Loan Eligibility with Ensemble Boosting

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1. Abstract

Banks and all sort of credit institutes which provide *loans* face great challenges when a new potential customer asks for a loan.
Those challenges translate into *risks* if not well balanced may end up with catastrophic consequences for all clients in the financial-chain and may have a big impact in the outside world too.
Technology can mitigate these risks.

By gathering a huge amout of *data*, and by applying some analytics we can see the *hidden shape* of the risks that credit institutes take.
Then, thanks to some state-of-the-art algotithms we can predict the potential risk that a new client may represent for a bank.
At the end of the day, the aim is to provide a robust model to support diffuclt *decision-making* scenarios.

The purpose of the notebook is to show and manipulate a huge dataset collected from Kaggle, then after some *feature engineering* we apply and compare the three State-of-the-Art *ensemble learning* algorithms:

- AdaBoost
- GradientBoost
- XGBoost

Based on statistics we decide which the best one is.
Further conlusions and possible expansions are presented.

pointer to the dataset on Kaggle

See Appendix 7.B. to understand how this image has been generated

2. Dataset Import

In [1]:
```
#import of all libraries and packages
import kagglehub #for downloading automatically the dataset from Kaggle IF it ha
import pandas as pd #data manipulation
import numpy as np #numerical manipulation
import matplotlib.pyplot as plt #data visualization
import matplotlib.patches as mpatches #for distinguishing the dots in the scatte
import sklearn #ML
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder #handling catego
import sys #get the real size of the DataFrames
```

In [2]:
```
#Code to fetch the data
try:
    #Download latest version
    path = kagglehub.dataset_download("yasserh/loan-default-dataset")

    #to check where the dataset has been located
    #print("Path to dataset files:", path)

    loan_data = pd.read_csv(path + '\Loan_Default.csv')

#if something goes wrong (e.g.: connection, wrong path, ...), use the copy of th
except:
    loan_data = pd.read_csv('Loan_Default.csv')
```

2.1. Dataset Description

In [3]:
```
pd.set_option('display.max_columns',
              None) #display all columns
loan_data.head()
```

Out[3]:

	ID	year	loan_limit	Gender	approv_in_adv	loan_type	loan_purpose	Credit_W
0	24890	2019	cf	Sex Not Available	nopre	type1	p1	
1	24891	2019	cf	Male	nopre	type2	p1	
2	24892	2019	cf	Male	pre	type1	p1	
3	24893	2019	cf	Male	nopre	type1	p4	
4	24894	2019	cf	Joint	pre	type1	p1	

This description may be very helpful through all the notebook's reading, so try to keep it in sight.

- **ID:** client loan application id
- **year:** year of loan application
- **loan limit:** indicates whether the loan is conforming (cf) or non-conforming (ncf)
- **Gender:** gender of the applicant (male, female, joint, sex not available)
- **approv_in_adv:** indicates whether the loan was approved in advance (pre, nopre)
- **loan_type:** type of loan (type1, type2, type3) :
  - *Type 1 (Conventional Loans):* Characterized by higher loan amounts, lower LTV ratios, and stronger credit scores, making them a preferred option for well-qualified, lower-risk borrowers.
  - *Type 2 (Government-Backed Loans):* Typically involve lower loan amounts, higher LTV ratios, and moderate credit scores, indicating they are used by borrowers with smaller down payments who benefit from government-backed programs.
  - *Type 3 (Non-Conventional Loans):* Feature moderate loan amounts, the highest LTV ratios, and lower credit scores, often associated with higher-risk products such as jumbo loans or adjustable-rate mortgages.
- **loan_purpose:** purpose of the loan (p1, p2, p3, p4):
  - *p1 (Home Purchase):* Represents loans taken out for primary residences, often displaying moderate credit scores and higher LTV ratios.
  - *p2 (Home Improvement):* Smaller loan amounts used for property renovations, with lower LTV ratios suggesting homeowners are leveraging built-up equity.
  - *p3 (Refinancing):* Applies to homeowners replacing an existing mortgage, characterized by moderate loan amounts and lower LTV ratios, indicating financial stability.

    - *p4 (Investment Property):* Involves larger loan amounts and higher risk profiles, primarily financed through conventional loans due to restrictions on Government-backed funding for investment properties.
- **Credit_Worthiness:** credit worthiness (l1, l2)
- **open_credit:** indicates whether the applicant has any open credit accounts (opc, nopc)
- **business_or_commercial:** indicates whether the loan is for business/commercial purposes (ob/c - business/commercial, nob/c - personal)
- **loan_amount:** amount of money being borrowed
- **rate_of_interest:** interest rate charged on the loan
- **Interest_rate_spread:** difference between the interest rate on the loan and a benchmark interest rate
- **Upfront_charges:** initial charges associated with securing the loan
- **term:** duration of the loan in months
- **Neg_ammortization:** indicates whether the loan allows for negative amortization (neg_amm, not_neg)
- **interest_only:** indicates whether the loan has an interest-only payment option (int_only, not_int)
- **lump_sum_payment:** indicates if a lump sum payment is required at the end of the loan term (lpsm, not_lpsm)
- **property_value:** value of the property being financed
- **construction_type:** type of construction (sb - site built, mh - manufactured home)
- **occupancy_type:** occupancy type (pr - primary residence, sr - secondary residence, ir - investment property)
- **Secured_by:** specifies the type of collateral securing the loan (home, land)
- **total_units:** number of units in the property being financed (1U, 2U, 3U, 4U)
- **income** * **:** applicant's annual income
- **credit_type:** applicant's type of credit (CIB - credit information bureau, CRIF - CIRF credit information bureau, EXP - experian, EQUI - equifax)
- **Credit_Score:** applicant's credit score
- **co-applicant_credit_type:** co-applicant's type of credit (CIB - credit information bureau, EXP - experian)
- **age:** the age of the applicant
- **submission_of_application:** indicates how the application was submitted (to_inst - to institution, not_inst - not to institution)
- **LTV:** loan-to-value ratio, calculated as the loan amount divided by the property value
- **Region:** geographic region where the property is located (North, South, Central, North-East)
- **Security_Type:** type of security or collateral backing the loan (direct, indirect)
- **Status:** indicates whether the loan has been defaulted (1) or not (0)
- **dtir1:** debt-to-income ratio

* The annual income is in thousands of dollars.

In [4]:
```
loan_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148670 entries, 0 to 148669
Data columns (total 34 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   ID                         148670 non-null  int64  
 1   year                       148670 non-null  int64  
 2   loan_limit                 145326 non-null  object 
 3   Gender                     148670 non-null  object 
 4   approv_in_adv              147762 non-null  object 
 5   loan_type                  148670 non-null  object 
 6   loan_purpose               148536 non-null  object 
 7   Credit_Worthiness          148670 non-null  object 
 8   open_credit                148670 non-null  object 
 9   business_or_commercial     148670 non-null  object 
 10  loan_amount                148670 non-null  int64  
 11  rate_of_interest           112231 non-null  float64
 12  Interest_rate_spread       112031 non-null  float64
 13  Upfront_charges            109028 non-null  float64
 14  term                       148629 non-null  float64
 15  Neg_ammortization          148549 non-null  object 
 16  interest_only              148670 non-null  object 
 17  lump_sum_payment           148670 non-null  object 
 18  property_value             133572 non-null  float64
 19  construction_type          148670 non-null  object 
 20  occupancy_type             148670 non-null  object 
 21  Secured_by                 148670 non-null  object 
 22  total_units                148670 non-null  object 
 23  income                     139520 non-null  float64
 24  credit_type                148670 non-null  object 
 25  Credit_Score               148670 non-null  int64  
 26  co-applicant_credit_type   148670 non-null  object 
 27  age                        148470 non-null  object 
 28  submission_of_application  148470 non-null  object 
 29  LTV                        133572 non-null  float64
 30  Region                     148670 non-null  object 
 31  Security_Type              148670 non-null  object 
 32  Status                     148670 non-null  int64  
 33  dtir1                      124549 non-null  float64
dtypes: float64(8), int64(5), object(21)
memory usage: 38.6+ MB
```

Notice: above the `info()` command, gives us a memory usage size that is actually a bit misleading, GitHub issue DataFrame.memory_usage.
That is the reason why we decided to use: `sys.getsizeof()`, since this data will be quite interesting especially for the next sections.

In [5]:
```
sys.getsizeof(loan_data)
```

Out[5]: 207281850

In [6]:
```
loan_data.describe()
```

Out[6]:

	ID	year	loan_amount	rate_of_interest	Interest_rate_spread	Up
count	148670.000000	148670.0	1.486700e+05	112231.000000	112031.000000	1
mean	99224.500000	2019.0	3.311177e+05	4.045476	0.441656	
std	42917.476598	0.0	1.839093e+05	0.561391	0.513043	
min	24890.000000	2019.0	1.650000e+04	0.000000	-3.638000	
25%	62057.250000	2019.0	1.965000e+05	3.625000	0.076000	
50%	99224.500000	2019.0	2.965000e+05	3.990000	0.390400	
75%	136391.750000	2019.0	4.365000e+05	4.375000	0.775400	
max	173559.000000	2019.0	3.576500e+06	8.000000	3.357000	

Since the columns: `ID` and `year` are not meaningful for any purposes, we can drop them since the very beginning and still be compliant to the preprocessing best practices.

In [7]:

```
#since they are not meaningful columns at all, we can drop them for the whole da
loan_data = loan_data.drop('ID', axis=1)
loan_data = loan_data.drop('year', axis=1)
```

In [8]:

```
#to get insights on the categorical data
categorical_values_counts = list()
for cat in loan_data.select_dtypes(include=['object']).columns: #extract the lis
    categorical_values_counts.append(loan_data[f"{cat}"].value_counts())
    categorical_values_counts.append('-'*45) #for spacing them
categorical_values_counts
```

Out[8]:
```
[cf     135348
 ncf      9978
 Name: loan_limit, dtype: int64,
 '-----------------------------------------------',
 Male                 42346
 Joint                41399
 Sex Not Available    37659
 Female               27266
 Name: Gender, dtype: int64,
 '-----------------------------------------------',
 nopre    124621
 pre       23141
 Name: approv_in_adv, dtype: int64,
 '-----------------------------------------------',
 type1    113173
 type2     20762
 type3     14735
 Name: loan_type, dtype: int64,
 '-----------------------------------------------',
 p3    55934
 p4    54799
 p1    34529
 p2     3274
 Name: loan_purpose, dtype: int64,
 '-----------------------------------------------',
 l1    142344
 l2      6326
 Name: Credit_Worthiness, dtype: int64,
 '-----------------------------------------------',
 nopc    148114
 opc        556
 Name: open_credit, dtype: int64,
 '-----------------------------------------------',
 nob/c    127908
 b/c       20762
 Name: business_or_commercial, dtype: int64,
 '-----------------------------------------------',
 not_neg    133420
 neg_amm     15129
 Name: Neg_ammortization, dtype: int64,
 '-----------------------------------------------',
 not_int     141560
 int_only      7110
 Name: interest_only, dtype: int64,
 '-----------------------------------------------',
 not_lpsm    145286
 lpsm          3384
 Name: lump_sum_payment, dtype: int64,
 '-----------------------------------------------',
 sb    148637
 mh        33
 Name: construction_type, dtype: int64,
 '-----------------------------------------------',
 pr    138201
 ir      7340
 sr      3129
 Name: occupancy_type, dtype: int64,
 '-----------------------------------------------',
 home    148637
 land        33
```

```
Name: Secured_by, dtype: int64,
'---------------------------------------------',
1U    146480
2U      1477
3U       393
4U       320
Name: total_units, dtype: int64,
'---------------------------------------------',
CIB     48152
CRIF    43901
EXP     41319
EQUI    15298
Name: credit_type, dtype: int64,
'---------------------------------------------',
CIB    74392
EXP    74278
Name: co-applicant_credit_type, dtype: int64,
'---------------------------------------------',
45-54    34720
35-44    32818
55-64    32534
65-74    20744
25-34    19142
>74       7175
<25       1337
Name: age, dtype: int64,
'---------------------------------------------',
to_inst     95814
not_inst    52656
Name: submission_of_application, dtype: int64,
'---------------------------------------------',
North         74722
south         64016
central        8697
North-East     1235
Name: Region, dtype: int64,
'---------------------------------------------',
direct      148637
Indriect        33
Name: Security_Type, dtype: int64,
'---------------------------------------------']
```

2.2. Missing Values

We can see that the biggest issues in terms of missing values come from: `Upfront_charges` , `Interest_rate_spread` , `rate_of_interest` . we could have some criticalities also on other features but still negligible, even though we have to keep in mind that the NaN are spread out as:

Numerical

- 39642 Upfront_charges
- 36639 Interest_rate_spread
- 36439 rate_of_interest
- 24121 dtir1
- 15098 LTV

- 15098 property_value
- 9150 income
- 41 term

Categorical

- 3344 loan_limit
- 908 approv_in_adv
- 200 age
- 200 submission_of_application
- 136 loan_purpose
- 121 Neg_ammortization

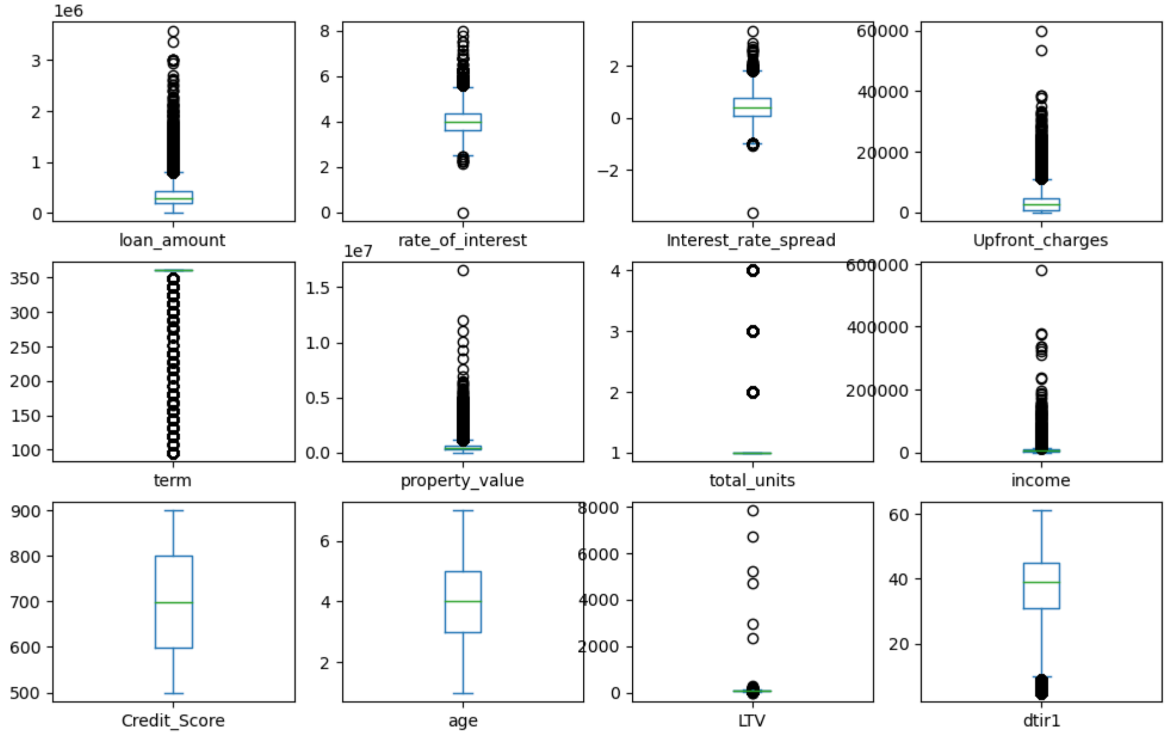
In the next block codes we will see how to approach this problem.

2.3. Numerical and Ordinal Data

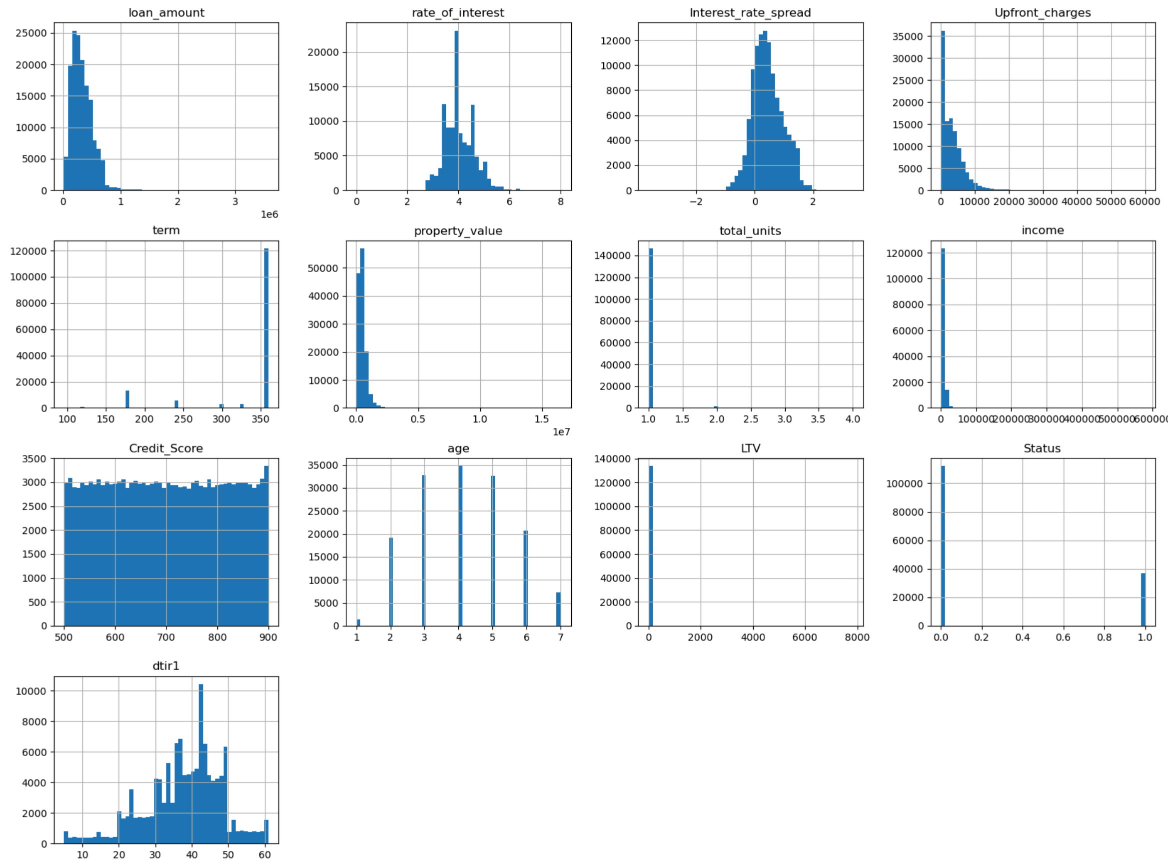
In [9]:
```
#converting 'total_units' and 'age' categorical data into ordinal
ordinal_encoder = OrdinalEncoder()

#just for the total_units and age features, since it makes sense a concept of or
total_units_cat = loan_data[['total_units']] #take the column we want to encode
total_units_encoded = ordinal_encoder.fit_transform(total_units_cat) + 1 #we shi
loan_data['total_units'] = total_units_encoded #replace the column in the datase

age_mapping = {
    '<25':1,
    '25-34':2,
    '35-44':3,
    '45-54':4,
    '55-64':5,
    '65-74':6,
    '>74':7
}
loan_data['age'] = loan_data['age'].map(age_mapping) #replace the column in the
```

In [10]:
```
#list containing all the numerical + ordinal features plus the target
numerical_ordinal_columns = [col for col in loan_data.columns if col not in loan
#list with only the numerical + ordinal features
numerical_ordinal_features = numerical_ordinal_columns.copy()
numerical_ordinal_features.remove('Status')
```

In [11]:
```
#boxplots
loan_data[numerical_ordinal_features].plot(kind='box',
                               subplots=True, #distinct box plots for each featu
                               layout= (int(len(numerical_ordinal_features) ** 0
                               figsize=((int(len(numerical_ordinal_features) **
                               sharex=False, #each subplot uses a different x sc
                               sharey=False #each subplot uses a different y sca
                              )
plt.show()
```



In [12]:
```
#plot the histograms
loan_data.hist(bins=50, #number of bins to encapsulate the data
               figsize=(20,15)
              );
```



Notice: There are some capped values, specifically concerning:

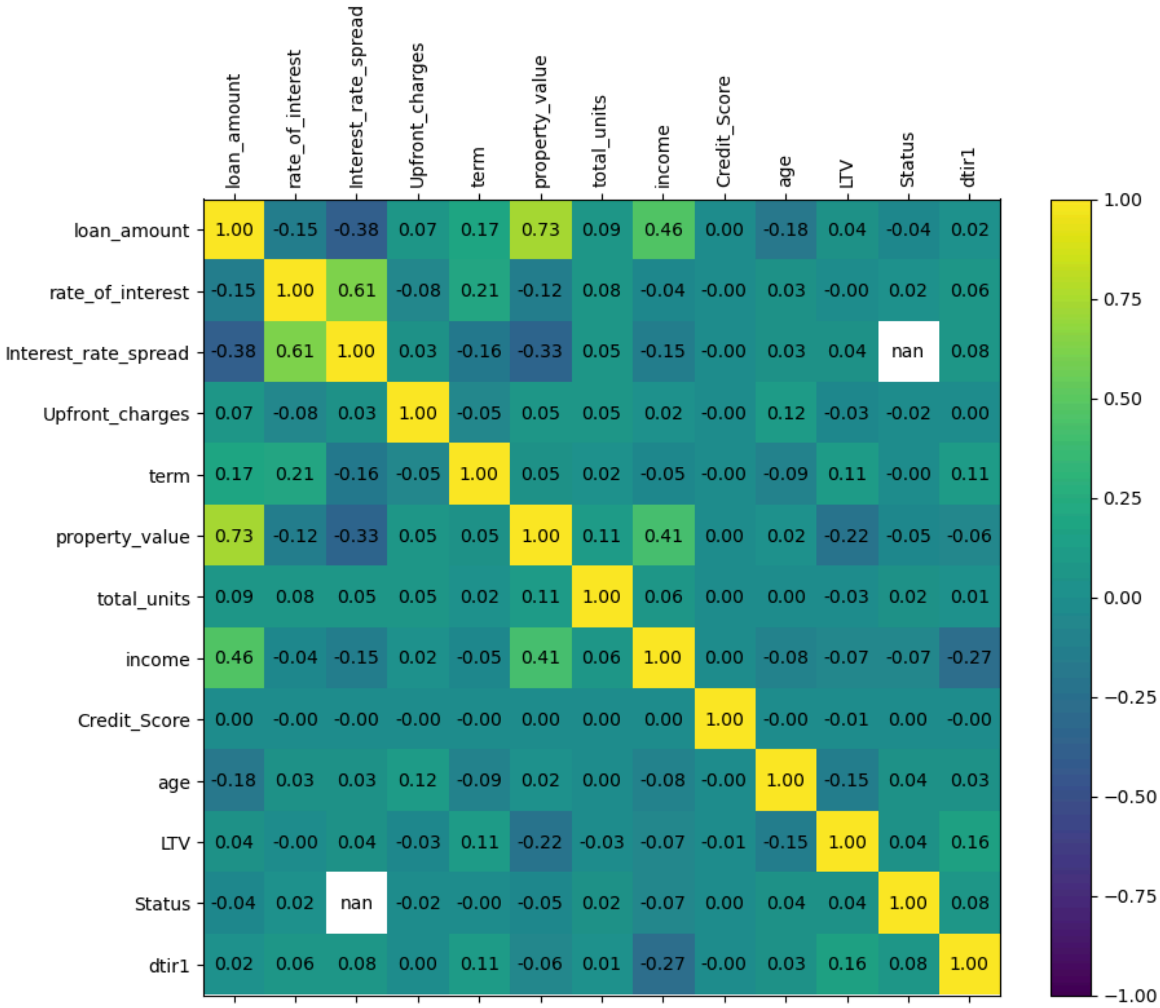
- term
- dtir1
- Credit_Score

`term` feature for sure is capped at: 360, probably also: `dtir1` and `Credit_Sore`, but with a lower impact.
In any case, since they are not our target attribute, this is not a big issue and we can actually ignore it.

In [13]:
```
loan_data.corr()["Status"].sort_values(ascending=False) #correlation related to
```

Out[13]:
```
Status                  1.000000
dtir1                   0.078083
age                     0.044600
LTV                     0.038895
total_units             0.023800
rate_of_interest        0.022957
Credit_Score            0.004004
term                   -0.000240
Upfront_charges        -0.019138
loan_amount            -0.036825
property_value         -0.048864
income                 -0.065119
Interest_rate_spread         NaN
Name: Status, dtype: float64
```

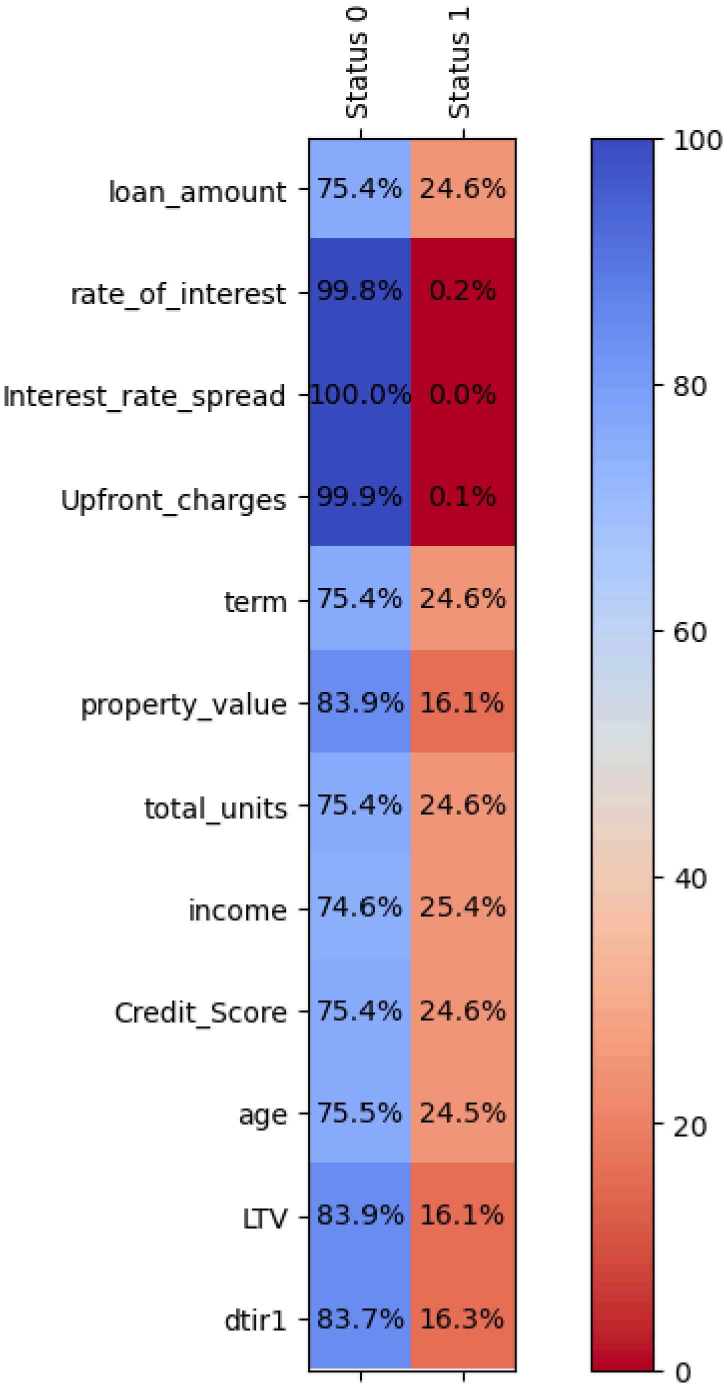
In [14]:
```
#compute the correlations
correlations = loan_data.corr()

#plot
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111)
cax = ax.matshow(correlations,
                 vmin=-1,
                 vmax=1)
fig.colorbar(cax)
ticks = np.arange(len(numerical_ordinal_columns))
ax.set_xticks(ticks)
ax.set_yticks(ticks)
ax.set_xticklabels(numerical_ordinal_columns,
                   rotation=90) #to see the column lables clearly
ax.set_yticklabels(numerical_ordinal_columns)

# Annotate cells with correlation values
for i in range(len(correlations)):
    for j in range(len(correlations)):
        value = correlations.iloc[i, j]
        ax.text(j,
                i,
                f'{value:.2f}',
                va='center',
                ha='center',
                color='black')

plt.show()
```



Notice: the correlation coefficient between `Status` and `interest_rate_spread` returns not a number, this is due to the fact that the latter feature is actually compromised, (we will see in few block codes how), furthermore the two standard deviations are too low.

In [15]:
```python
#showing the percentages of data grouped by target values
def compute_feature_target_percentages(df, features, target='Status'):
    rows = []
    for feat in features:
        #Discharge NaN values for feature and target
        feature_data = df[[feat, target]].dropna()

        #total valid values for this feature
        total = len(feature_data)

        #How many of these are target=0 and target=1
        count_0 = feature_data[feature_data[target] == 0].shape[0]
        count_1 = feature_data[feature_data[target] == 1].shape[0]

        #we translate the above data into percentages
        pct_0 = (count_0 / total) * 100 if total > 0 else 0
        pct_1 = (count_1 / total) * 100 if total > 0 else 0

        rows.append({'feature': feat,
                     'target=0 %': pct_0,
                     'target=1 %': pct_1})
    return pd.DataFrame(rows)
```

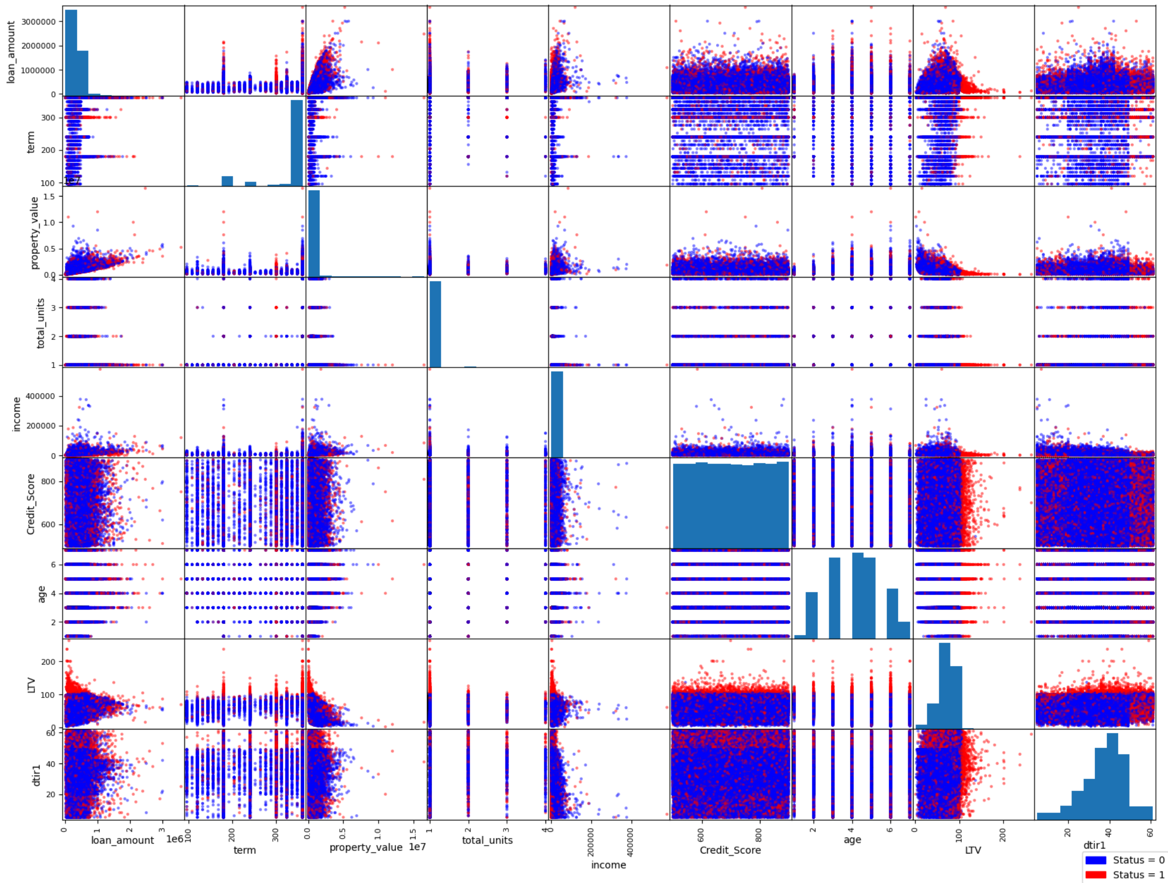
```python
result = compute_feature_target_percentages(loan_data, numerical_ordinal_feature

#Extract data and labels
data_matrix = result[['target=0 %',
                      'target=1 %']].to_numpy()
feature_labels = result['feature'].tolist()
target_labels = ['Status 0',
                 'Status 1']

#Plot
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111)
cax = ax.matshow(data_matrix,
                 vmin=0,
                 vmax=100,
                 cmap='coolwarm_r')
fig.colorbar(cax)

#Ticks
ax.set_xticks(np.arange(len(target_labels)))
ax.set_yticks(np.arange(len(feature_labels)))
ax.set_xticklabels(target_labels,
                   rotation=90)
ax.set_yticklabels(feature_labels)

#Values
for i in range(data_matrix.shape[0]):
    for j in range(data_matrix.shape[1]):
        value = data_matrix[i, j]
        ax.text(j,
                i, f'{value:.1f}%',
                va='center',
                ha='center',
                color='black')
plt.show()
```



Due to what we saw in section: 2.2. Missing Values, we can say that: `rate_of_interest`, `Interest_rate_spread` and `Upfront_charges`, when they are not missing they are always with `Status=0`, hence we must drop them entirely from the whole dataset, because they are not meaningful.

In [16]:
```
#discharge the not desired columns
data = loan_data.drop(['rate_of_interest',
                       'Interest_rate_spread',
                       'Upfront_charges'],
                      axis=1)

#discharge the rows without elemnts
data = data.dropna()

#prepare the colors based on the Status (0 o 1)
color_map = {0: 'blue',
```

```
            1: 'red'
           }
colors = data['Status'].map(color_map)

# Plot dello scatter_matrix
pd.plotting.scatter_matrix(data.drop(columns=['Status']),
                            figsize=(20, 15),
                            diagonal='hist',
                            color=colors,
                            alpha=0.5
            )

#patch for the legend
legend_handles = [mpatches.Patch(color='blue',
                                label='Status = 0'
                               ),
                  mpatches.Patch(color='red',
                                label='Status = 1'
                               )
                 ]

plt.legend(handles=legend_handles,
           loc='upper right',
           bbox_to_anchor=(1.15, -0.3)
          )
plt.show()
```



Notice: grouping dots based on the the target condition is very helpful for data visualization, there is a Python library for data visualization Seaborn * that allows to plot directly these types of graphs in a very straightforward way, but it is a more computational expensive tool, that in cases of big datasets can slow down the process a lot, this is the reason why we implemented the solution in `matplotlib` in a longer way.

*: Here is a project of mine with an implention using Seaborn

General Categorical and Binary Categorical Data

Notice: in the following block of code, we decided to transform manually the binary categorical data in binary ordinal data, assigning 0 or 1 with the following concept: 0 whether the associated variable has lower probability of deafult, 1 viceversa. (where possible).

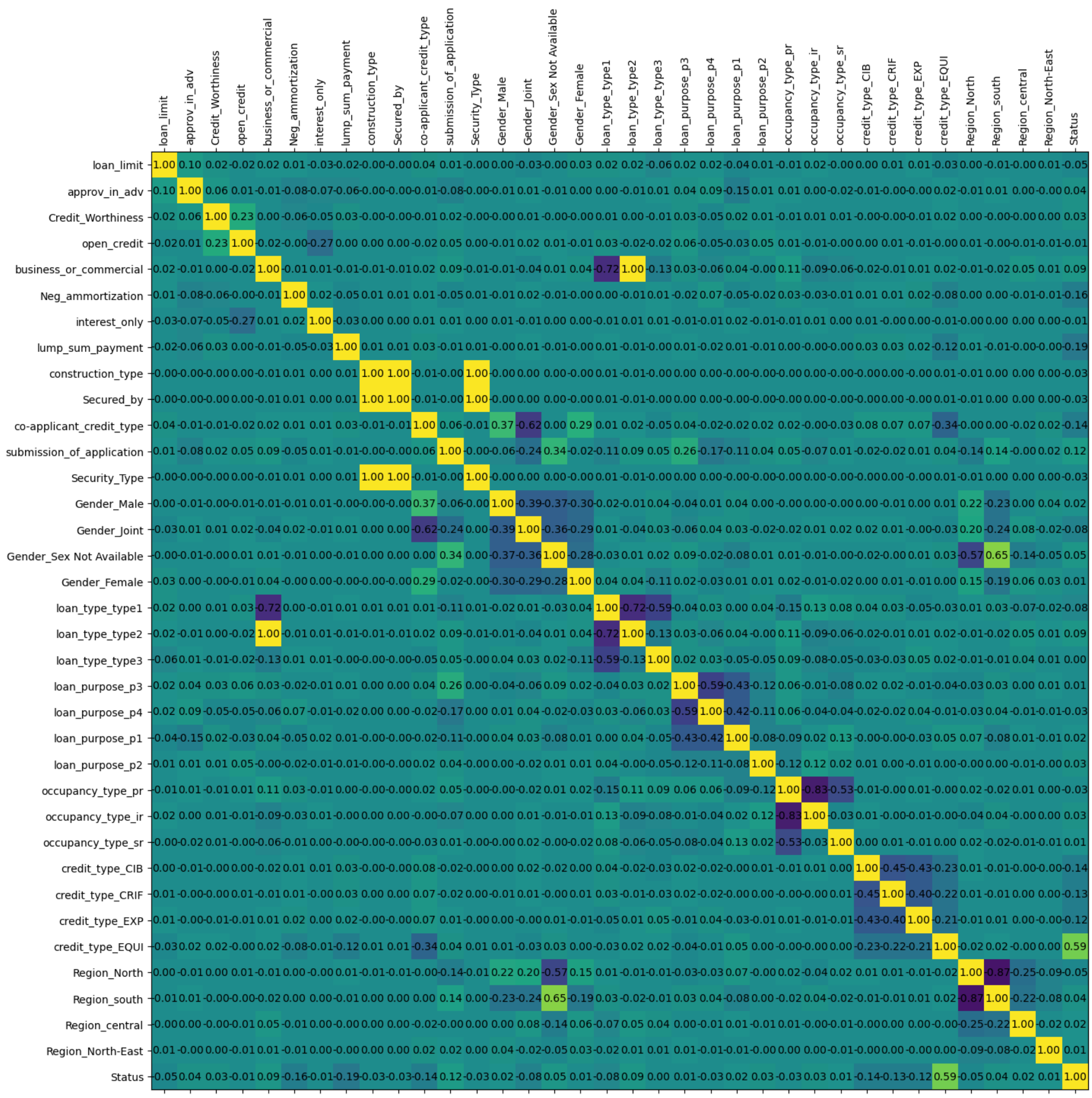
In [17]:
```
#convert all the categorical binary columns to ordinal binary
loan_data['loan_limit'] = loan_data['loan_limit'].map({'cf': 1,'ncf': 0})
loan_data['approv_in_adv'] = loan_data['approv_in_adv'].map({'nopre': 1,'pre': 0
loan_data['Credit_Worthiness'] = loan_data['Credit_Worthiness'].map({'l2': 1,'l1
loan_data['open_credit'] = loan_data['open_credit'].map({'opc': 1,'nopc': 0})
loan_data['business_or_commercial'] = loan_data['business_or_commercial'].map({'
loan_data['Neg_ammortization'] = loan_data['Neg_ammortization'].map({'not_neg':
loan_data['interest_only'] = loan_data['interest_only'].map({'not_int': 1,'int_c
loan_data['lump_sum_payment'] = loan_data['lump_sum_payment'].map({'not_lpsm': 1
loan_data['construction_type'] = loan_data['construction_type'].map({'sb': 1,'mh
loan_data['Secured_by'] = loan_data['Secured_by'].map({'home': 1,'land': 0})
loan_data['co-applicant_credit_type'] = loan_data['co-applicant_credit_type'].ma
loan_data['submission_of_application'] = loan_data['submission_of_application'].
loan_data['Security_Type'] = loan_data['Security_Type'].map({'direct': 1,'Indrie
```

In [18]:
```
#list of categorical non-binary columns
cat_columns = ['Gender',
               'loan_type',
               'loan_purpose',
               'occupancy_type',
               'credit_type',
               'Region']

# Loop through each column
for col in cat_columns:
    encoder = OneHotEncoder(sparse=False,
                            handle_unknown='ignore')  #new encoder for each
    encoded_array = encoder.fit_transform(loan_data[[col]])
    encoded_df = pd.DataFrame(encoded_array,
                              columns=encoder.get_feature_names_out([col]),
                              index=loan_data.index)

    # Drop original column and concatenate the encoded DataFrame
    loan_data.drop(columns=[col],
                   inplace=True)
    loan_data = pd.concat([loan_data,
                           encoded_df
                          ],
                          axis=1)
```

In [19]:
```
#list of all categorical columns
categorical_columns = [
                      'loan_limit',
                      'approv_in_adv',
```

```
                          'Credit_Worthiness',
                          'open_credit',
                          'business_or_commercial',
                          'Neg_ammortization',
                          'interest_only',
                          'lump_sum_payment',
                          'construction_type',
                          'Secured_by',
                          'co-applicant_credit_type',
                          'submission_of_application',
                          'Security_Type',
                          'Gender_Male', 'Gender_Joint', 'Gender_Sex Not Available',
                          'loan_type_type1', 'loan_type_type2', 'loan_type_type3',
                          'loan_purpose_p3', 'loan_purpose_p4', 'loan_purpose_p1', '
                          'occupancy_type_pr', 'occupancy_type_ir', 'occupancy_type_
                          'credit_type_CIB', 'credit_type_CRIF', 'credit_type_EXP',
                          'Region_North', 'Region_south', 'Region_central', 'Region_
                          'Status'
                        ]


categorical_features = categorical_columns.copy()
#list of all categorical features
categorical_features.remove('Status')
```

In [20]:
```
binary_correlation = loan_data[categorical_columns].corr()

#plot
fig = plt.figure(figsize=(20, 16))
ax = fig.add_subplot(111)
cax = ax.matshow(binary_correlation,
                 vmin=-1,
                 vmax=1)

ticks = np.arange(len(categorical_columns))
ax.set_xticks(ticks)
ax.set_yticks(ticks)
ax.set_xticklabels(categorical_columns,
                   rotation=90) #to see the column lables clearly
ax.set_yticklabels(categorical_columns)

#annotate cells with correlation values
for i in range(len(binary_correlation)):
    for j in range(len(binary_correlation)):
        value = binary_correlation.iloc[i, j]
        ax.text(j,
                i,
                f'{value:.2f}',
                va='center',
                ha='center',
                color='black')

plt.show()
```



Pandas `dataframe.corr()` method computes the Pearson's correlation coefficient:

$$\rho_{x,y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$$

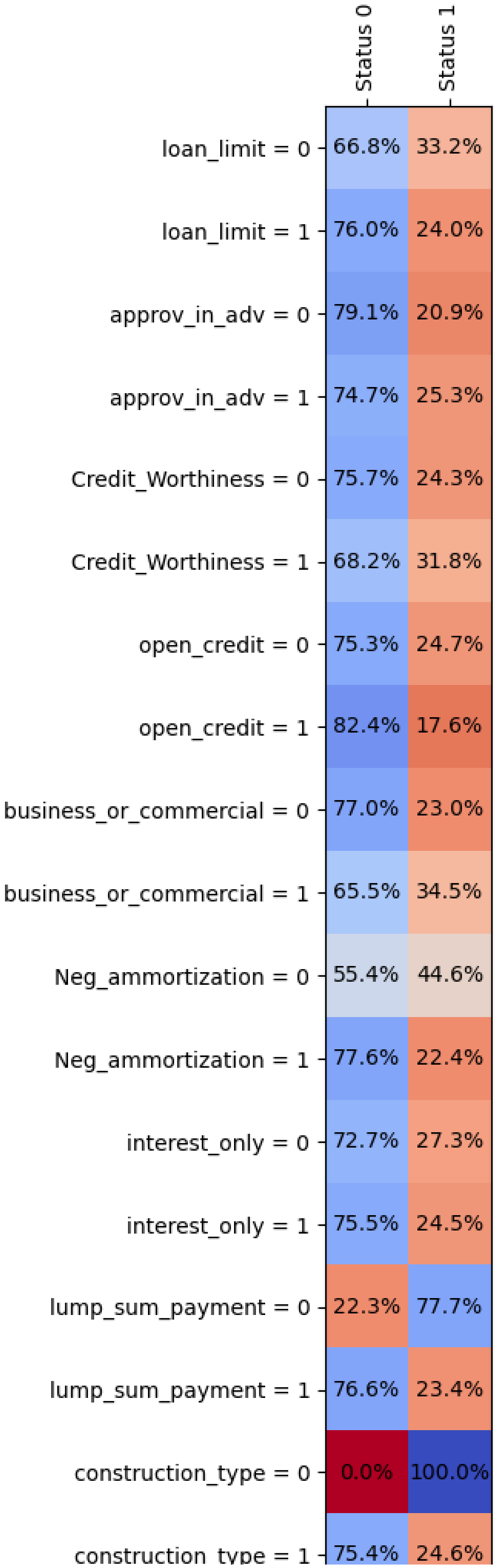
where:

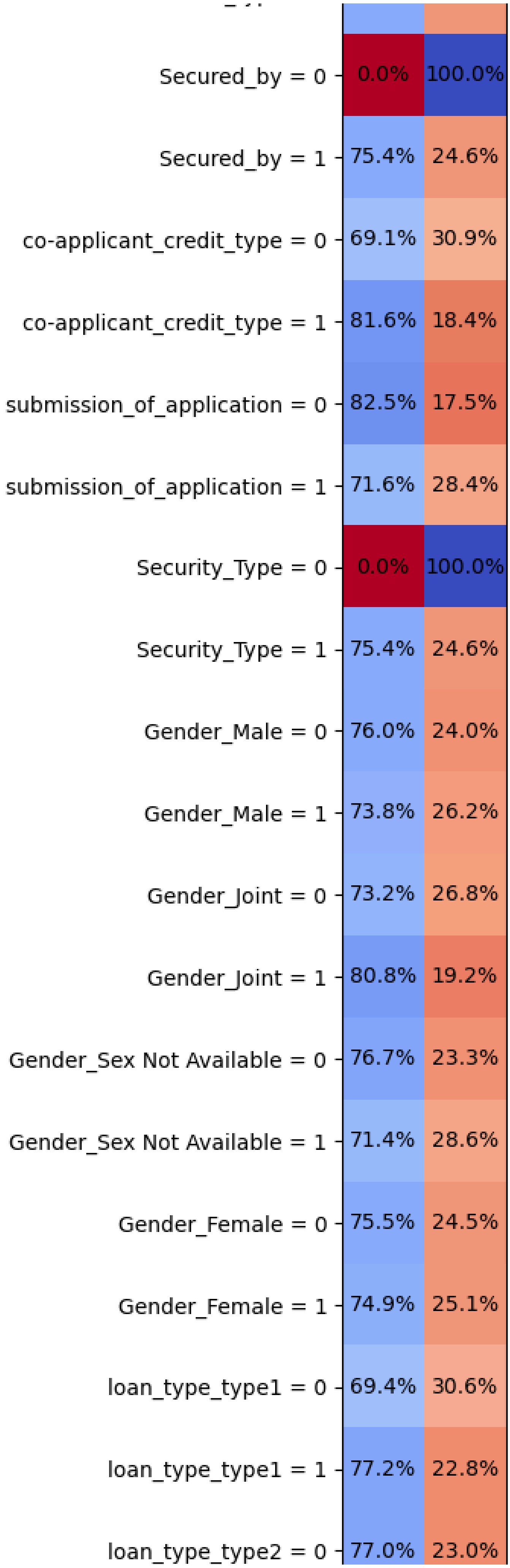
- cov is the covariance computed as: $cov(X,Y) = \mathbb{E}[(X - \mu_X)(Y - \mu_Y)]$
- σ_X is the standard deviation of X
- σ_Y is the sandard deviation of Y

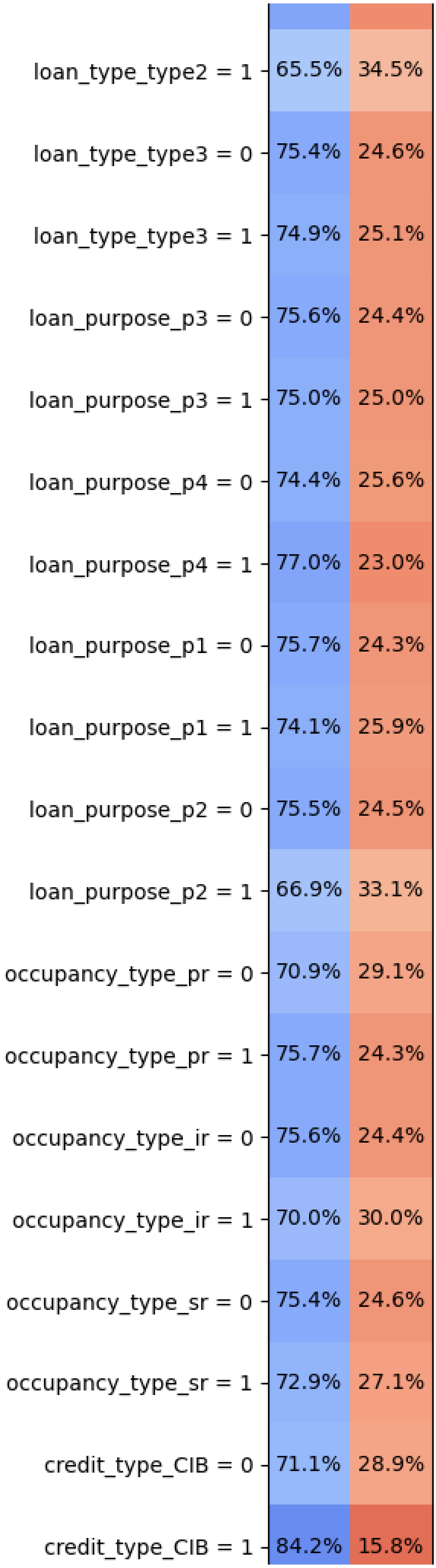
In the case of binary variables that assume only values in $\{0, 1\}$, using Pearson's coefficient is a possible way to gain an overview of the correlation between variables, but keep in mind that in literature there many other methods to achieve so.

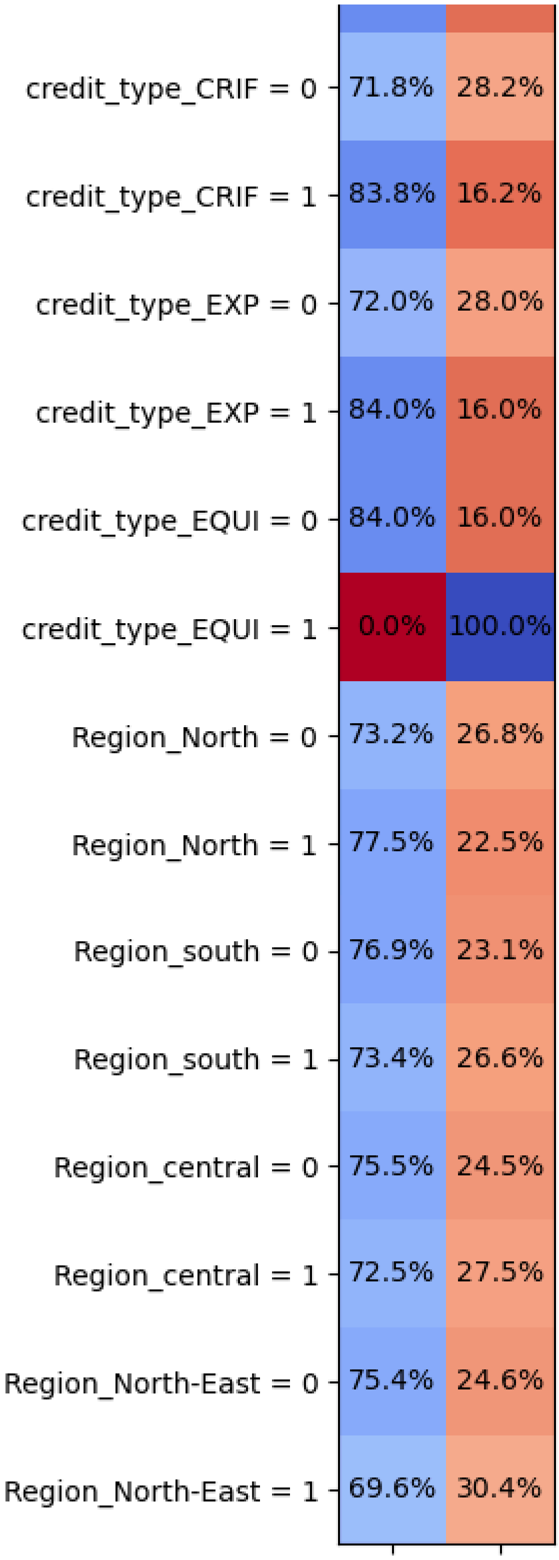
In [21]:
```
def compute_binary_feature_target_distribution(df, binary_features, target='Stat
    rows = []
    for feat in binary_features:
        for val in [0, 1]:
            #filter for feature value
            subset = df[(df[feat] == val) & (df[target].isin([0, 1]))]
```

```
            total = len(subset)
            count_0 = subset[subset[target] == 0].shape[0]
            count_1 = subset[subset[target] == 1].shape[0]

            pct_0 = (count_0 / total) * 100 if total > 0 else 0
            pct_1 = (count_1 / total) * 100 if total > 0 else 0

            rows.append({
                'feature': feat,
                'value': val,
                'Status 0 %': pct_0,
                'Status 1 %': pct_1
            })
    return pd.DataFrame(rows)


result_bin = compute_binary_feature_target_distribution(loan_data, categorical_f

#extract data for heatmap
data_matrix = result_bin[['Status 0 %', 'Status 1 %']].to_numpy()
row_labels = [f"{f} = {v}" for f, v in zip(result_bin['feature'], result_bin['va
col_labels = ['Status 0', 'Status 1']

#plot
fig = plt.figure(figsize=(15, len(row_labels) * 0.7))
ax = fig.add_subplot(111)
cax = ax.matshow(data_matrix,
                 vmin=0,
                 vmax=100,
                 cmap='coolwarm_r')
# ticks
ax.set_xticks(np.arange(len(col_labels)))
ax.set_yticks(np.arange(len(row_labels)))
ax.set_xticklabels(col_labels, rotation=90)
ax.set_yticklabels(row_labels)

#annotate values
for i in range(data_matrix.shape[0]):
    for j in range(data_matrix.shape[1]):
        value = data_matrix[i, j]
        ax.text(j,
                i,
                f'{value:.1f}%',
                va='center',
                ha='center',
                color='black')

plt.show()
```


Status 0
Status 1
loan_limit = 0
66.8%
33.2%
loan_limit = 1
76.0%
24.0%
approv_in_adv = 0
79.1%
20.9%
approv_in_adv = 1
74.7%
25.3%
Credit_Worthiness = 0
75.7%
24.3%
Credit_Worthiness = 1
68.2%
31.8%
open_credit = 0
75.3%
24.7%
open_credit = 1
82.4%
17.6%
business_or_commercial = 0
77.0%
23.0%
business_or_commercial = 1
65.5%
34.5%
Neg_ammortization = 0
55.4%
44.6%
Neg_ammortization = 1
77.6%
22.4%
interest_only = 0
72.7%
27.3%
interest_only = 1
75.5%
24.5%
lump_sum_payment = 0
22.3%
77.7%
lump_sum_payment = 1
76.6%
23.4%
construction_type = 0
0.0%
100.0%
construction_type = 1
75.4%
24.6%


Secured_by = 0
0.0%
100.0%
Secured_by = 1
75.4%
24.6%
co-applicant_credit_type = 0
69.1%
30.9%
co-applicant_credit_type = 1
81.6%
18.4%
submission_of_application = 0
82.5%
17.5%
submission_of_application = 1
71.6%
28.4%
Security_Type = 0
0.0%
100.0%
Security_Type = 1
75.4%
24.6%
Gender_Male = 0
76.0%
24.0%
Gender_Male = 1
73.8%
26.2%
Gender_Joint = 0
73.2%
26.8%
Gender_Joint = 1
80.8%
19.2%
Gender_Sex Not Available = 0
76.7%
23.3%
Gender_Sex Not Available = 1
71.4%
28.6%
Gender_Female = 0
75.5%
24.5%
Gender_Female = 1
74.9%
25.1%
loan_type_type1 = 0
69.4%
30.6%
loan_type_type1 = 1
77.2%
22.8%
loan_type_type2 = 0
77.0%
23.0%


loan_type_type2 = 1
65.5%
34.5%
loan_type_type3 = 0
75.4%
24.6%
loan_type_type3 = 1
74.9%
25.1%
loan_purpose_p3 = 0
75.6%
24.4%
loan_purpose_p3 = 1
75.0%
25.0%
loan_purpose_p4 = 0
74.4%
25.6%
loan_purpose_p4 = 1
77.0%
23.0%
loan_purpose_p1 = 0
75.7%
24.3%
loan_purpose_p1 = 1
74.1%
25.9%
loan_purpose_p2 = 0
75.5%
24.5%
loan_purpose_p2 = 1
66.9%
33.1%
occupancy_type_pr = 0
70.9%
29.1%
occupancy_type_pr = 1
75.7%
24.3%
occupancy_type_ir = 0
75.6%
24.4%
occupancy_type_ir = 1
70.0%
30.0%
occupancy_type_sr = 0
75.4%
24.6%
occupancy_type_sr = 1
72.9%
27.1%
credit_type_CIB = 0
71.1%
28.9%
credit_type_CIB = 1
84.2%
15.8%



3. Data Preprocessing

So far we have handled the whole dataset manually in order to better manipulate it and visualize relevant characteristics.
In machine learning, it is way better to use **pipelines**, which are automated and organized series of steps that orchestrate the entire machine learning lifecycle, from data collection and preprocessing to model training, validation, and deployment.

In [22]:
```
#import of packages and libraries useful for fitting, transforming hence pipelin
from sklearn.pipeline import Pipeline
```

```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import FunctionTransformer
from sklearn.impute import SimpleImputer
import warnings #for ignoring the warnings while the models run
```

In [23]:
```
#while running some code blocks we encounter some useless warnings that in produ
#ignore the FutureWarning
warnings.filterwarnings("ignore", category=FutureWarning)
#ignore the UserWarning
#warnings.filterwarnings("ignore", category=UserWarning)
```

In [24]:
```
#features are now only numerical and ordinal, the number of them increased, as t
loan_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148670 entries, 0 to 148669
Data columns (total 49 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   loan_limit                 145326 non-null  float64
 1   approv_in_adv              147762 non-null  float64
 2   Credit_Worthiness          148670 non-null  int64  
 3   open_credit                148670 non-null  int64  
 4   business_or_commercial     148670 non-null  int64  
 5   loan_amount                148670 non-null  int64  
 6   rate_of_interest           112231 non-null  float64
 7   Interest_rate_spread       112031 non-null  float64
 8   Upfront_charges            109028 non-null  float64
 9   term                       148629 non-null  float64
 10  Neg_ammortization          148549 non-null  float64
 11  interest_only              148670 non-null  int64  
 12  lump_sum_payment           148670 non-null  int64  
 13  property_value             133572 non-null  float64
 14  construction_type          148670 non-null  int64  
 15  Secured_by                 148670 non-null  int64  
 16  total_units                148670 non-null  float64
 17  income                     139520 non-null  float64
 18  Credit_Score               148670 non-null  int64  
 19  co-applicant_credit_type   148670 non-null  int64  
 20  age                        148470 non-null  float64
 21  submission_of_application  148470 non-null  float64
 22  LTV                        133572 non-null  float64
 23  Security_Type              148670 non-null  int64  
 24  Status                     148670 non-null  int64  
 25  dtir1                      124549 non-null  float64
 26  Gender_Female              148670 non-null  float64
 27  Gender_Joint               148670 non-null  float64
 28  Gender_Male                148670 non-null  float64
 29  Gender_Sex Not Available   148670 non-null  float64
 30  loan_type_type1            148670 non-null  float64
 31  loan_type_type2            148670 non-null  float64
 32  loan_type_type3            148670 non-null  float64
 33  loan_purpose_p1            148670 non-null  float64
 34  loan_purpose_p2            148670 non-null  float64
 35  loan_purpose_p3            148670 non-null  float64
 36  loan_purpose_p4            148670 non-null  float64
 37  loan_purpose_nan           148670 non-null  float64
 38  occupancy_type_ir          148670 non-null  float64
 39  occupancy_type_pr          148670 non-null  float64
 40  occupancy_type_sr          148670 non-null  float64
 41  credit_type_CIB            148670 non-null  float64
 42  credit_type_CRIF           148670 non-null  float64
 43  credit_type_EQUI           148670 non-null  float64
 44  credit_type_EXP            148670 non-null  float64
 45  Region_North               148670 non-null  float64
 46  Region_North-East          148670 non-null  float64
 47  Region_central             148670 non-null  float64
 48  Region_south               148670 non-null  float64
dtypes: float64(37), int64(12)
memory usage: 55.6 MB
```

Notice: the memory usage given directly by Pandas has increased by 17+ MB, due to the transformation into ordinal data.

In order to have a clearer idea of the actual memory used, as already mentioned in section 2.1. Dataset Description, we should use `sys.gestsizeof()` as below.

In [25]:
```
#the result is in bytes
sys.getsizeof(loan_data)
```

Out[25]: 58278784

The number shows that actually the memory used is way less with respect to the beginning, this is due to the fact that integer objects take less memory compared to string objects.

Since we want embrace the *pipeline* approach we drop the previous manually manipulated dataset, and we take a new one.

In [26]:
```
try:
    loan_data = pd.read_csv(path + '\Loan_Default.csv')

except:
    loan_data = pd.read_csv('Loan_Default.csv') #if something goes wrong. use th
```

In the following code block we apply column removal, based on the characteristics that emerged in sections 2.3. and 2.4..
It is important to point out that the column removal has been applied on the whole dataset, because the criticalities on those features were so strong that allowed us to procede without compromising the effectiveness of the test set.
In order to better explain how the decisions have been taken we divide the data into numerical and categorical:

- **Numerical**:
  - **`ID`**, **`year`**: have been removed since they did not bring any relevant information for predictive purposes.
  - **`rate_of_interest`**, **`Interest_rate_spread`**, **`Upfront_charges`**: have been removed, because they were strongly compromised, they have the highest missing values and furthermore whenever they are not missing, the target is nearly always: **`Status=0`**
- **Categorical**:
  - **`business_or_commercial`**: has been removed because from the correlation matrix emerges that is strongly correlated to **`loan_type_2`**
  - **`Secured_by`**, **`Security_Type`**: have been removed because from the correlation matrix emerged that they were strongly correlated to each other and to **`construction_type`**, furthermore whenever **`Secured_by=land`** or **`Security_Type=indirect`** the target always assumes: **'Status=1'**
  - The feature **`credit_type`** when assumes the value **`EQUI`** the target is always **`Status=1`**, hence it does not bring any relevant information. This column has been transformed with one-hot encoding, because it can assume four different

values, hence we decided to set it to `NaN` whenever it assumes `EQUI`, this is due to the way we handle missing values (we will see it in few code blocks).

It is important to point out that the threshold of correlation by which we decided to remove columns has been set to 0.90 since decision trees and even better ensemble learning algorithms are quite robust when they face correlation.

In [27]:
```
#removing the non-relevant features
loan_data = loan_data.drop([#numerical
                            'ID',
                            'year',
                            'rate_of_interest',
                            'Interest_rate_spread',
                            'Upfront_charges',
                             #categorical
                            'Security_Type',
                            'Secured_by',
                            'business_or_commercial',
                               ],
                               axis=1
                              )

#setting to NaN the non-relevant columns
loan_data.loc[loan_data['credit_type'] == 'EQUI', 'credit_type'] = np.nan
```

In [28]:
```
#map for the ordinal mapping of age groups
age_mapping = {'<25': 1,
                '25-34': 2,
                '35-44': 3,
                '45-54': 4,
                '55-64': 5,
                '65-74': 6,
                '>74': 7
                }
#map for the ordinal mapping of the total_units
total_units_mapping = {'1U': 1,
                    '2U': 2,
                    '3U': 3,
                    '4U': 4
                }

#list of the names of the ordinal features
ordinal_features = ['age',
                'total_units',
               ]
#list of the names of the categorical features where we will apply OneHotEncodin
onehot_features = ['loan_limit',
               'approv_in_adv',
               'Credit_Worthiness',
               'open_credit',
               'Neg_ammortization',
               'interest_only',
               'lump_sum_payment',
               'construction_type',
               'co-applicant_credit_type',
               'submission_of_application',
               'Gender',
               'loan_type',
```

```
                'loan_purpose',
                'occupancy_type',
                'credit_type',
                'Region',
               ]
#list of the numerical features
numerical_features = ['loan_amount',
                      'term',
                      'property_value',
                      'income',
                      'Credit_Score',
                      'LTV',
                      'dtir1'
                     ]
```

In [29]:
```
# Categorical one-hot
cat_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore')) #we ignore the unknown ca
])

# Numerical
num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='median'))
])

# Ordinal
#age ordinal pipeline
age_pipeline = Pipeline([
    ('mapper', FunctionTransformer(
        lambda x: x.iloc[:, 0].map(age_mapping).to_frame(), #anonymous function,
        validate=False)),                                   #the mapping we have
    ('imputer', SimpleImputer(strategy='most_frequent'))
])
#total_units ordinal pipeline
total_units_pipeline = Pipeline([
    ('mapper', FunctionTransformer(
        lambda x: x.iloc[:, 0].map(total_units_mapping).to_frame(),
        validate=False)), #since we want to work with DataFrame we must set vali
    ('imputer', SimpleImputer(strategy='most_frequent'))
])

#Full pipeline, merging all type of data
preprocessor = ColumnTransformer([
    ('cat_onehot', cat_pipeline, onehot_features),
    ('num', num_pipeline, numerical_features),
    ('age_ord', age_pipeline, ['age']), #since ColumnTransformer apply transform
    ('units_ord', total_units_pipeline, ['total_units']),

])
```

In [30]:
```
#memory usage in bytes of the processed dataset with the pipeline
sys.getsizeof(preprocessor.fit_transform(loan_data))
```

Out[30]: 59468120

Notice: now that we have applied the `preprocessor` (that is a pipeline for column transformation) to the original dataset, we see that the memory used is again way less

with respect to the original one, buth slightly more compared to the manually transformed dataset obtained at the end of section 2. (that contained 49 columns), even though now we have removed nine features.
This is simply due to the fact that with the `preprocessor` the one-hot encoding is fully applied to all categorical data (except: `age` , `total_units`), resulting with 50 columns.

4. Training the Models

In [31]:
```
#import of all libraries and packages
from sklearn.model_selection import GridSearchCV, StratifiedKFold, train_test_sp
from xgboost import XGBClassifier #XGBoostClassifier
from sklearn.ensemble import AdaBoostClassifier #AdaBoost
from sklearn.tree import DecisionTreeClassifier #for AdaBoost
from sklearn.ensemble import GradientBoostingClassifier #GradientBoost
#instead of Joblib, we use Cloudpickle, since it is able to save also the lambda
import cloudpickle #for saving the models
#for getting all the metrics and displaying them
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, average_pr
import time #for counting the amount of time it takes for the algorithm to run
```

In [32]:
```
#for converting seconds into readable format, for the runtime
def convert_time(seconds):
    seconds = seconds % (24 * 3600)
    hour = seconds // 3600
    seconds %= 3600
    minutes = seconds // 60
    seconds %= 60

    return "%d:%02d:%02d" % (hour, minutes, seconds)
```

In [33]:
```
#Separate features and target
X = loan_data.drop(columns=['Status'])
y = loan_data['Status']

#split the dataset into train and test sets, with a proportion of 90-10%, since
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.10,
                                                    random_state=42)


#stratified K-Fold for balanced class distribution over the target
strat_kfold = StratifiedKFold(n_splits=5, #number of folds
                              shuffle=True, #before creating the fold, it shuffl
                              random_state=42, #footnote following block
                             )
```

Notice: our dataset is a bit unbalanced in terms of target values, since the samples with `Status=0` are way more than the ones with `Status=1` , this can lead to slighlty biased models. In order to overcome this issue we tweak some models' paramaters accordingly.

This practice is especially useful for improving the `recall` of our models.

$$Recall = \frac{\text{True Positives}}{\text{True Positives } + \text{ False Negatives}}$$

As opposed to:

$$Precision = \frac{\text{True Positives}}{\text{True Positives } + \text{ False Positives}}$$

Since credit institutes tend to be risk adverse in front of potential loan clients, they ***prefer recall over precision***, and this is the way we approach our three following models.

`random_state = 42` is an inside joke of machine learning base on the famous book: *The Hitchhiker's Guide to the Galaxy, Douglas Adams*, see

4.1. eXtreme Gradient Boosting

In [34]:
```
#counting the number of positive and negative samples for balancing the model
num_negatives = loan_data['Status'].value_counts()[0]
num_positives = loan_data['Status'].value_counts()[1]
```

In [35]:
```
#setting the XGBoost classifier
xgb_model = XGBClassifier(eval_metric='logloss',
                          random_state=42, #to control the internal random compo
                          scale_pos_weight = num_negatives / num_positives #it g
                         )                                                 #sinc
                                                                           #unba
#adding to the pipeline the algorithm
full_pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', xgb_model)
])

#parameter grid for GridSearch
param_grid = {
    'classifier__n_estimators': [50, 100],
    'classifier__max_depth': [3, 6],
    'classifier__learning_rate': [0.01, 0.1],
    'classifier__subsample': [0.8, 1],  #fraction of samples used for fitting ea
}

# Grid search setup
grid_search_XGBoost = GridSearchCV(full_pipeline,
                           param_grid,
                           cv=strat_kfold,
                           n_jobs=-1, #it uses all the CPU cores availbale in pa
                           verbose=2, #it shows all details for each combination
                           #scoring = 'recall' #to find hyperparameters to maxim
                          )

start_time = time.time() #for counting the time
# Fit GridSearchCV on training data
grid_search_XGBoost.fit(X_train,
                y_train
               )
end_time = time.time() #end time of execution
elapsed_time = convert_time(end_time - start_time)
print(f"XGBoosting training + grid search took {elapsed_time}")
```

```
# Best params and score
print("Best parameters found:", grid_search_XGBoost.best_params_)
print("Best cross-validation accuracy:", grid_search_XGBoost.best_score_)

# Optional: Evaluate on the test set
test_score = grid_search_XGBoost.score(X_test, y_test)
print(f"Test set accuracy: {test_score:.4f}") #we print the accuracy with the fo
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
XGBoosting training + grid search took 0:03:32
Best parameters found: {'classifier__learning_rate': 0.1, 'classifier__max_dept
h': 6, 'classifier__n_estimators': 100, 'classifier__subsample': 1}
Best cross-validation accuracy: 0.8728429363860769
Test set accuracy: 0.8743
```

In [36]:

```
#try to see whether the above cell has been run
try:
    grid_search_XGBoost
    recovered = False #boolean variable to understand wheter the model has been

#otherwise open the serialized model
except:
    with open("XGBoost_loan.pkl", mode="rb") as f: #rb stands for reading binary
        grid_search_XGBoost = cloudpickle.load(f)
    recovered = True
```

In [37]:

```
pd.DataFrame(grid_search_XGBoost.cv_results_)
```

Out[37]:

ıssifier__subsample	params	split0_test_score	split1_test_score	split2_test_
0.8	{'classifier__learning_rate': 0.01, 'classifie...	0.857105	0.862374	0.8
1	{'classifier__learning_rate': 0.01, 'classifie...	0.857330	0.857218	0.8
0.8	{'classifier__learning_rate': 0.01, 'classifie...	0.860917	0.858675	0.8
1	{'classifier__learning_rate': 0.01, 'classifie...	0.860917	0.858189	0.8
0.8	{'classifier__learning_rate': 0.01, 'classifie...	0.867531	0.871941	0.8
1	{'classifier__learning_rate': 0.01, 'classifie...	0.868839	0.872987	0.8
0.8	{'classifier__learning_rate': 0.01, 'classifie...	0.872613	0.873921	0.8
1	{'classifier__learning_rate': 0.01, 'classifie...	0.872725	0.871791	0.8
0.8	{'classifier__learning_rate': 0.1, 'classifier...	0.862300	0.863981	0.8
1	{'classifier__learning_rate': 0.1, 'classifier...	0.862449	0.864093	0.8
0.8	{'classifier__learning_rate': 0.1, 'classifier...	0.864691	0.862636	0.8
1	{'classifier__learning_rate': 0.1, 'classifier...	0.862823	0.865140	0.8
0.8	{'classifier__learning_rate': 0.1, 'classifier...	0.870595	0.869960	0.8
1	{'classifier__learning_rate': 0.1, 'classifier...	0.871679	0.870334	0.8
0.8	{'classifier__learning_rate': 0.1, 'classifier...	0.871231	0.873996	0.8
1	{'classifier__learning_rate': 0.1, 'classifier...	0.873585	0.872650	0.8

In [38]:

```
#we encapsulate just the best model
XGBoost_whole_model = grid_search_XGBoost.best_estimator_ #here we save the whol
XGBoost_classifier = XGBoost_whole_model.named_steps['classifier'] #here we save
```

In [39]:

```
#recover just the preprocessor from the whole model
preprocessor = XGBoost_whole_model.named_steps['preprocessor']
feature_names = []

for name, transformer, cols in preprocessor.transformers_:
    #if the transformer is a drop operator
    if transformer == 'drop':
```

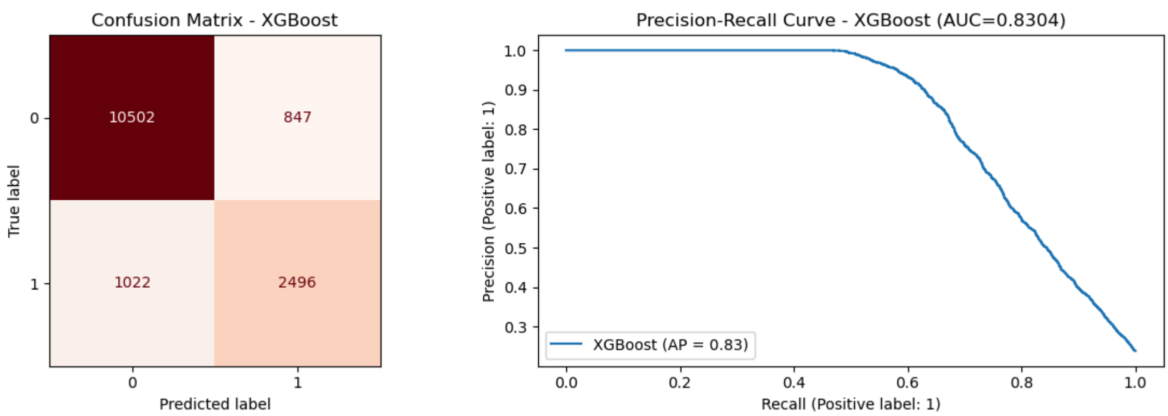
```
        continue
    #if the transformer is actually a pipeline object, so that has inside other
    if isinstance(transformer, Pipeline):
        #get the last step of the pipeline, because the last step is the one tha
        last_step = transformer.steps[-1][1]
        if hasattr(last_step, 'get_feature_names_out'):
            names = last_step.get_feature_names_out(cols)
        else:
            names = cols
    #if the transformer is directly a transformer
    else:
        if hasattr(transformer, 'get_feature_names_out'):
            names = transformer.get_feature_names_out(cols)
        else:
            names = cols

    feature_names.extend(names)

feat_imp = pd.DataFrame({
                        'feature': feature_names,
                        'importance': XGBoost_classifier.feature_importances_
                        }).sort_values(
                                        by="importance",
                                        ascending=False
                                        )

print(feat_imp)
```

```
                             feature  importance
43                    property_value    0.110603
12               lump_sum_payment_lpsm    0.105424
46                                 LTV    0.101989
8            Neg_ammortization_neg_amm    0.073284
34                     credit_type_CIB    0.073172
18   submission_of_application_not_inst    0.055749
4                  Credit_Worthiness_l1    0.043453
24                     loan_type_type1    0.043202
47                               dtir1    0.042422
0                        loan_limit_cf    0.028888
25                     loan_type_type2    0.026857
26                     loan_type_type3    0.026608
27                     loan_purpose_p1    0.020804
44                              income    0.019346
32                   occupancy_type_pr    0.019235
10               interest_only_int_only    0.017363
2                  approv_in_adv_nopre    0.016886
37                        Region_North    0.016690
29                     loan_purpose_p3    0.016467
49                         total_units    0.013241
21                        Gender_Joint    0.013088
28                     loan_purpose_p2    0.012605
30                     loan_purpose_p4    0.011667
41                         loan_amount    0.010784
31                   occupancy_type_ir    0.010308
16          co-applicant_credit_type_CIB    0.010225
14                 construction_type_mh    0.009525
42                                term    0.007672
22                         Gender_Male    0.007316
48                                 age    0.005338
6                    open_credit_nopc    0.005161
33                   occupancy_type_sr    0.004921
40                        Region_south    0.003721
23             Gender_Sex Not Available    0.003419
35                    credit_type_CRIF    0.003211
45                        Credit_Score    0.002650
36                     credit_type_EXP    0.002287
39                      Region_central    0.002118
20                       Gender_Female    0.001518
38                   Region_North-East    0.000784
15                 construction_type_sb    0.000000
7                     open_credit_opc    0.000000
17          co-applicant_credit_type_EXP    0.000000
9            Neg_ammortization_not_neg    0.000000
5                  Credit_Worthiness_l2    0.000000
19    submission_of_application_to_inst    0.000000
3                   approv_in_adv_pre    0.000000
13           lump_sum_payment_not_lpsm    0.000000
1                       loan_limit_ncf    0.000000
11               interest_only_not_int    0.000000
```

In [40]:

```python
# Predict on the test set
y_pred = grid_search_XGBoost.predict(X_test)

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Get predicted probabilities for the positive class
y_scores = grid_search_XGBoost.predict_proba(X_test)[:, 1]
```

```
# Compute average precision (AUC-PR)
auc_pr = average_precision_score(y_test, y_scores)

# Create a figure
fig, axes = plt.subplots(1, # one row
                         2, # two columns
                         figsize=(12, 4)
                        )

# --- Confusion Matrix ---
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=grid_search_XGBoost.classes_
                             )
disp.plot(cmap="Reds",
          values_format='d',
          colorbar=False, #don't show the legend colormap
          ax=axes[0])
axes[0].set_title("Confusion Matrix - XGBoost")

# --- Precision-Recall Curve ---
PrecisionRecallDisplay.from_predictions(y_test,
                                        y_scores,
                                        name="XGBoost",
                                        ax=axes[1]
                                       )
axes[1].set_title(f"Precision-Recall Curve - XGBoost (AUC={auc_pr:.4f})")

plt.tight_layout()
plt.show()
```

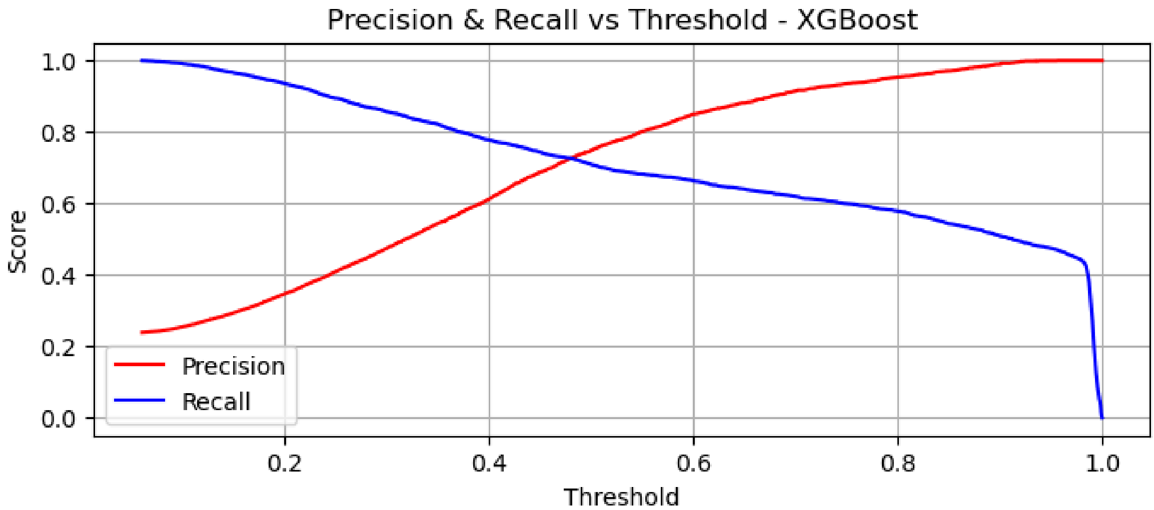


In [41]:
```
# Predict on test set
y_pred = grid_search_XGBoost.predict(X_test)

# Accuracy
acc = accuracy_score(y_test, y_pred)
# Precision (by default, for positive class in binary classification)
prec = precision_score(y_test, y_pred)
# Recall
rec = recall_score(y_test, y_pred)
# F1-score
f1 = f1_score(y_test, y_pred)

print(f"Accuracy: {acc:.4f}")
print(f"Precision: {prec:.4f}")
```

```
print(f"Recall: {rec:.4f}")
print(f"F1-score: {f1:.4f}")
```

```
Accuracy: 0.8743
Precision: 0.7466
Recall: 0.7095
F1-score: 0.7276
```

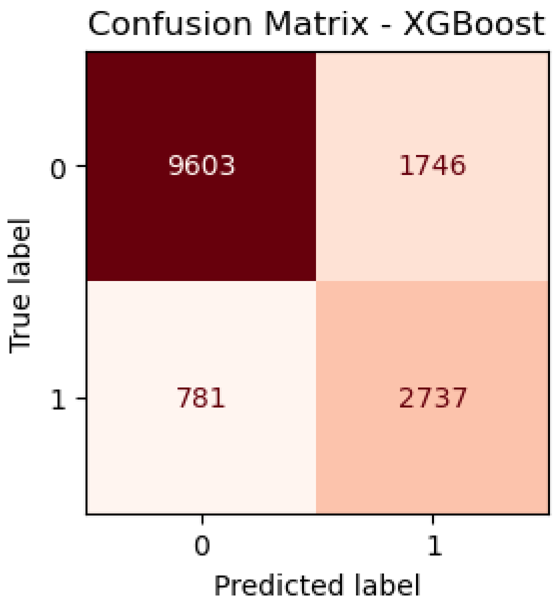
In [42]:
```
# Get predicted probabilities for the positive class
y_scores = grid_search_XGBoost.predict_proba(X_test)[:, 1]

# Compute precision, recall, thresholds
precision, recall, thresholds = precision_recall_curve(y_test, y_scores)

# Plot Precision and Recall vs Threshold
plt.figure(figsize=(8, 3))
plt.plot(thresholds, precision[:-1], label='Precision', color='red')
plt.plot(thresholds, recall[:-1], label='Recall', color='blue')
plt.xlabel('Threshold')
plt.ylabel('Score')
plt.title('Precision & Recall vs Threshold - XGBoost')
plt.legend()
plt.grid(True)
plt.show()
```



In [43]:
```
y_scores = grid_search_XGBoost.predict_proba(X_test)[:, 1]
threshold = 0.4  # Lower than 0.5, where it is centered
y_pred_adjusted = (y_scores >= threshold).astype(int)
```

In [44]:
```
# Compute confusion matrix
cm = confusion_matrix(y_test,
                      y_pred_adjusted
                     )

# Display confusion matrix as a heatmap
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=grid_search_XGBoost.classes_
                             )
plt.figure(figsize=(3, 3)) #create a specific figure object in order to better m

disp.plot(cmap="Reds",
          values_format='d', #show numbers as integers
          colorbar = False, #colorbar as legend disactivated
```

```
            ax=plt.gca() #plot inn the figure created
          )

plt.title("Confusion Matrix - XGBoost")
plt.show()
```



In [45]:
```
# Accuracy
acc = accuracy_score(y_test, y_pred_adjusted)
# Precision (by default, for positive class in binary classification)
prec = precision_score(y_test, y_pred_adjusted)
# Recall
rec = recall_score(y_test, y_pred_adjusted)
# F1-score
f1 = f1_score(y_test, y_pred_adjusted)

print(f"Accuracy: {acc:.4f}")
print(f"Precision: {prec:.4f}")
print(f"Recall: {rec:.4f}")
print(f"F1-score: {f1:.4f}")
```

```
Accuracy: 0.8300
Precision: 0.6105
Recall: 0.7780
F1-score: 0.6842
```

The following code block performs *serialization*, it is a very helpful practice that allows to save a model once has been trained, so it saves the training time every time you open the notebook by simply opening directly the saved model.
There are many libraries that apply serialization and probably one of the best-known is `pickle`, even though it is not able to save `lambda` functions when present.
Since this practice can also save the full pipeline, and in our case there are `lambda` functions, we ended up using `cloudpickle`, that also saves the anonymous functions.
The storing format is binary.

In [46]:
```
# --- Saving ---
if recovered is False: #if the model currently used has not been recovered from
    with open("XGBoost_loan.pkl", mode="wb") as f: #wb stands for Writing Binary
        cloudpickle.dump(grid_search_XGBoost, f)
```

```
# --- Loading ---
"""
with open("XGBoost_loan.pkl", mode="rb") as f: #rb stands for reading binary
    XGBoost_recovered = cloudpickle.load(f)
"""
```

Out[46]:
```
'\nwith open("XGBoost_loan.pkl", mode="rb") as f: #rb stands for reading binary
\n    XGBoost_recovered = cloudpickle.load(f)\n'
```

4.2. Adaptive Boosting

In [ ]:
```
#Setting AdaBoost classifier (with Decision Tree as base estimator)
ada_model = AdaBoostClassifier(
                                base_estimator=DecisionTreeClassifier(class_weig
                                                                      ),
                                random_state=42
                            )

#adding to the pipeline the algorithm
full_pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', ada_model)
])

# Parameter grid for GridSearch
param_grid = {
    'classifier__base_estimator__max_depth': [2,3],       #Maximum depth of deci
    'classifier__n_estimators': [50, 100, 200],            #Number of boosting s
    'classifier__learning_rate': [0.01, 0.1, 0.5, 1.0],    #Shrinkage (learning)
    'classifier__algorithm': [#'SAMME', # Boosting algorithms, for our case SAMM
                              'SAMME.R']
}

# Grid search setup
grid_search_AdaBoost = GridSearchCV(
                            full_pipeline,
                            param_grid,
                            cv=strat_kfold,
                            n_jobs=-1,
                            verbose=2,
                        )

start_time = time.time() #for counting the time
# Fit GridSearchCV on training data
grid_search_AdaBoost.fit(X_train,
                y_train
               )
end_time = time.time() #end time of execution
elapsed_time = convert_time(end_time - start_time)
print(f"AdaBoost training + grid search took {elapsed_time}")

# Best params and score
print("Best parameters found:", grid_search_AdaBoost.best_params_)
print("Best cross-validation accuracy:", grid_search_AdaBoost.best_score_)

# Evaluate on the test set
test_score = grid_search_AdaBoost.score(X_test, y_test)
print(f"Test set accuracy: {test_score:.4f}")
```

In [47]:
```
#try to see whether the above cell has been run
try:
    grid_search_AdaBoost
    recovered = False #boolean variable to understand wheter the model has been

#otherwise open the serialized model
except:
    with open("AdaBoost_loan.pkl", mode="rb") as f: #rb stands for reading binar
        grid_search_AdaBoost = cloudpickle.load(f)
    recovered = True
```

In [48]:
```
pd.DataFrame(grid_search_AdaBoost.cv_results_)
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_14124\2811122147.py in <cell line: 1>()
----> 1 pd.DataFrame(grid_search_AdaBoost.cv_results_)

AttributeError: 'Pipeline' object has no attribute 'cv_results_'
```

In [51]:
```
#we encapsulate just the best model
AdaBoost_whole_model = grid_search_AdaBoost.best_estimator_ #here we save the wh
AdaBoost_classifier = AdaBoost_whole_model.named_steps['classifier'] #here we sa
```

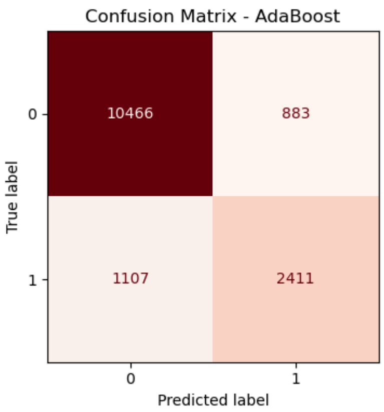
```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_14124\1057454025.py in <cell line: 2>()
      1 #we encapsulate just the best model
----> 2 AdaBoost_whole_model = grid_search_AdaBoost.best_estimator_ #here we save
the whole best model full pipeline (prepocessor + classifier)
      3 AdaBoost_classifier = AdaBoost_whole_model.named_steps['classifier'] #her
e we save just the best classifier

AttributeError: 'Pipeline' object has no attribute 'best_estimator_'
```

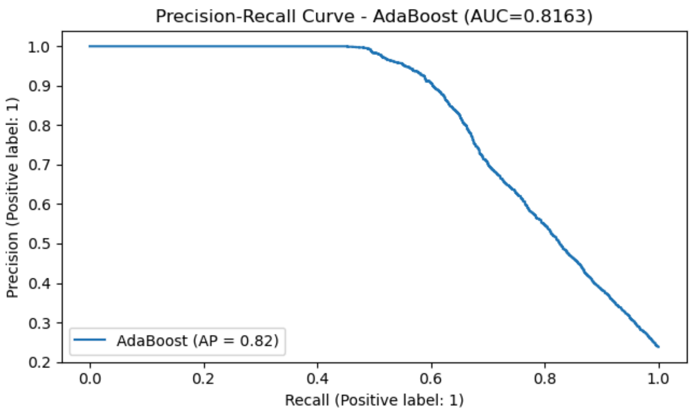
In [52]:
```
#recover just the preprocessor from the whole model
preprocessor = AdaBoost_whole_model.named_steps['preprocessor']
feature_names = []

for name, transformer, cols in preprocessor.transformers_:
    #if the transformer is a drop operator
    if transformer == 'drop':
        continue
    #if the transformer is actually a pipeline object, so that has inside other
    if isinstance(transformer, Pipeline):
        #get the last step of the pipeline, because the last step is the one tha
        last_step = transformer.steps[-1][1]
        if hasattr(last_step, 'get_feature_names_out'):
            names = last_step.get_feature_names_out(cols)
        else:
            names = cols
    #if the transformer is directly a transformer
    else:
        if hasattr(transformer, 'get_feature_names_out'):
            names = transformer.get_feature_names_out(cols)
        else:
            names = cols

    feature_names.extend(names)

feat_imp = pd.DataFrame({
                        'feature': feature_names,
                        'importance': AdaBoost_classifier.feature_importances_
                        }).sort_values(
                                        by="importance",
                                        ascending=False
                                        )

print(feat_imp)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_14124\2077480982.py in <cell line: 2>()
      1 #recover just the preprocessor from the whole model
----> 2 preprocessor = AdaBoost_whole_model.named_steps['preprocessor']
      3 feature_names = []
      4 
      5 for name, transformer, cols in preprocessor.transformers_:

NameError: name 'AdaBoost_whole_model' is not defined
```

In [53]:

```
# Predict on the test set
y_pred = grid_search_AdaBoost.predict(X_test)

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Get predicted probabilities for the positive class
y_scores = grid_search_AdaBoost.predict_proba(X_test)[:, 1]

# Compute average precision (AUC-PR)
auc_pr = average_precision_score(y_test, y_scores)

# Create a figure
fig, axes = plt.subplots(1, # one row
                         2, # two columns
                         figsize=(12, 4)
                        )

# --- Confusion Matrix ---
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=grid_search_AdaBoost.classes_
                             )
disp.plot(cmap="Reds",
          values_format='d',
          colorbar=False, #don't show the legend colormap
          ax=axes[0])
axes[0].set_title("Confusion Matrix - AdaBoost")

# --- Precision-Recall Curve ---
PrecisionRecallDisplay.from_predictions(y_test,
                                        y_scores,
                                        name="AdaBoost",
                                        ax=axes[1]
                                       )
axes[1].set_title(f"Precision-Recall Curve - AdaBoost (AUC={auc_pr:.4f})")

plt.tight_layout()
plt.show()
```

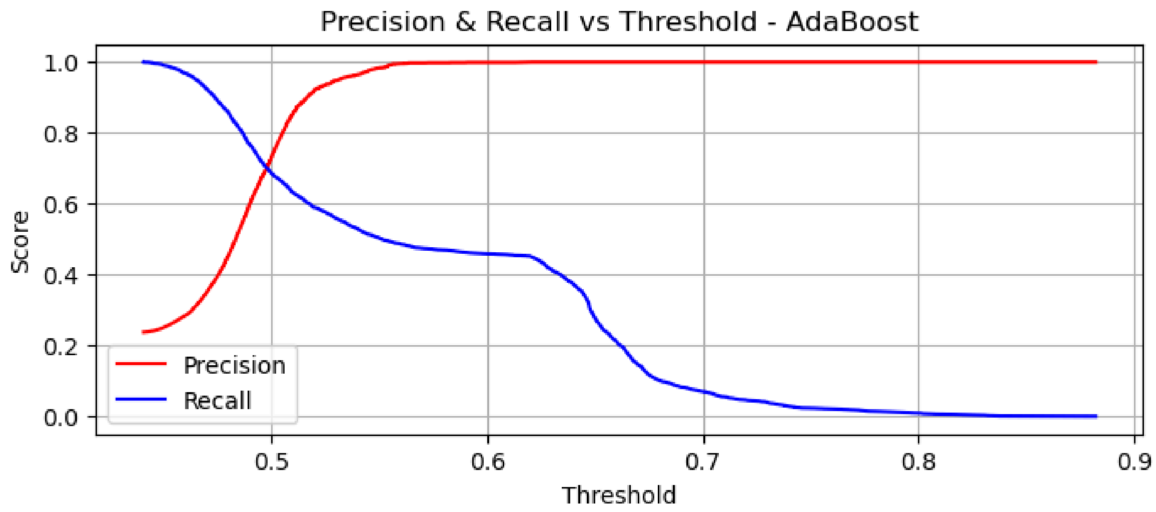




In [54]:
```
# Predict on test set
y_pred = grid_search_AdaBoost.predict(X_test)

# Accuracy
acc = accuracy_score(y_test, y_pred)
# Precision (by default, for positive class in binary classification)
prec = precision_score(y_test, y_pred)
# Recall
rec = recall_score(y_test, y_pred)
# F1-score
f1 = f1_score(y_test, y_pred)

print(f"Accuracy: {acc:.4f}")
print(f"Precision: {prec:.4f}")
print(f"Recall: {rec:.4f}")
print(f"F1-score: {f1:.4f}")
```

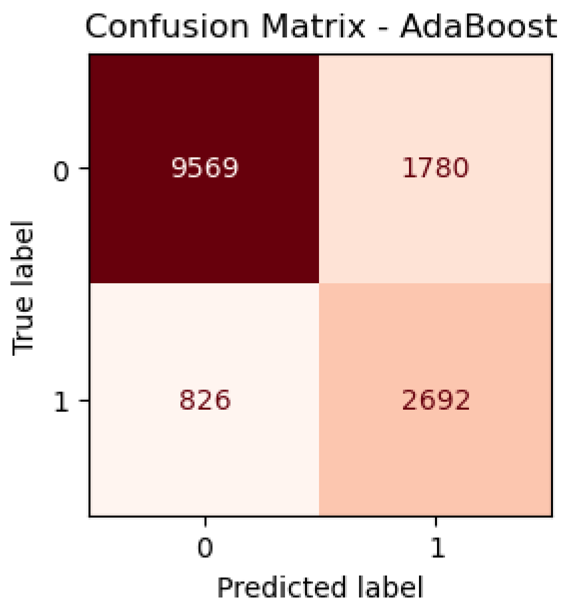
```
Accuracy: 0.8661
Precision: 0.7319
Recall: 0.6853
F1-score: 0.7079
```

In [55]:
```
# Get predicted probabilities for the positive class
y_scores = grid_search_AdaBoost.predict_proba(X_test)[:, 1]

# Compute precision, recall, thresholds
precision, recall, thresholds = precision_recall_curve(y_test, y_scores)

# Plot Precision and Recall vs Threshold
plt.figure(figsize=(8, 3))
plt.plot(thresholds, precision[:-1], label='Precision', color='red')
plt.plot(thresholds, recall[:-1], label='Recall', color='blue')
plt.xlabel('Threshold')
plt.ylabel('Score')
plt.title('Precision & Recall vs Threshold - AdaBoost')
plt.legend()
plt.grid(True)
plt.show()
```



In [56]:
```python
y_scores = grid_search_AdaBoost.predict_proba(X_test)[:, 1]
threshold = 0.49  # lower than 0.5, where it is centered
y_pred_adjusted = (y_scores >= threshold).astype(int)
```

In [57]:
```python
# Compute confusion matrix
cm = confusion_matrix(y_test,
                      y_pred_adjusted
                     )

# Display confusion matrix as a heatmap
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=grid_search_AdaBoost.classes_
                             )
plt.figure(figsize=(3, 3)) #create a specific figure object in order to better m

disp.plot(cmap="Reds",
          values_format='d', #show numbers as integers
          colorbar = False, #colorbar as legend disactivated
          ax=plt.gca() #plot inn the figure created
         )

plt.title("Confusion Matrix - AdaBoost")
plt.show()
```



In [58]:
```
# Accuracy
acc = accuracy_score(y_test, y_pred_adjusted)
# Precision (by default, for positive class in binary classification)
prec = precision_score(y_test, y_pred_adjusted)
# Recall
rec = recall_score(y_test, y_pred_adjusted)
# F1-score
f1 = f1_score(y_test, y_pred_adjusted)

print(f"Accuracy: {acc:.4f}")
print(f"Precision: {prec:.4f}")
print(f"Recall: {rec:.4f}")
print(f"F1-score: {f1:.4f}")
```

```
Accuracy: 0.8247
Precision: 0.6020
Recall: 0.7652
F1-score: 0.6738
```

In [59]:
```
# --- Saving ---
if recovered is False: #if the model currently used has not been recovered from
    with open("AdaBoost_loan.pkl", mode="wb") as f: #wb stands for Writing Binar
        cloudpickle.dump(grid_search_AdaBoost, f)

# --- Loading ---
"""
with open("AdaBoost_loan.pkl", mode="rb") as f: #rb stands for reading binary
    AdaBoost_recovered = cloudpickle.load(f)
"""
```

Out[59]:
```
'\nwith open("AdaBoost_loan.pkl", mode="rb") as f: #rb stands for reading binar
y\n    AdaBoost_recovered = cloudpickle.load(f)\n'
```

4.3. Gradient Boosting

In [ ]:
```
#setting the GradientBoosting model
gb_model = GradientBoostingClassifier(
                                    random_state=42
                                )

#adding to the pipeline the algorithm
full_pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', gb_model)
])

# Parameter grid for GridSearch
param_grid = {
    'classifier__n_estimators': [50, 100, 200],          #Number of boosting sta
    'classifier__learning_rate': [0.01, 0.1, 0.2],       #Shrinkage (learning) r
    'classifier__max_depth': [2, 3],                    #Maximum depth of decision
    'classifier__subsample': [0.8, 1.0],                 #fraction of samples us
    'classifier__min_samples_split': [2, 5]              #minimum samples requir
}

# Grid search setup
grid_search_GradientBoost = GridSearchCV(
                            full_pipeline,
                            param_grid,
```

```
                            cv=strat_kfold,
                            n_jobs=-1,
                            verbose=2
                        )

start_time = time.time() #for counting the time
# Fit GridSearchCV on training data
grid_search_GradientBoost.fit(X_train,
                              y_train
                             )
end_time = time.time() #end time of execution
elapsed_time = convert_time(end_time - start_time)
print(f"GradientBoost training + grid search took {elapsed_time}")

# Best params and score
print("Best parameters found:", grid_search_GradientBoost.best_params_)
print("Best cross-validation accuracy:", grid_search_GradientBoost.best_score_)

# Optional: Evaluate on the test set
test_score = grid_search_GradientBoost.score(X_test, y_test)
print(f"Test set accuracy: {test_score:.4f}")
```

In [60]:
```
#try to see whether the above cell has been run
try:
    grid_search_GradientBoost
    recovered = False #boolean variable to understand wheter the model has been

#otherwise open the serialized model
except:
    with open("GradientBoost_loan.pkl", mode="rb") as f: #rb stands for reading
        grid_search_GradientBoost = cloudpickle.load(f)
    recovered = True
```

In [61]:
```
pd.DataFrame(grid_search_GradientBoost.cv_results_)
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_14124\3663306907.py in <cell line: 1>()
----> 1 pd.DataFrame(grid_search_GradientBoost.cv_results_)

AttributeError: 'Pipeline' object has no attribute 'cv_results_'
```

In [62]:
```
#we encapsulate just the best model
GradientBoost_whole_model = grid_search_GradientBoost.best_estimator_ #here we s
GradientBoost_classifier = GradientBoost_whole_model.named_steps['classifier'] #
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_14124\244217999.py in <cell line: 2>()
      1 #we encapsulate just the best model
----> 2 GradientBoost_whole_model = grid_search_GradientBoost.best_estimator_ #he
re we save the whole best model full pipeline (prepocessor + classifier)
      3 GradientBoost_classifier = GradientBoost_whole_model.named_steps['classif
ier'] #here we save just the best classifier

AttributeError: 'Pipeline' object has no attribute 'best_estimator_'
```

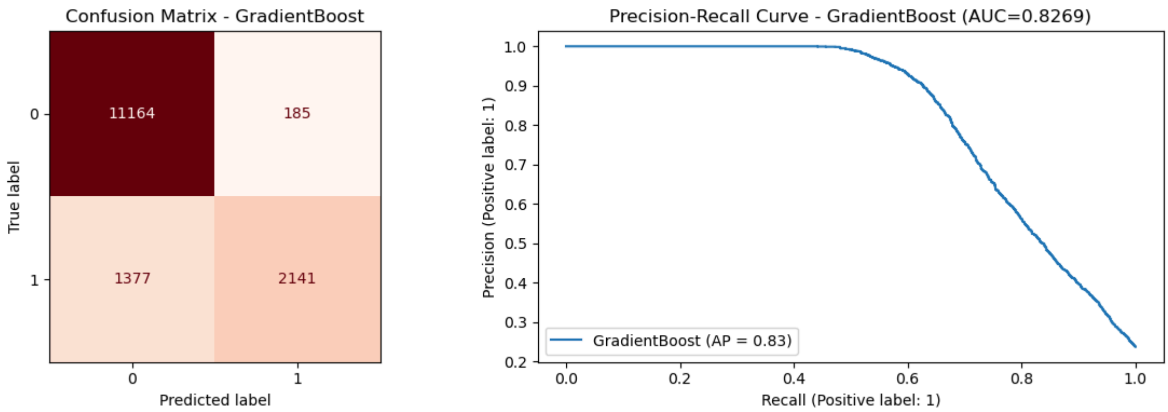
In [63]:
```
#recover just the preprocessor from the whole model
preprocessor = GradientBoost_whole_model.named_steps['preprocessor']
feature_names = []
```

```
for name, transformer, cols in preprocessor.transformers_:
    #if the transformer is a drop operator
    if transformer == 'drop':
        continue
    #if the transformer is actually a pipeline object, so that has inside other
    if isinstance(transformer, Pipeline):
        #get the last step of the pipeline, because the last step is the one tha
        last_step = transformer.steps[-1][1]
        if hasattr(last_step, 'get_feature_names_out'):
            names = last_step.get_feature_names_out(cols)
        else:
            names = cols
    #if the transformer is directly a transformer
    else:
        if hasattr(transformer, 'get_feature_names_out'):
            names = transformer.get_feature_names_out(cols)
        else:
            names = cols

    feature_names.extend(names)

feat_imp = pd.DataFrame({
                        'feature': feature_names,
                        'importance': AdaBoost_classifier.feature_importances_
                        }).sort_values(
                                        by="importance",
                                        ascending=False
                                        )

print(feat_imp)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_14124\2084709128.py in <cell line: 2>()
      1 #recover just the preprocessor from the whole model
----> 2 preprocessor = GradientBoost_whole_model.named_steps['preprocessor']
      3 feature_names = []
      4 
      5 for name, transformer, cols in preprocessor.transformers_:

NameError: name 'GradientBoost_whole_model' is not defined
```

In [64]:
```
# Predict on the test set
y_pred = grid_search_GradientBoost.predict(X_test)

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Get predicted probabilities for the positive class
y_scores = grid_search_GradientBoost.predict_proba(X_test)[:, 1]

# Compute average precision (AUC-PR)
auc_pr = average_precision_score(y_test, y_scores)

# Create a figure
fig, axes = plt.subplots(1, # one row
                         2, # two columns
                         figsize=(12, 4)
                        )
```

```
# --- Confusion Matrix ---
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=grid_search_GradientBoost.classes_
                             )
disp.plot(cmap="Reds",
          values_format='d',
          colorbar=False, #don't show the legend colormap
          ax=axes[0])
axes[0].set_title("Confusion Matrix - GradientBoost")

# --- Precision-Recall Curve ---
PrecisionRecallDisplay.from_predictions(y_test,
                                        y_scores,
                                        name="GradientBoost",
                                        ax=axes[1]
                                       )
axes[1].set_title(f"Precision-Recall Curve - GradientBoost (AUC={auc_pr:.4f})")

plt.tight_layout()
plt.show()
```



In [65]:

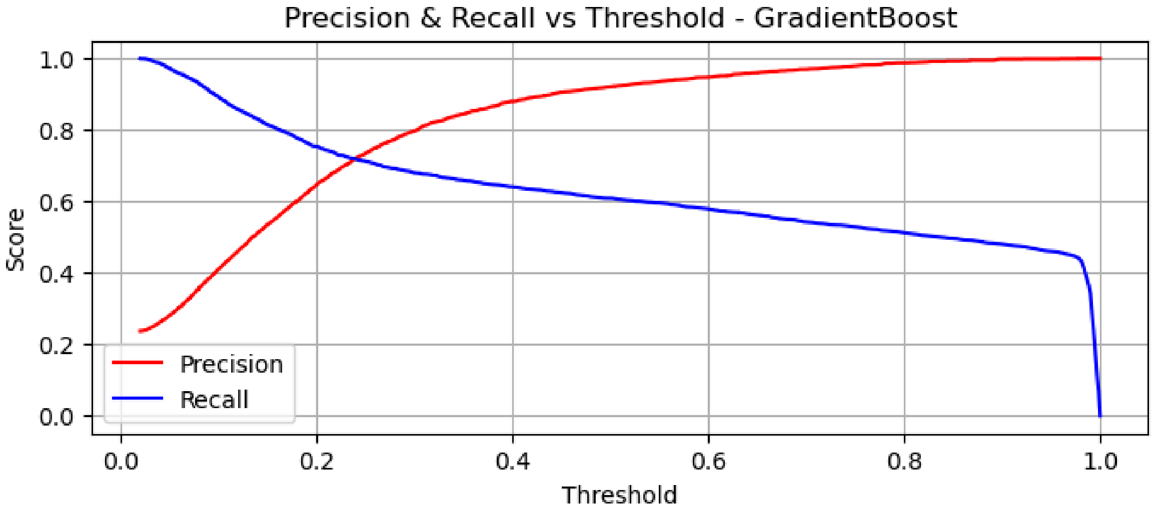
```
# Predict on test set
y_pred = grid_search_GradientBoost.predict(X_test)

# Accuracy
acc = accuracy_score(y_test, y_pred)
# Precision (by default, for positive class in binary classification)
prec = precision_score(y_test, y_pred)
# Recall
rec = recall_score(y_test, y_pred)
# F1-score
f1 = f1_score(y_test, y_pred)

print(f"Accuracy: {acc:.4f}")
print(f"Precision: {prec:.4f}")
print(f"Recall: {rec:.4f}")
print(f"F1-score: {f1:.4f}")
```

```
Accuracy: 0.8949
Precision: 0.9205
Recall: 0.6086
F1-score: 0.7327
```

In [66]:

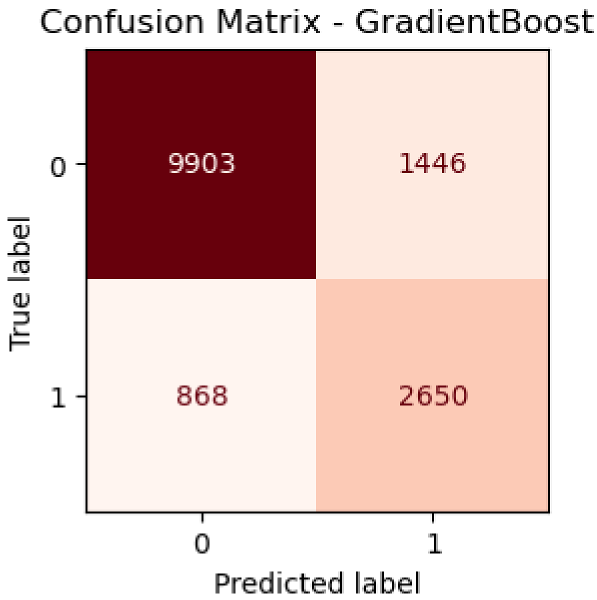
```
# Get predicted probabilities for the positive class
y_scores = grid_search_GradientBoost.predict_proba(X_test)[:, 1]
```

```
# Compute precision, recall, thresholds
precision, recall, thresholds = precision_recall_curve(y_test, y_scores)

# Plot Precision and Recall vs Threshold
plt.figure(figsize=(8, 3))
plt.plot(thresholds, precision[:-1], label='Precision', color='red')
plt.plot(thresholds, recall[:-1], label='Recall', color='blue')
plt.xlabel('Threshold')
plt.ylabel('Score')
plt.title('Precision & Recall vs Threshold - GradientBoost')
plt.legend()
plt.grid(True)
plt.show()
```



In [67]:
```
y_scores = grid_search_GradientBoost.predict_proba(X_test)[:, 1]
threshold = 0.2  # Lower than 0.5, where it is centered
y_pred_adjusted = (y_scores >= threshold).astype(int)
```

In [68]:
```
# Compute confusion matrix
cm = confusion_matrix(y_test,
                      y_pred_adjusted
                     )

# Display confusion matrix as a heatmap
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=grid_search_GradientBoost.classes_
                             )
plt.figure(figsize=(3, 3)) #create a specific figure object in order to better m

disp.plot(cmap="Reds",
          values_format='d', #show numbers as integers
          colorbar = False, #colorbar as legend disactivated
          ax=plt.gca() #plot inn the figure created
         )

plt.title("Confusion Matrix - GradientBoost")
plt.show()
```



In [69]:
```
# Accuracy
acc = accuracy_score(y_test, y_pred_adjusted)
# Precision (by default, for positive class in binary classification)
prec = precision_score(y_test, y_pred_adjusted)
# Recall
rec = recall_score(y_test, y_pred_adjusted)
# F1-score
f1 = f1_score(y_test, y_pred_adjusted)

print(f"Accuracy: {acc:.4f}")
print(f"Precision: {prec:.4f}")
print(f"Recall: {rec:.4f}")
print(f"F1-score: {f1:.4f}")
```

```
Accuracy: 0.8444
Precision: 0.6470
Recall: 0.7533
F1-score: 0.6961
```

In [70]:
```
# --- Saving ---
if recovered is False: #if the model currently used has not been recovered from
    with open("GradientBoost_loan.pkl", mode="wb") as f: #wb stands for Writing
        cloudpickle.dump(grid_search_GradientBoost, f)

# --- Loading ---
"""
with open("GradientBoost_loan.pkl", mode="rb") as f: #rb stands for reading bina
    GradientBoost_recovered = cloudpickle.load(f)
"""
```

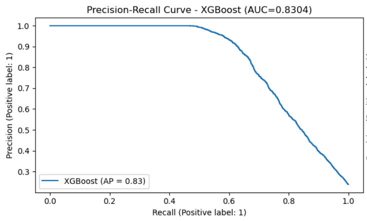
Out[70]:
```
'\nwith open("GradientBoost_loan.pkl", mode="rb") as f: #rb stands for reading
binary\n    GradientBoost_recovered = cloudpickle.load(f)\n'
```

5. Comparisons

Now that all three models have been run we can make comparisons and draw conclusions.

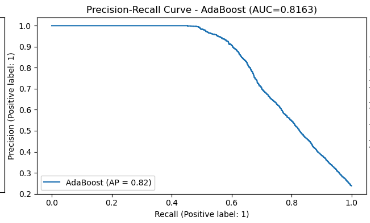
Since in our dataset the positive class is rare, as a rule of thumb we should prefer the Precision-Recall curves for comparison, hence we will combine them with the best scores found after tweaking the precision-recall threshold, in order to choose the best model.

XGBoost



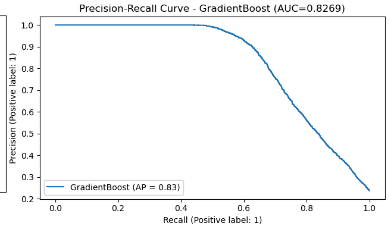
Accuracy: 0.8300
Precision: 0.6105
Recall: 0.7780
F1-score: 0.6842

AdaBoost



Accuracy: 0.8247
Precision: 0.6020
Recall: 0.7652
F1-score: 0.6738

GradientBoost



Accuracy: 0.8444
Precision: 0.6470
Recall: 0.7533
F1-score: 0.6961

See Appendix 7.B. to understand how these images have been generated

All three models are quite good, and have similar scores, even though AdaBoost is clearly the one with the lowest scores.
On the other hand XGBoost and GradientBoost have different scores each one with its own pros and cons, if we take into account the overall F1-score that is basically the harmonic mean between precision and recall:

$$\text{F1-score} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

we would choose GradientBoost, since this metric is comprehensive of both Precision and Recall.
On the other hand if we take into account the general principle that for this project we want to prioritize recall over precision and even further we take a look at the training time:

XGBoost	AdaBoost	GradientBoost
00:03:48	01:36:11	03:15:27

XGBoost is the one that performs better.
This is due to some intrinsic characteristics of the implementation of the algorithm itself. XGBoost is built upon the core Gradient Boosting framework, but it has some key features such as smarter penalizations and regularization, adopts Newton Boosting, furthermore XGBoost can build parts of the model in parallel. This not only speeds up the training process but also makes it scalable, allowing it to handle very large datasets by distributing the workload across multiple machines or processing units.

6. Conclusion and Possible Expansions

This project can be further improved under some aspects that can be seen as a good starting point for future directions.

One of the first improvement that can come up in mind straight away after analyzing section 4 is the further feature selection, since all three algorithms under the hood of features importance show that: `open_credit_opc` , `open_credit_nopc` and `construction_type_sb` have no importance in reducing impurity.
Plotting the **learning curves** and eventually implementing some strategies such as **early stopping** can be very beneficial especially for Adaptive Boosting and Gradient Boosting, since they take long time for training.
Since the dataset results a bit unbalanced towards the negative samples, we could implement **SMOTE** *(Synthetic Minority Over-sampling Technique)* techniques in order to generate synthetic samples from the minority class, so to compensate it.
Furthermore we can try to apply dimensionality reduction and/or different models, maybe even approaching the field of Artificial Neural Netwroks, starting with the base model of the Multilayer Perceptron.

The main purpose of this notebook has originally started as a Kaggle challenge, it can be actually seen a good starting point for many other interesting applications, not necessarily related to the credit industry.
For example with the same binary classifier concept we can implement fraud dectors, spam email dector, malicious cyber attacks identifications and so on...

7. Appendix

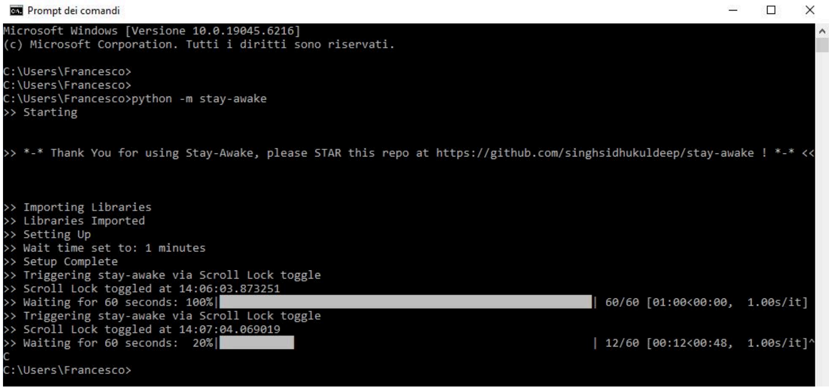
This section contains some tips and interesting tricks that I have used during the execution of this Notebook.

7.A. Python stay-awake module

At the end of section 5. we higlighted the training time for the three models. If we sum all training times we quickly understand that in total, running this notebook from scratch requires approximately five hours.
If we do not want to change the settings of our computer in order to prevent sleep mode, we can use a python script that runs in a different thread as a background daemon, since it requires very few CPU.
Online there are many modules from which we can take advantage of.

For example this one here is very easy and straighforward to implement, even though if you run it on Windows 10 or newer versions you need to adjust it a bit, because you need to automatic mouse moving does not prevent sleep mode anymore see.
For example once you have found out the location of the script in your computer with: `pip show stay-awake` you can change the `__init__.py` inside the `stay-wake` folder script so that instead of moving the mouse it activates/deactives the ScrollLock button.

Once the script is ready, it is very easy to use it, just open a Shell prompt ad type: `python -m stay-awake`



See Appendix 7.B. to understand how this image has been generated

7.B. Python image converter base64 (PDF exporting)

If we want to convert a file Jupyter Notebook with images into PDF format, all the media attachments will be lost, this is a well-known bug of ipynb files.
In order to overcome this issue there a few tricks, the one I have implemented is based on the Python library `base64` . Basically it converts images into ASCII characters, by opening the attachments in binary mode and then encoding it in series of printable characters limited to a set of 64 unique characters. More specifically, the source binary data is taken 6 bits at a time, then this group of 6 bits is mapped to one of 64 unique characters.

Base64 encoding causes an overhead of 33–37% relative to the size of the original binary data (33% by the encoding itself; up to 4% more by the inserted line breaks).

For further explanations see: GitHub issue, Base64

The following block of codes are the ones that generated the encoding and stored directly the content into `HTML` tags for the images we saw through this notebook earlier.
Of course, once the attachment has been encoded, we can remove it from the directory.

For the sake of brevity we do not show the output of the blocks.

Each block is led by the `Markdown` referenced cell, that we would have written in case we had not had any issues.

In [ ]:
```
<img src="loan.JPG" style="width:75%;">
```

In [2]:
```
import base64 #library for base64 encoding

file = "loan.JPG"

with open(file, "rb") as f:
    data = f.read()
```

```
encoded = base64.b64encode(data).decode("utf-8")

# Genera il tag HTML con base64
html_code = f'<img src="data:image/jpeg;base64,{encoded}" style="width:75%;">'

# print(html_code)
```

In [ ]:

```
<div style="display: flex;
            justify-content: center;
            text-align: center;">

  <div>
      XGBoost
    <img src="PR-curve XGBoost.png" style="padding:1%"><br>
    Accuracy: 0.8300 <br>
    Precision: 0.6105 <br>
    Recall: 0.7780 <br>
    F1-score: 0.6842
  </div>

  <div>
      AdaBoost
    <img src="PR-curve AdaBoost.png" style="padding:1%"><br>
    Accuracy: 0.8247 <br>
    Precision: 0.6020 <br>
    Recall: 0.7652 <br>
    F1-score: 0.6738
  </div>

  <div>
      GradientBoost
    <img src="PR-curve GradientBoost.png" style="padding:1%"><br>
    Accuracy: 0.8444 <br>
    Precision: 0.6470 <br>
    Recall: 0.7533 <br>
    F1-score: 0.6961
  </div>

</div>
```

In [3]:

```
files = ["PR-curve XGBoost.png",
         "PR-curve AdaBoost.png",
         "PR-curve GradientBoost.png",
        ]
labels = ["XGBoost",
          "AdaBoost",
          "GradientBoost",
         ]
accuracy = [0.8300,
            0.8247,
            0.8444,
           ]
precision = [0.6105,
             0.6020,
             0.6470,
            ]
recall = [0.7780,
          0.7652,
          0.7533,
```

```
         ]
f1 = [0.6842,
      0.6738,
      0.6961,
     ]

html = '<div style="display: flex; justify-content: center; text-align: center;"

for i in range(len(files)):
    with open(files[i], "rb") as f:
        data = f.read()
    encoded = base64.b64encode(data).decode("utf-8")

    html += f'''  <div>
      {labels[i]}
      <img src="data:image/png;base64,{encoded}" style="padding:1%"><br>
      Accuracy: {accuracy[i]:.4f} <br>
      Precision: {precision[i]:.4f} <br>
      Recall: {recall[i]:.4f} <br>
      F1-score: {f1[i]:.4f}
  </div>\n\n'''

html += '</div>'

# print(html)
```

In [ ]:
```
<img src="stay-awake.JPG" style="width:75%;">
```

In [4]:
```
file = "stay-awake.JPG"

with open(file, "rb") as f:
    data = f.read()

encoded = base64.b64encode(data).decode("utf-8")

html_code = f'<img src="data:image/jpeg;base64,{encoded}" style="width:75%;">'

# print(html_code)
```

TODO!

- usa delle curve e grafici per mostrare la qualità del modello:
    - Parametri specifici dei due boosting;
- take a look at the jupyter notebook files of: Classificators, Decision Trees and Ensemble Learning;
- adjusting other models for Recall;