(mean_scores)
scores_table3['Std Above Baseline'] = (np.array(mean_scores) - 0.
 ↪09754308570704885) / np.array(std_score)

#get best model
best_model_index = np.argmax(scores)
best_model3 = best_models[best_model_index]

#get X and y's test set
test_set3 = test_sets[best_model_index]
X_test3, y_test3 = test_set3
```

```
Search1, random_state = 82
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
```

```
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9382335922697143
Test Score (F-beta): 0.9476268412438624

Search2, random_state = 15
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9393240652836065
Test Score (F-beta): 0.9436152570480928

Search3, random_state = 4
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 30,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9404063264582645
Test Score (F-beta): 0.9378117725307614

Search4, random_state = 95
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9400670776450917
Test Score (F-beta): 0.9403285283271875

Search5, random_state = 36
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
```

```
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 100}
Best Score: 0.9399183042987798
Test Score (F-beta): 0.941156803744567

Search6, random_state = 32
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9392317557407501
Test Score (F-beta): 0.9440211990725407

Search7, random_state = 29
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': None,
'randomforestclassifier__n_estimators': 100}
Best Score: 0.9408247448112503
Test Score (F-beta): 0.9344700768973587

Search8, random_state = 18
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9410297117030277
Test Score (F-beta): 0.9365456396335256

Search9, random_state = 14
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 58)
```

```
X_test Shape after preprocessing: (9106, 58)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9406848356033403
Test Score (F-beta): 0.9382382720215997

Search10, random_state = 87
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9399915328946808
Test Score (F-beta): 0.9407432206226984

Search1, random_state = 82
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9382335922697143
Test Score (F-beta): 0.9476268412438624

Search2, random_state = 15
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9393240652836065
Test Score (F-beta): 0.9436152570480928

Search3, random_state = 4
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
```

```
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 30,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9404063264582645
Test Score (F-beta): 0.9378117725307614

Search4, random_state = 95
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9400670776450917
Test Score (F-beta): 0.9403285283271875

Search5, random_state = 36
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 100}
Best Score: 0.9399183042987798
Test Score (F-beta): 0.941156803744567

Search6, random_state = 32
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9392317557407501
Test Score (F-beta): 0.9440211990725407

Search7, random_state = 29
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
```

```
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': None,
'randomforestclassifier__n_estimators': 100}
Best Score: 0.9408247448112503
Test Score (F-beta): 0.9344700768973587

Search8, random_state = 18
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9410297117030277
Test Score (F-beta): 0.9365456396335256

Search9, random_state = 14
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 58)
X_test Shape after preprocessing: (9106, 58)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9406848356033403
Test Score (F-beta): 0.9382382720215997

Search10, random_state = 87
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9399915328946808
Test Score (F-beta): 0.9407432206226984

Search1, random_state = 82
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
```

```
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9382335922697143
Test Score (F-beta): 0.9476268412438624

Search2, random_state = 15
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9393240652836065
Test Score (F-beta): 0.9436152570480928

Search3, random_state = 4
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 30,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9404063264582645
Test Score (F-beta): 0.9378117725307614

Search4, random_state = 95
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9400670776450917
Test Score (F-beta): 0.9403285283271875

Search5, random_state = 36
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
```

```
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 100}
Best Score: 0.9399183042987798
Test Score (F-beta): 0.941156803744567

Search6, random_state = 32
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9392317557407501
Test Score (F-beta): 0.9440211990725407

Search7, random_state = 29
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': None,
'randomforestclassifier__n_estimators': 100}
Best Score: 0.9408247448112503
Test Score (F-beta): 0.9344700768973587

Search8, random_state = 18
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 61)
X_test Shape after preprocessing: (9106, 61)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9410297117030277
Test Score (F-beta): 0.9365456396335256

Search9, random_state = 14
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 58)
```

```
X_test Shape after preprocessing: (9106, 58)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9406848356033403
Test Score (F-beta): 0.9382382720215997

Search10, random_state = 87
X_other Shape before preprocessing: (36422, 16)
X_test Shape before preprocessing: (9106, 16)
X_other Shape after preprocessing: (36422, 60)
X_test Shape after preprocessing: (9106, 60)
Fitting 4 folds for each of 12 candidates, totalling 48 fits
GridSearchCV Results:
Best Parameters: {'randomforestclassifier__max_depth': 10,
'randomforestclassifier__n_estimators': 50}
Best Score: 0.9399915328946808
Test Score (F-beta): 0.9407432206226984
Mean of Test Scores = 0.9404557611142194, Standard Deviation of Test Scores =
0.0037112643880534736
```

[27]:
```
# 4.Methods_XGBoost
```

[28]:
```
y = df['credit_card_default']
customer_id = df['customer_id']
name = df['name']
# drop ID,name, and 4 features which are produced by log-transformation in EDA
X = df.
 ↪drop(columns=['credit_card_default','customer_id','name','log_net_yearly_income','log_no_of
```

[29]:
```
#check whether retrieve data correctly or not
print('data dimensions:',X.shape)
perc_missing_per_ftr = X.isnull().sum(axis=0)/X.shape[0]
print('fraction of missing values in features:')
print(perc_missing_per_ftr[perc_missing_per_ftr >0])
print('data types of the features with missing values:')
print(df[perc_missing_per_ftr[perc_missing_per_ftr > 0].index].dtypes)
frac_missing = sum(X.isnull().sum(axis=1)!=0)/df.shape[0]
print('fraction of points with missing values:',frac_missing)
```

```
data dimensions: (45528, 16)
fraction of missing values in features:
owns_car                0.012015
no_of_children          0.017001
no_of_days_employed     0.010170
total_family_members    0.001823
migrant_worker          0.001911
```

```
yearly_debt_payments    0.002087
credit_score            0.000176
dtype: float64
data types of the features with missing values:
owns_car                 object
no_of_children          float64
no_of_days_employed     float64
total_family_members    float64
migrant_worker          float64
yearly_debt_payments    float64
credit_score            float64
dtype: object
fraction of points with missing values: 0.04434633632050606
```

[30]:
```
pip install xgboost
```

```
Requirement already satisfied: xgboost in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (2.0.2)
Requirement already satisfied: numpy in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from xgboost) (1.24.3)
Requirement already satisfied: scipy in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from xgboost) (1.10.1)
Note: you may need to restart the kernel to use updated packages.
```

[31]:
```
import xgboost as xgb

# Define the features and preprocessor
onehot_ftrs = ['gender', 'owns_car', 'owns_house', 'no_of_children',
 ↪'occupation_type', 'total_family_members', 'migrant_worker']
minmax_ftrs = ['age', 'credit_limit_used(%)', 'credit_score', 'prev_defaults',
 ↪'default_in_last_6months']
std_ftrs = ['net_yearly_income', 'no_of_days_employed', 'yearly_debt_payments',
 ↪'credit_limit']

preprocessor = ColumnTransformer(
    transformers=[
        ('onehot', OneHotEncoder(sparse_output=False, handle_unknown='ignore'),
 ↪onehot_ftrs),
        ('minmax', MinMaxScaler(), minmax_ftrs),
        ('std', StandardScaler(), std_ftrs)
    ]
)

# Initialize lists for storing test scores and best models
test_scores = []
best_models = []
test_sets = []
```

```
# Define the stratified k-fold splitting strategy with 4 folds
kf = StratifiedKFold(n_splits=4, shuffle=True, random_state=42)

# Iterate through 10 different random states
random_state = random.sample(range(1, 101), 10)
for i, rs in enumerate(random_state):
    # Split the data into other and test sets (80-20)
    X_other, X_test, y_other, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=rs, stratify=y)

    # Define the XGBoost model with its specific parameters
    xgb_model = xgb.XGBClassifier()

    # Set the parameters for GridSearchCV
    param_grid = {'xgbclassifier__learning_rate': [0.01, 0.1, 0.3, 0.5],␣
 ↪'xgbclassifier__max_depth': [3, 5, 7]}

    # Create the pipeline with preprocessor and XGBoost model
    pipe = make_pipeline(preprocessor, xgb_model)

    # Use GridSearchCV for hyperparameter tuning
    grid = GridSearchCV(pipe, param_grid=param_grid,␣
 ↪scoring=make_scorer(fbeta_score, beta=0.5), cv=kf, return_train_score=True,␣
 ↪n_jobs=-1, verbose=True)

    # Fit the model
    grid.fit(X_other, y_other)

    # Get the best model
    best_model = grid.best_estimator_
    best_models.append(best_model)

    # Calculate F-beta score with a beta of 0.5 for test set
    y_test_prob = best_model.predict_proba(X_test)[:, 1]
    test_fbeta = fbeta_score(y_test, (y_test_prob > 0.5).astype(int), beta=0.5)
    test_scores.append(test_fbeta)
    test_sets.append([X_test, y_test])

    # Print the results for each iteration
    print(f'\nSearch{i+1}, random_state = {rs}')
    print("GridSearchCV Results:")
    print('Best Parameters:', grid.best_params_)
    print('Best Score:', grid.best_score_)
    print("Test F1 Score (beta=0.5):", test_fbeta)

# Print the final scores
mean_scores = np.mean(test_scores)
```

```
std_score = np.std(test_scores)
print(f'Mean of Test F1 Scores (beta=0.5) = {mean_scores}, Standard Deviation␣
↪of Test Scores = {std_score}')

# Save result and best model
scores_table4 = {}
scores_table4['Model'] = 'XGBoost'
scores_table4['Mean of Test Score'] = mean_scores
scores_table4['Standard Deviation of Test Score'] = std_score
scores_table4['Coefficient of Variation'] = np.array(std_score) / np.
↪array(mean_scores)
scores_table4['Std Above Baseline'] = (np.array(mean_scores) - 0.
↪09754308570704885) / np.array(std_score)

#get best model
best_model_index = np.argmax(test_scores)
best_model4 = best_models[best_model_index]

#get X and y's test set
test_set4 = test_sets[best_model_index]
X_test4, y_test4 = test_set4
```

```
Fitting 4 folds for each of 12 candidates, totalling 48 fits

Search1, random_state = 95
GridSearchCV Results:
Best Parameters: {'xgbclassifier__learning_rate': 0.01,
'xgbclassifier__max_depth': 3}
Best Score: 0.9400264939111435
Test F1 Score (beta=0.5): 0.9403285283271875
Fitting 4 folds for each of 12 candidates, totalling 48 fits

Search2, random_state = 70
GridSearchCV Results:
Best Parameters: {'xgbclassifier__learning_rate': 0.01,
'xgbclassifier__max_depth': 3}
Best Score: 0.940210795734641
Test F1 Score (beta=0.5): 0.9394957983193276
Fitting 4 folds for each of 12 candidates, totalling 48 fits

Search3, random_state = 12
GridSearchCV Results:
Best Parameters: {'xgbclassifier__learning_rate': 0.01,
'xgbclassifier__max_depth': 3}
Best Score: 0.9409700313548903
Test F1 Score (beta=0.5): 0.9365456396335256
Fitting 4 folds for each of 12 candidates, totalling 48 fits
```

```
Search4, random_state = 76
GridSearchCV Results:
Best Parameters: {'xgbclassifier__learning_rate': 0.01,
'xgbclassifier__max_depth': 7}
Best Score: 0.9412498082753685
Test F1 Score (beta=0.5): 0.9356924123851651
Fitting 4 folds for each of 12 candidates, totalling 48 fits

Search5, random_state = 55
GridSearchCV Results:
Best Parameters: {'xgbclassifier__learning_rate': 0.01,
'xgbclassifier__max_depth': 3}
Best Score: 0.9413990317743762
Test F1 Score (beta=0.5): 0.934834527465029
Fitting 4 folds for each of 12 candidates, totalling 48 fits

Search6, random_state = 5
GridSearchCV Results:
Best Parameters: {'xgbclassifier__learning_rate': 0.01,
'xgbclassifier__max_depth': 3}
Best Score: 0.9407588893337234
Test F1 Score (beta=0.5): 0.9373942470389172
Fitting 4 folds for each of 12 candidates, totalling 48 fits

Search7, random_state = 4
GridSearchCV Results:
Best Parameters: {'xgbclassifier__learning_rate': 0.01,
'xgbclassifier__max_depth': 3}
Best Score: 0.9402236942240538
Test F1 Score (beta=0.5): 0.9394957983193276
Fitting 4 folds for each of 12 candidates, totalling 48 fits

Search8, random_state = 28
GridSearchCV Results:
Best Parameters: {'xgbclassifier__learning_rate': 0.01,
'xgbclassifier__max_depth': 3}
Best Score: 0.9400183950826914
Test F1 Score (beta=0.5): 0.9399127223900638
Fitting 4 folds for each of 12 candidates, totalling 48 fits

Search9, random_state = 30
GridSearchCV Results:
Best Parameters: {'xgbclassifier__learning_rate': 0.01,
'xgbclassifier__max_depth': 3}
Best Score: 0.9387608865183495
Test F1 Score (beta=0.5): 0.9452325965028043
Fitting 4 folds for each of 12 candidates, totalling 48 fits
```

```
Search10, random_state = 65
GridSearchCV Results:
Best Parameters: {'xgbclassifier__learning_rate': 0.01,
'xgbclassifier__max_depth': 3}
Best Score: 0.9399520368934995
Test F1 Score (beta=0.5): 0.9407432206226984
Mean of Test F1 Scores (beta=0.5) = 0.9389675491004047, Standard Deviation of
Test Scores = 0.002861063665346118
```

12 4.Results_Baseline_Test Score_Best Model

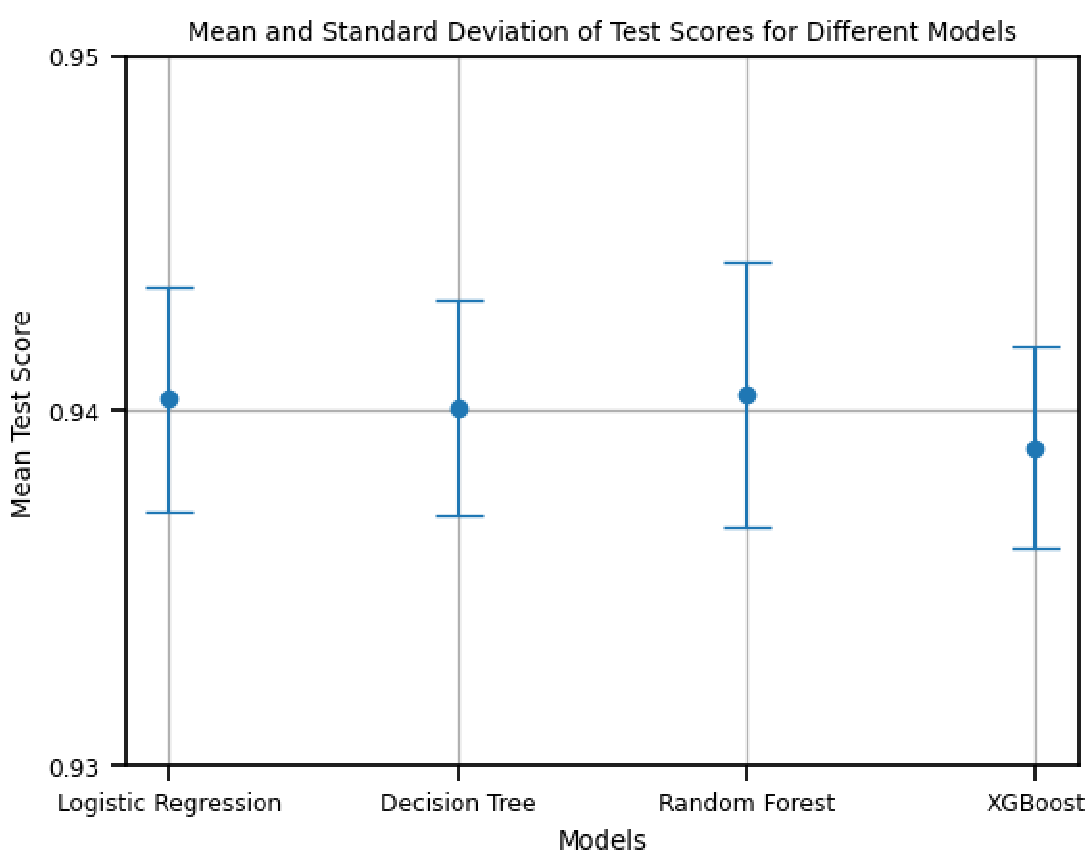
[32]:
```
# In the baseline model, it predicts all points as class 1
TP = 3697
FP = 41831
FN = 3697

P = TP / (TP + FP)

R = TP / (TP + FN)

F0_5 = (1.25 * P * R) / (0.25 * P + R)

print("F0.5 Score:", F0_5)
```

```
F0.5 Score: 0.09754308570704885
```

[33]:
```
scores_table = pd.DataFrame([scores_table1, scores_table2, scores_table3,
 ↪scores_table4])

print(scores_table)

desktop_path = "/Users/emmasun/Desktop/final/results"
scores_table.to_csv(f"{desktop_path}/test scores and best model.csv",
 ↪index=False)
```

```
                 Model  Mean of Test Score  Standard Deviation of Test Score  \
0  Logistic Regression            0.940336                          0.003163
1        Decision Tree            0.940080                          0.003013
2        Random Forest            0.940456                          0.003711
3              XGBoost            0.938968                          0.002861

   Coefficient of Variation  Std Above Baseline
0                  0.003363          266.482289
1                  0.003205          279.637737
2                  0.003946          227.122777
3                  0.003047          294.094981
```

[34]:
```
import os
dpi = 350

plt.grid(True)

model_names = scores_table['Model'].values
model_mean = scores_table['Mean of Test Score'].values
model_std = scores_table['Standard Deviation of Test Score'].values

plt.errorbar(model_names, model_mean, yerr=model_std, fmt='o', capsize=9)

plt.title('Mean and Standard Deviation of Test Scores for Different Models')
plt.xlabel('Models')
plt.ylabel('Mean Test Score')

plt.yticks([0.93, 0.94, 0.95])

plt.show()

desktop_path = "/Users/emmasun/Desktop/final/figures"
plt.savefig(os.path.join(desktop_path, "test_scores_plot.png"), dpi=dpi)
```



```
<Figure size 640x480 with 0 Axes>
```

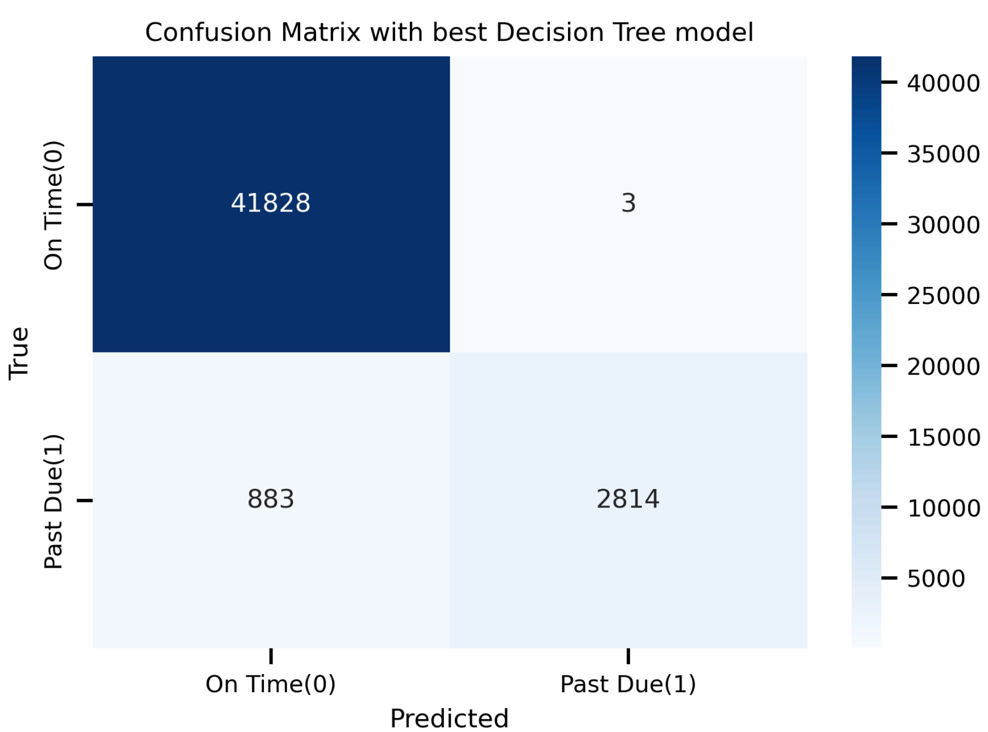
13 4.Results_Predict Y

[35]:
```
y = df['credit_card_default']
customer_id = df['customer_id']
name = df['name']

# Drop ID, name, and 4 features which are produced by log-transformation in EDA
X = df.drop(columns=['credit_card_default', 'customer_id', 'name',␣
↪'log_net_yearly_income', 'log_no_of_days_employed',␣
↪'log_yearly_debt_payments', 'log_credit_limit'])

continuous_features =␣
↪['credit_score','no_of_days_employed','yearly_debt_payments']

X_continuous = X[continuous_features]

imputer = SimpleImputer(strategy='mean')
X_continuous_imputed = pd.DataFrame(imputer.fit_transform(X_continuous),␣
↪columns=continuous_features)

X[continuous_features] = X_continuous_imputed

prediction_y = best_model2.predict(X)

results_df = pd.DataFrame({
    'True_y': y,
    'Prediction_y': prediction_y
})

results_df.to_csv('dataset_with_predictions.csv', index=False)
```

14 4.Results_Confusion Matrix

[36]:
```
from sklearn.metrics import confusion_matrix, classification_report

conf_matrix = confusion_matrix(y, prediction_y)
colors = ['orange', 'blue']
sns.set_palette(sns.color_palette(colors))
plt.figure(figsize=(6, 4), dpi=dpi)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['On␣
↪Time(0)', 'Past Due(1)'], yticklabels=['On Time(0)', 'Past Due(1)'])
plt.xlabel('Predicted')
```

```
plt.ylabel('True')
plt.title('Confusion Matrix with best Decision Tree model')
plt.show()

file_path = '/Users/emmasun/Desktop/final/figures/'
# Set DPI
dpi = 350
plt.savefig(file_path + 'confusion_matrix.png')

tn, fp, fn, tp = conf_matrix.ravel()

print(f'True Negatives (TN): {tn}')
print(f'True Positives (TP): {tp}')
print(f'False Negatives (FN): {fn}')
print(f'False Positives (FP): {fp}')

precision = tp / (tp + fp)
recall = tp / (tp + fn)

beta = 1.25
f_beta = (1.25 * precision * recall) / (0.25 * precision + recall)

f_beta
```



```
True Negatives (TN): 41828
True Positives (TP): 2814
False Negatives (FN): 883
False Positives (FP): 3
```

[36]:

```
0.9401937854994987
```

```
<Figure size 640x480 with 0 Axes>
```

15 4.Results_Global_Permutation Importance

[37]:

```python
print(X_test2.shape)
print(y_test2.shape)
print(X_test2.head())
```

```
(9106, 16)
(9106,)
       age gender owns_car owns_house  no_of_children  net_yearly_income  \
37626   54      F        Y          Y             0.0          178103.36
32631   33      F        N          N             0.0          124731.83
7323    40      F        Y          N             0.0          110770.06
28010   54      F        N          Y             NaN          167024.03
16021   48      F        N          Y             0.0          244831.06

       no_of_days_employed occupation_type  total_family_members  \
37626             365241.0         Unknown                   2.0
32631             365250.0         Unknown                   1.0
7323                3464.0         Unknown                   2.0
28010               1594.0         Unknown                   1.0
16021                593.0      Core staff                   2.0

       migrant_worker  yearly_debt_payments  credit_limit  \
37626             0.0              29076.45      23841.88
32631             0.0              11735.69      22793.84
7323              0.0              17068.97      24939.58
28010             0.0              46454.97      59116.13
16021             0.0              61090.35      56431.18

       credit_limit_used(%)  credit_score  prev_defaults  \
37626                    95         776.0              0
32631                    74         768.0              0
7323                     29         699.0              0
28010                    55         795.0              0
16021                    47         670.0              0

       default_in_last_6months
37626                        0
32631                        0
```

```
7323                           0
28010                          0
16021                          0
```

[38]:
```
continuous_features =␣
↪['credit_score','no_of_days_employed','yearly_debt_payments']

X_continuous = X_test2[continuous_features]

imputer = SimpleImputer(strategy='mean')
X_continuous_imputed = pd.DataFrame(imputer.fit_transform(X_continuous),␣
↪columns=continuous_features)

X_test2[continuous_features] = X_continuous_imputed
```

[39]:
```
X_test2_proprocessed = best_model2.steps[0][1].transform(X_test2)
```

[40]:
```
X_test2_proprocessed = pd.DataFrame(data=X_test2_proprocessed, columns =␣
↪best_model2[0].get_feature_names_out())
```

[41]:
```
X_test2_proprocessed
```

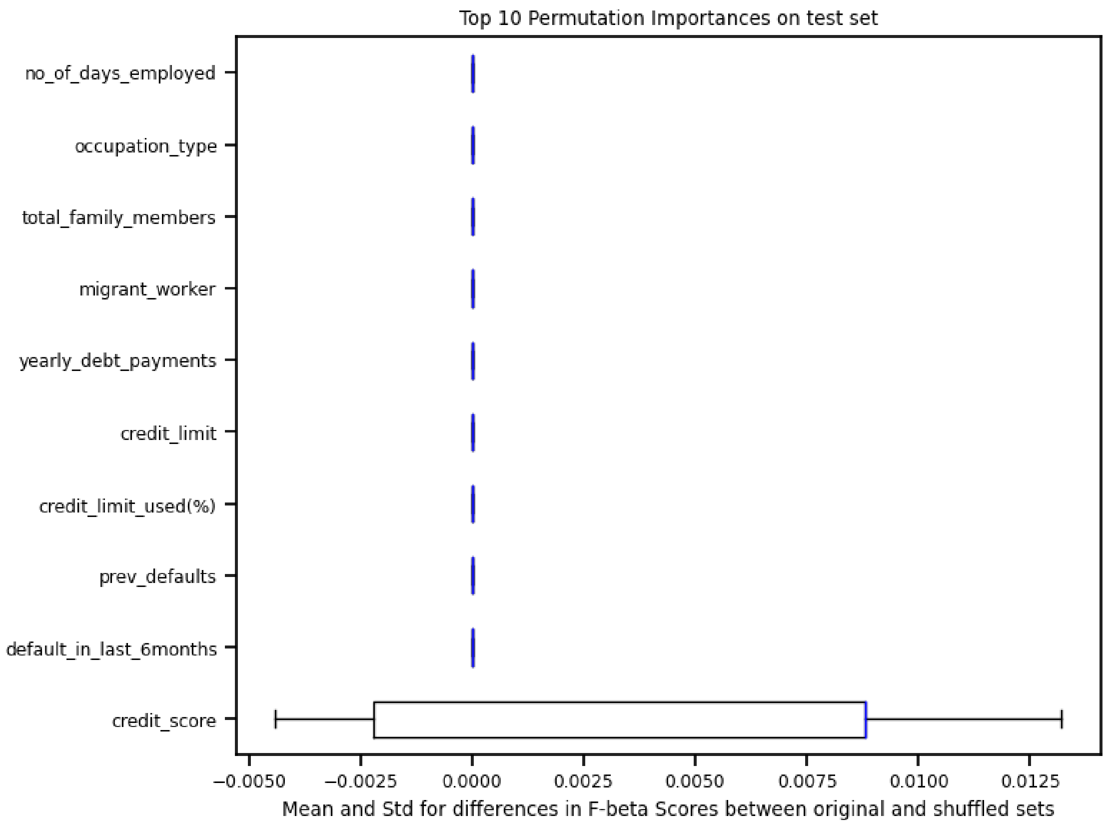
[41]:
```
      onehot__gender_F  onehot__gender_M  onehot__owns_car_N  \
0                  1.0               0.0                 0.0
1                  1.0               0.0                 1.0
2                  1.0               0.0                 0.0
3                  1.0               0.0                 1.0
4                  1.0               0.0                 1.0
…                  …                 …                   …
9101               0.0               1.0                 0.0
9102               1.0               0.0                 0.0
9103               1.0               0.0                 1.0
9104               1.0               0.0                 1.0
9105               0.0               1.0                 0.0

      onehot__owns_car_Y  onehot__owns_car_nan  onehot__owns_house_N  \
0                    1.0                   0.0                   0.0
1                    0.0                   0.0                   1.0
2                    1.0                   0.0                   1.0
3                    0.0                   0.0                   0.0
4                    0.0                   0.0                   0.0
…                    …                     …                     …
9101                 1.0                   0.0                   0.0
9102                 1.0                   0.0                   1.0
9103                 0.0                   0.0                   0.0
9104                 0.0                   0.0                   1.0
9105                 1.0                   0.0                   0.0
```

```
      onehot__owns_house_Y  onehot__no_of_children_0.0  \
0                      1.0                         1.0
1                      0.0                         1.0
2                      0.0                         1.0
3                      1.0                         0.0
4                      1.0                         1.0
…                        …                           …
9101                   1.0                         0.0
9102                   0.0                         0.0
9103                   1.0                         1.0
9104                   0.0                         1.0
9105                   1.0                         1.0

      onehot__no_of_children_1.0  onehot__no_of_children_2.0  …  \
0                            0.0                         0.0  …
1                            0.0                         0.0  …
2                            0.0                         0.0  …
3                            0.0                         0.0  …
4                            0.0                         0.0  …
…                              …                           …  …
9101                         1.0                         0.0  …
9102                         0.0                         1.0  …
9103                         0.0                         0.0  …
9104                         0.0                         0.0  …
9105                         0.0                         0.0  …

      onehot__migrant_worker_nan  minmax__age  minmax__credit_limit_used(%)  \
0                            0.0      0.96875                      0.959596
1                            0.0      0.31250                      0.747475
2                            0.0      0.53125                      0.292929
3                            0.0      0.96875                      0.555556
4                            0.0      0.78125                      0.474747
…                              …            …                             …
9101                         0.0      0.81250                      0.565657
9102                         0.0      0.03125                      0.929293
9103                         0.0      0.93750                      0.494949
9104                         0.0      0.00000                      0.303030
9105                         0.0      0.12500                      0.515152

      minmax__credit_score  minmax__prev_defaults  \
0                      NaN                    0.0
1                      NaN                    0.0
2                 0.363029                    0.0
3                      NaN                    0.0
4                      NaN                    0.0
…                        …                      …
```

```
9101               0.734967                    0.0
9102                    NaN                    1.0
9103                    NaN                    0.0
9104                    NaN                    0.0
9105                    NaN                    0.0

      minmax__default_in_last_6months  std__net_yearly_income  \
0                                 0.0               -0.167800
1                                 0.0               -0.630338
2                                 0.0               -0.751336
3                                 0.0               -0.263817
4                                 0.0                0.410488
…                                   …                     …
9101                              0.0                1.137321
9102                              0.0                4.165196
9103                              0.0               -1.168504
9104                              0.0               -0.471771
9105                              0.0                0.200736

      std__no_of_days_employed  std__yearly_debt_payments  std__credit_limit
0                          NaN                        NaN          -0.634749
1                          NaN                        NaN          -0.669630
2                    -0.466517                   0.242753          -0.598215
3                          NaN                        NaN           0.539267
4                          NaN                        NaN           0.449905
…                            …                          …                  …
9101                 -0.472358                  -0.383530           0.723598
9102                       NaN                        NaN           3.027203
9103                       NaN                        NaN          -1.019781
9104                       NaN                        NaN          -0.578909
9105                       NaN                        NaN           0.156292

[9106 rows x 60 columns]
```

[42]:
```
from sklearn.inspection import permutation_importance

feature_names = X_test2.columns
np.random.seed(100)
nr_runs = 10
scores = np.zeros([len(feature_names), nr_runs])

for i in range(len(feature_names)):
    fbeta_scores = []
    for j in range(nr_runs):
        X_test_shuffled = X_test2.copy()
        X_test_shuffled[feature_names[i]] = np.random.
 ↪permutation(X_test2[feature_names[i]].values)
```

```
        y_test_prob = best_model.predict_proba(X_test2)[:, 1]
        fbeta_original = fbeta_score(y_test2, (y_test_prob > 0.5).astype(int),␣
↪beta=0.5)

        shuffled_prob = best_model.predict_proba(X_test_shuffled)[:, 1]
        fbeta_shuffled = fbeta_score(y_test2, (shuffled_prob > 0.5).
↪astype(int), beta=0.5)

        fbeta_scores.append(fbeta_original-fbeta_shuffled)

    mean_mse = np.mean(fbeta_scores)
    std_mse = np.std(fbeta_scores)
    scores[i] = fbeta_scores

top_indices = np.argsort(np.mean(scores, axis=1))[::-1][:10]
top_scores = scores[top_indices]
top_feature_names = feature_names[top_indices]

plt.rcParams.update({'font.size': 11})
plt.figure(figsize=(8, 6))
plt.boxplot(top_scores.T, labels=top_feature_names, vert=False)
plt.title("Top 10 Permutation Importances on test set")
plt.xlabel('Mean and Std for differences in F-beta Scores between original and␣
↪shuffled sets')
plt.tight_layout()
plt.show()

file_path = '/Users/emmasun/Desktop/final/figures/'
# Set DPI
dpi = 350
plt.savefig(file_path + 'Top 10 Permutation Importances on test set.png')
```

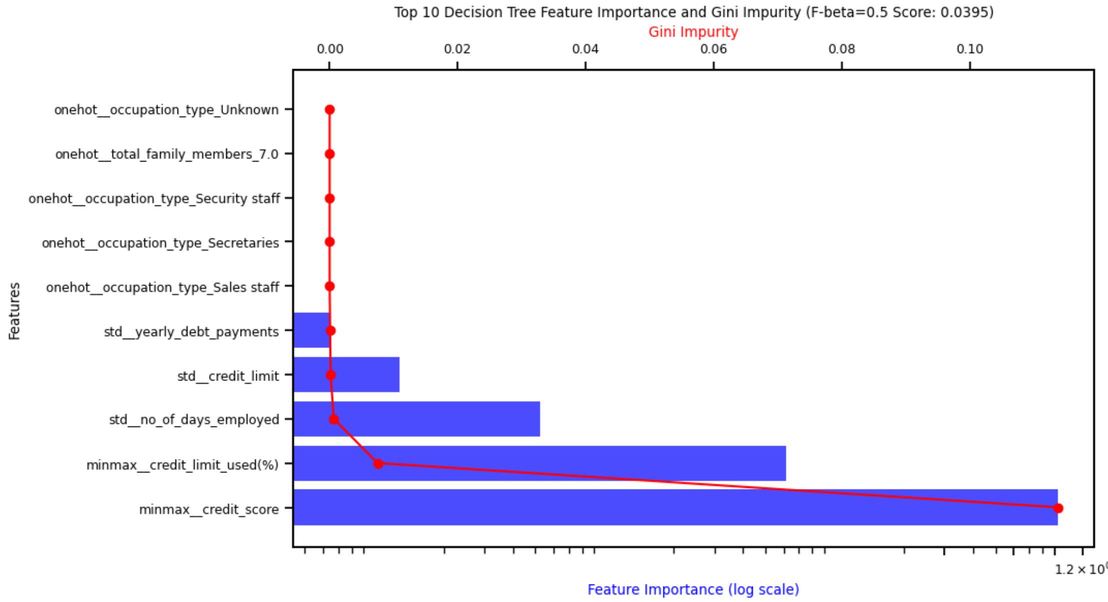



```
<Figure size 640x480 with 0 Axes>
```

16 4.Results_Global_Gini Importance

[43]:
```
from sklearn.tree import plot_tree

y_pred = best_model2.predict(X_test2)

beta = 0.5
fbeta = fbeta_score(y_test2, y_pred, beta=beta)

feature_importances = best_model2.steps[1][1].feature_importances_

gini_importance = best_model2.steps[1][1].tree_.
  ↪compute_feature_importances(normalize=False)

feature_names =X_test2_proprocessed.columns.tolist()

data = {'Feature': feature_names, 'Importance': feature_importances, 'Gini␣
  ↪Impurity': gini_importance}
```

```
df = pd.DataFrame(data)

df = df.sort_values(by='Gini Impurity', ascending=False)

df_top10 = df.head(10)

fig, ax1 = plt.subplots(figsize=(10, 6))

ax1.barh(df_top10['Feature'], df_top10['Importance'], alpha=0.7, color='b',␣
↪log=True, label='Feature Importance')

ax2 = ax1.twiny()
ax2.plot(df_top10['Gini Impurity'], df_top10['Feature'], color='r', marker='o',␣
↪label='Gini Impurity')

ax1.set_ylabel('Features')
ax1.set_xlabel('Feature Importance (log scale)', color='b')

ax1.set_xscale('log')
ax1.xaxis.set_major_locator(plt.MaxNLocator(nbins=5))  # Adjust the number of␣
↪ticks as needed

ax2.set_xlabel('Gini Impurity', color='r')
plt.title(f'Top 10 Decision Tree Feature Importance and Gini Impurity␣
↪(F-beta={beta:.1f} Score: {fbeta:.4f})')

file_path = '/Users/emmasun/Desktop/final/figures/'
# Set DPI
dpi = 350
plt.savefig(file_path + 'op 10 Decision Tree Feature Importance and Gini␣
↪Impurity.png')

plt.show()
```



17 4.Results_Global_SHAP Value

[49]:
```
import shap
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
```

[50]:
```
pip install shap
```

```
Requirement already satisfied: shap in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (0.43.0)
Requirement already satisfied: numpy in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from shap) (1.24.3)
Requirement already satisfied: scipy in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from shap) (1.10.1)
Requirement already satisfied: scikit-learn in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from shap) (1.3.0)
Requirement already satisfied: pandas in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from shap) (1.5.3)
Requirement already satisfied: tqdm>=4.27.0 in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from shap) (4.65.0)
Requirement already satisfied: packaging>20.9 in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from shap) (23.0)
Requirement already satisfied: slicer==0.0.7 in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from shap) (0.0.7)
Requirement already satisfied: numba in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from shap) (0.57.0)
```

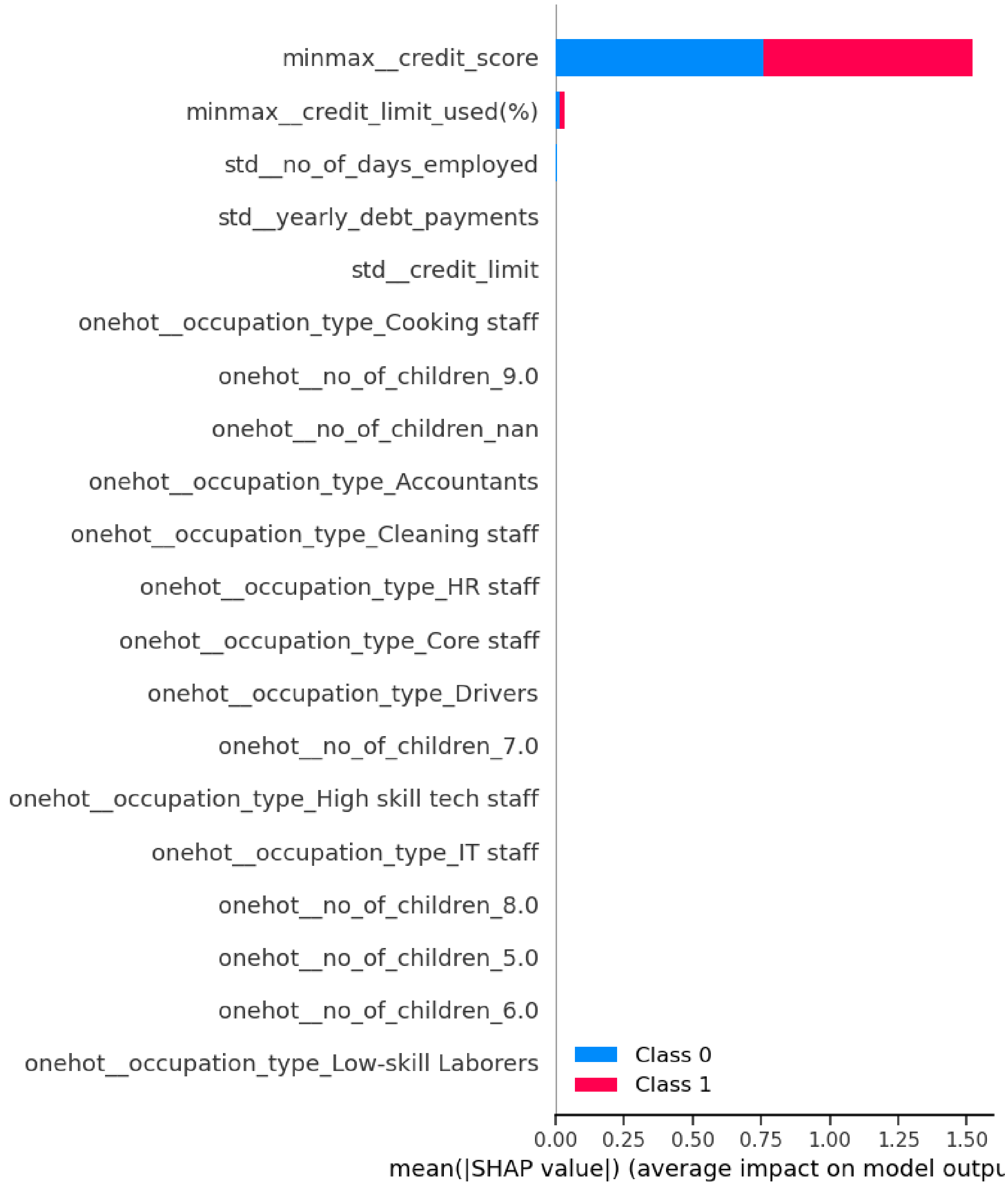
```
Requirement already satisfied: cloudpickle in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from shap) (2.2.1)
Requirement already satisfied: llvmlite<0.41,>=0.40.0dev0 in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from numba->shap)
(0.40.0)
Requirement already satisfied: python-dateutil>=2.8.1 in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from pandas->shap)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from pandas->shap)
(2022.7)
Requirement already satisfied: joblib>=1.1.1 in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from scikit-learn->shap)
(1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from scikit-learn->shap)
(2.2.0)
Requirement already satisfied: six>=1.5 in
/Users/emmasun/anaconda3/lib/python3.11/site-packages (from python-
dateutil>=2.8.1->pandas->shap) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

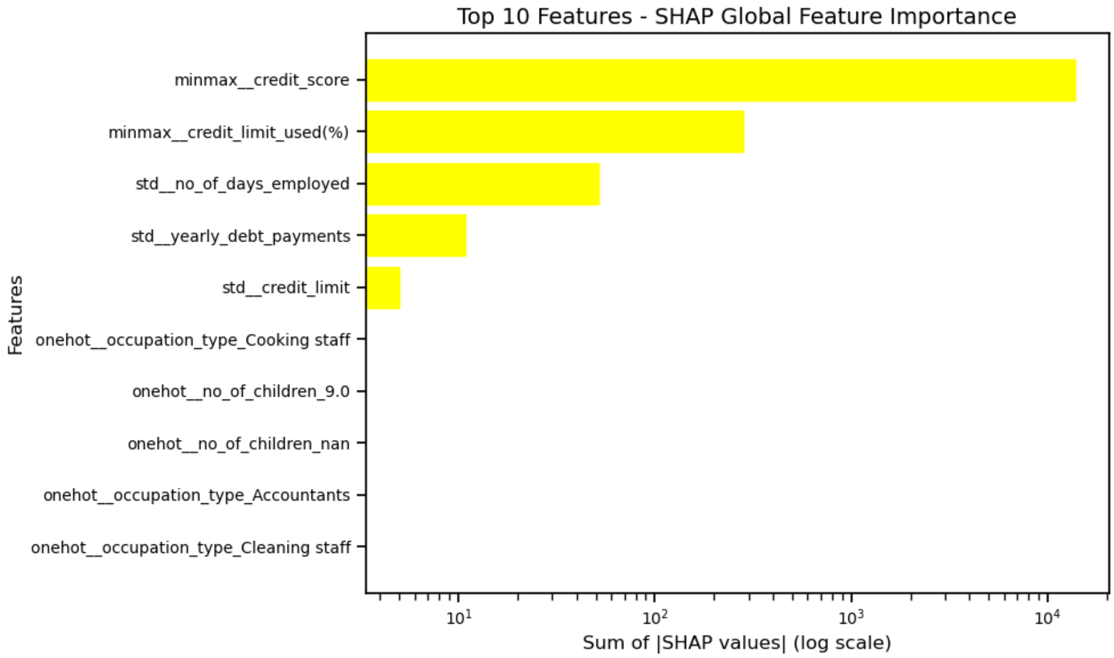
[59]:

```
shap.initjs()

explainer = shap.TreeExplainer(best_model2.steps[1][1])

shap_values = explainer.shap_values(X_test2_proprocessed)

shap_summary = np.sum(np.abs(shap_values), axis=0)

shap.summary_plot(shap_values, X_test2_proprocessed, show=True)

shap_summary_combined = np.sum(np.abs(shap_values[0]), axis=0) + np.sum(np.
 ↪abs(shap_values[1]), axis=0)

feature_names = X_test2_proprocessed.columns
indcs = np.argsort(shap_summary_combined)

plt.figure(figsize=(10, 6))
bars = plt.barh(feature_names[indcs[-10:]], shap_summary_combined[indcs[-10:]],␣
 ↪log=True, color='orange')  # Set logarithmic scale for better visualization

plt.yticks(rotation=0)

plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
```

```
plt.ylabel('Features', fontsize=12)

for bar in bars:
    bar.set_color('yellow')

plt.xlabel('Sum of |SHAP values| (log scale)', fontsize=12)
plt.title('Top 10 Features - SHAP Global Feature Importance', fontsize=14)
plt.tight_layout()
plt.show()
```

<IPython.core.display.HTML object>


minmax__credit_score
minmax__credit_limit_used(%)
std__no_of_days_employed
std__yearly_debt_payments
std__credit_limit
onehot__occupation_type_Cooking staff
onehot__no_of_children_9.0
onehot__no_of_children_nan
onehot__occupation_type_Accountants
onehot__occupation_type_Cleaning staff
onehot__occupation_type_HR staff
onehot__occupation_type_Core staff
onehot__occupation_type_Drivers
onehot__no_of_children_7.0
onehot__occupation_type_High skill tech staff
onehot__occupation_type_IT staff
onehot__no_of_children_8.0
onehot__no_of_children_5.0
onehot__no_of_children_6.0
onehot__occupation_type_Low-skill Laborers
Class 0
Class 1
0.00
0.25
0.50
0.75
1.00
1.25
1.50
mean(|SHAP value|) (average impact on model outpu



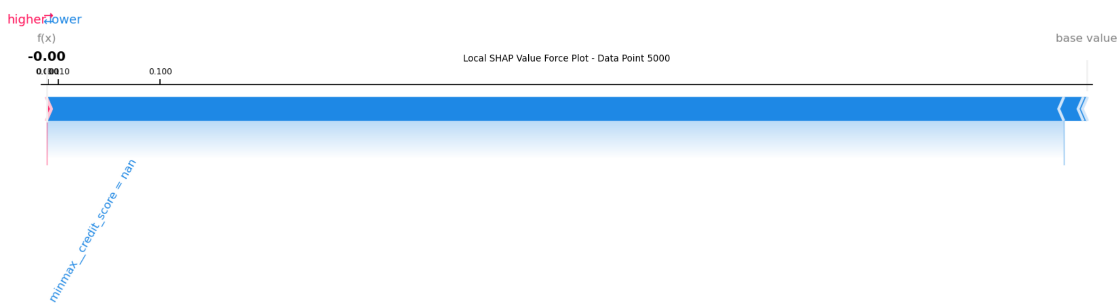
18 4.Results_Local_SHAP Value

[57]:
```
import os

index_points = [1000, 5000, 9000]

file_path = '/Users/emmasun/Desktop/final/figures/'
os.makedirs(file_path, exist_ok=True)

for index in index_points:
    print(f'index: {index}')

    force_plot = shap.force_plot(
    base_value=explainer.expected_value[0],
    shap_values=shap_values[0][index, :],
    features=X_test2_proprocessed.iloc[index, :],
    feature_names=X_test2_proprocessed.columns,
    matplotlib=True,
    text_rotation=60,
    show=False
)

    plt.gca().xaxis.set_major_locator(plt.LogLocator(numticks=100))
```

```
    plt.title(f"Local SHAP Value Force Plot - Data Point {index}")

    plt.savefig(file_path + f'Local_SHAP_Value_Force_Plot_{index}.png', dpi=350)
    plt.show()
```

```
index: 1000
```


```
index: 5000
```




```
index: 9000
```


higher ⇄ lower
f(x)
0.00
base value
Local SHAP Value Force Plot - Data Point 9000
0.01
0.10
std__yearly_debt_payments = nan
minmax__credit_limit_used(%) = 0.29292929292929293
minmax__credit_score = nan