LOAN DEFAULT PREDICTION

Dataset Source: *https://www.kaggle.com/datasets/wordsforthewise/lending-club*
Platform: Google Colab

This project aims to build a machine learning model that predicts loan defaults using the Lending Club dataset. This notebook serves as a complete end-to-end documentation and walkthrough, covering the following key stages:

- **Exploratory Data Analysis (EDA)**: Investigate and understand the structure of the dataset, identifying key features relevant to loan default prediction.
- **Data Cleaning & Preprocessing**: Handle missing values, remove irrelevant or redundant columns, and prepare the data for modeling.
- **Feature Selection**: Identify and use highly correlated features to improve model performance.
- **Model Training & Evaluation**: Train machine learning models and evaluate their effectiveness in predicting loan defaults.

Import Dependencies

In this section, we import the necessary libraries for data manipulation, visualization, and analysis. These include:

- ***pandas*** and ***numpy*** for data handling and preprocessing,
- ***seaborn*** and ***matplotlib.pyplot*** for data visualization and pattern exploration.

```
import pandas as pd
import numpy as np
import seaborn as sns
from datetime import datetime
import matplotlib.pyplot as plt
```

Load Dataset from Google Drive

After mounting Google Drive, we load the Lending Club dataset using `pandas`. This dataset contains loan application data from 2007 to 2018Q4, which will be used for analysis and model training.

```
dataset = '/content/drive/MyDrive/Machine Learning Datasets/Loan Default Prediction Dataset/accepted_2007_to_2018Q4.csv'
dataset = pd.read_csv(dataset, low_memory=False)
dataset.head(5)
```

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	...	hardship_payoff_ba
0	68407277	NaN	3600.0	3600.0	3600.0	36 months	13.99	123.03	C	C4	...	
1	68355089	NaN	24700.0	24700.0	24700.0	36 months	11.99	820.28	C	C1	...	
2	68341763	NaN	20000.0	20000.0	20000.0	60 months	10.78	432.66	B	B4	...	
3	66310712	NaN	35000.0	35000.0	35000.0	60 months	14.85	829.90	C	C5	...	
4	68476807	NaN	10400.0	10400.0	10400.0	60 months	22.45	289.91	F	F1	...	

5 rows × 151 columns

Exploratory Data Analysis

In this section, we perform exploratory data analysis to better understand the structure, quality, and key patterns in the dataset. This analysis includes:

- Checking dataset dimensions.
- Identifying data types of each column.
- Evaluate missing values.

- Summarizing key statistics and correlations to inform data cleaning and feature engineering steps.

The insights gathered here will guide the subsequent data cleaning and preprocessing steps.

Dataset Overview

We begin by examining the dataset's dimensions and previewing the top records to understand the structure.

```
print(f"The dataset has {dataset.shape[0]:,} rows and {dataset.shape[1]:,} columns.")
dataset.head(5)
```

```
The dataset has 2,260,701 rows and 151 columns.
```

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	...	hardship_payoff_ba
0	68407277	NaN	3600.0	3600.0	3600.0	36 months	13.99	123.03	C	C4	...	
1	68355089	NaN	24700.0	24700.0	24700.0	36 months	11.99	820.28	C	C1	...	
2	68341763	NaN	20000.0	20000.0	20000.0	60 months	10.78	432.66	B	B4	...	
3	66310712	NaN	35000.0	35000.0	35000.0	60 months	14.85	829.90	C	C5	...	
4	68476807	NaN	10400.0	10400.0	10400.0	60 months	22.45	289.91	F	F1	...	

5 rows × 151 columns

Data Types and Missing Values

Inspecting column data types and identifying missing values is essential for cleaning and preprocessing.

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2260701 entries, 0 to 2260700
Columns: 151 entries, id to settlement_term
dtypes: float64(113), object(38)
memory usage: 2.5+ GB
```

```
total_rows = dataset.shape[0]

missing_values = dataset.isnull().sum()
missing_percentage = (missing_values / total_rows) * 100

missing_df = pd.DataFrame({
    'Column Name': missing_values.index,
    'Number of Missing Values': missing_values.values,
    'Percentage of Missing Values': missing_percentage.values
})

missing_df = missing_df[missing_df['Percentage of Missing Values'] > 0]
missing_df = missing_df.sort_values(by='Number of Missing Values', ascending=False)
missing_df.reset_index(drop=True, inplace=True)
missing_df
```

	Column Name	Number of Missing Values	Percentage of Missing Values
0	member_id	2260701	100.000000
1	orig_projected_additional_accrued_interest	2252050	99.617331
2	hardship_payoff_balance_amount	2249784	99.517097
3	hardship_last_payment_amount	2249784	99.517097
4	payment_plan_start_date	2249784	99.517097
...	...	...	...
145	total_rec_int	33	0.001460
146	total_rec_prncp	33	0.001460
147	hardship_flag	33	0.001460
148	disbursement_method	33	0.001460
149	debt_settlement_flag	33	0.001460

150 rows × 3 columns

Statistical Summary

We use the `.describe()` method to obtain a statistical summary of the numerical features. This includes measures such as mean, standard deviation, and quartiles, which help assess the central tendency and spread of data.

```
dataset.describe()
```

	member_id	loan_amnt	funded_amnt	funded_amnt_inv	int_rate	installment	annual_inc	dti	delinq_2yrs	fico_
count	0.0	2.260668e+06	2.260668e+06	2.260668e+06	2.260668e+06	2.260668e+06	2.260664e+06	2.258957e+06	2.260639e+06	2.2
mean	NaN	1.504693e+04	1.504166e+04	1.502344e+04	1.309283e+01	4.458068e+02	7.799243e+04	1.882420e+01	3.068792e-01	6.9
std	NaN	9.190245e+03	9.188413e+03	9.192332e+03	4.832138e+00	2.671735e+02	1.126962e+05	1.418333e+01	8.672303e-01	3.3
min	NaN	5.000000e+02	5.000000e+02	0.000000e+00	5.310000e+00	4.930000e+00	0.000000e+00	-1.000000e+00	0.000000e+00	6.1
25%	NaN	8.000000e+03	8.000000e+03	8.000000e+03	9.490000e+00	2.516500e+02	4.600000e+04	1.189000e+01	0.000000e+00	6.7
50%	NaN	1.290000e+04	1.287500e+04	1.280000e+04	1.262000e+01	3.779900e+02	6.500000e+04	1.784000e+01	0.000000e+00	6.9
75%	NaN	2.000000e+04	2.000000e+04	2.000000e+04	1.599000e+01	5.933200e+02	9.300000e+04	2.449000e+01	0.000000e+00	7.1
max	NaN	4.000000e+04	4.000000e+04	4.000000e+04	3.099000e+01	1.719830e+03	1.100000e+08	9.990000e+02	5.800000e+01	8.4

8 rows × 113 columns

Class Distribution

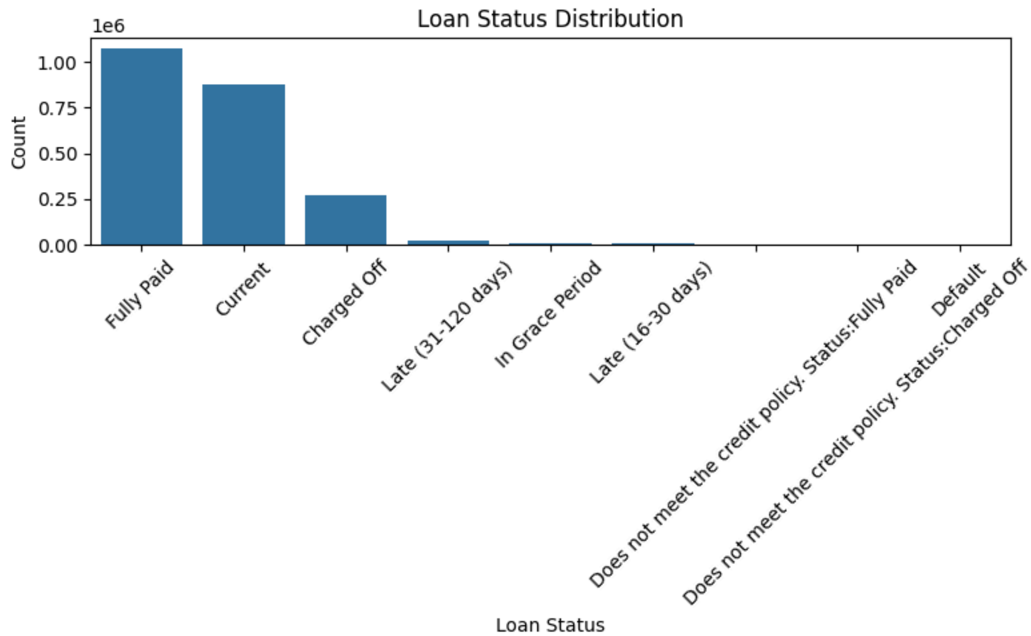
Understanding the balance of the target variable ***(loan status)*** is important for model training.

```
dataset['loan_status'].value_counts()
```

loan_status	count
Fully Paid	1076751
Current	878317
Charged Off	268559
Late (31-120 days)	21467
In Grace Period	8436
Late (16-30 days)	4349
Does not meet the credit policy. Status:Fully Paid	1988
Does not meet the credit policy. Status:Charged Off	761
Default	40

dtype: int64

```
plt.figure(figsize=(8, 5))
sns.countplot(data=dataset, x='loan_status', order=dataset['loan_status'].value_counts().index)
plt.title('Loan Status Distribution')
plt.xlabel('Loan Status')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

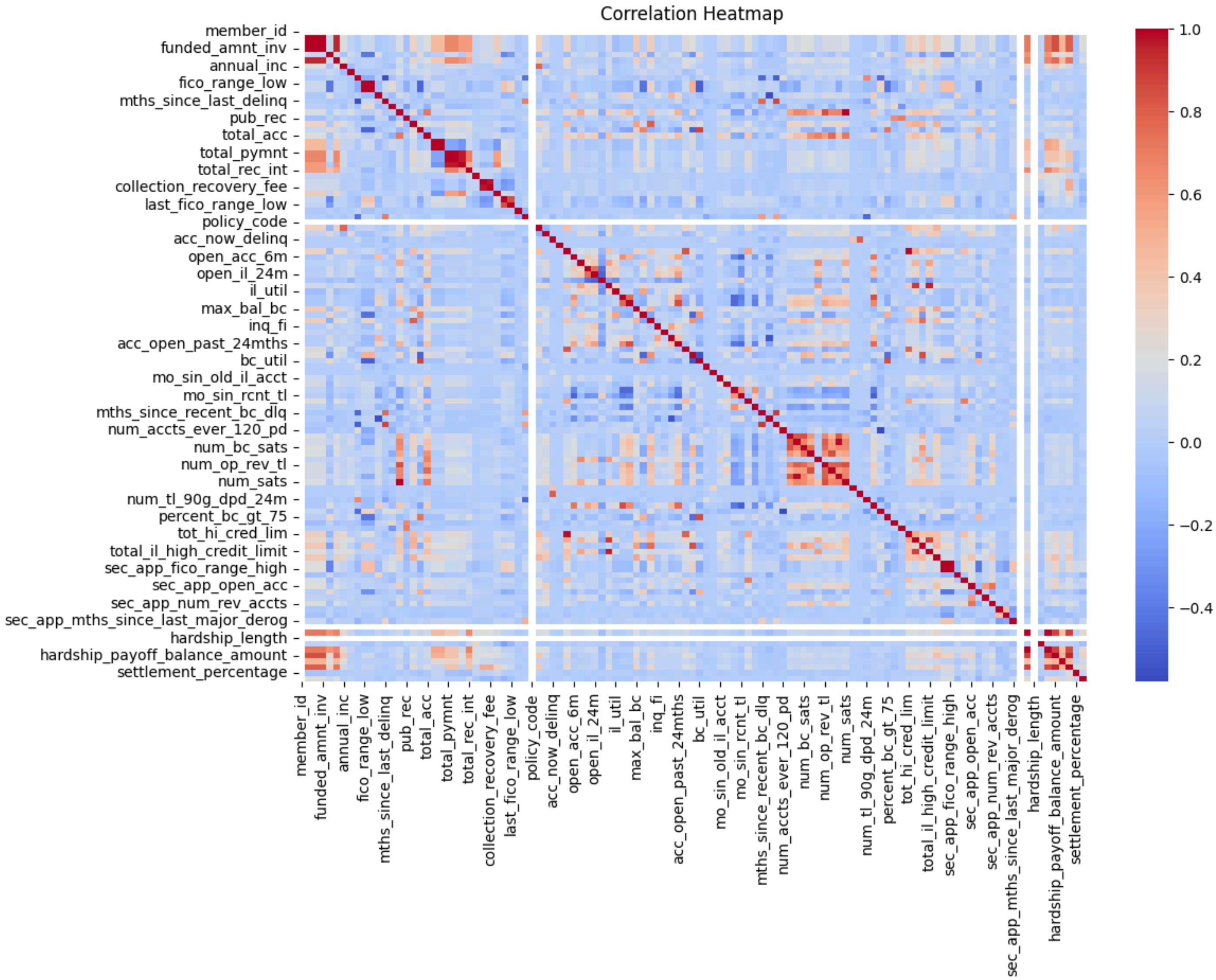


Note: We can observe a `class imbalance` between the various classes.

Correlation Matrix

We compute and visualize the correlation matrix for numerical features to identify relationships and potential predictors for the model.

```
correlation_matrix = dataset.corr(numeric_only=True)

plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, cmap='coolwarm', annot=False)
plt.title('Correlation Heatmap')
plt.show()
```



Data Cleaning

In this section, we clean the dataset based on insights from the exploratory analysis. This includes removing irrelevant or low-value columns, handling missing values, and preparing the data for modeling.

Have a "**Rule of Thumb**" for missing data. If the missing or null values in a column is beyond `80%` of the total rows then it is likely to be dropped unless that column has **critical meaning**, you have domain knowledge or external data to fill those missing values.

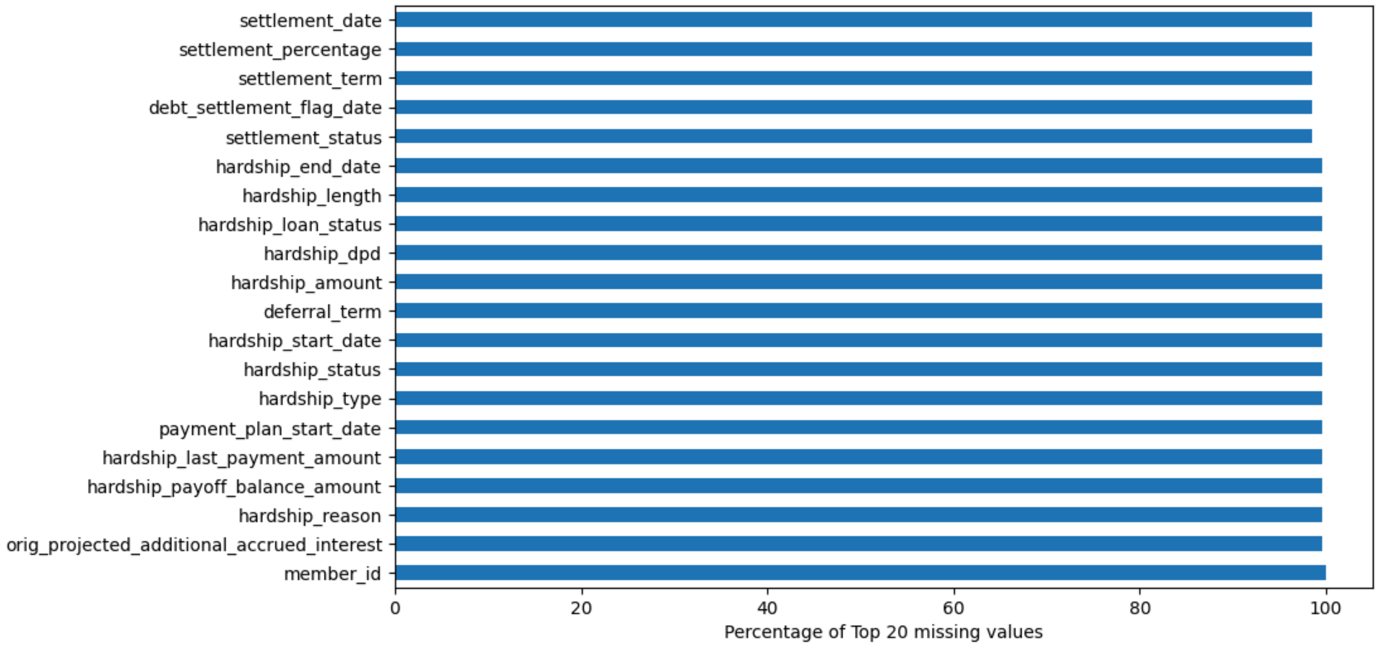
```
threshold = dataset.isnull().mean() * 100
high_missing_val = threshold[threshold > 80].sort_values(ascending=False).index

print(high_missing_val)
```

```
Index(['member_id', 'orig_projected_additional_accrued_interest',
       'hardship_end_date', 'hardship_reason', 'hardship_status',
       'hardship_type', 'hardship_start_date', 'hardship_loan_status',
       'hardship_dpd', 'hardship_length', 'payment_plan_start_date',
       'hardship_amount', 'hardship_payoff_balance_amount',
       'hardship_last_payment_amount', 'deferral_term', 'settlement_date',
       'settlement_amount', 'settlement_percentage', 'settlement_term',
       'settlement_status', 'debt_settlement_flag_date',
       'sec_app_mths_since_last_major_derog', 'sec_app_revol_util',
       'revol_bal_joint', 'sec_app_fico_range_low',
       'sec_app_collections_12_mths_ex_med', 'sec_app_fico_range_high',
       'sec_app_inq_last_6mths', 'sec_app_earliest_cr_line',
```

```
           'sec_app_chargeoff_within_12_mths', 'sec_app_num_rev_accts',
           'sec_app_open_acc', 'sec_app_mort_acc', 'sec_app_open_act_il',
           'verification_status_joint', 'dti_joint', 'annual_inc_joint', 'desc',
           'mths_since_last_record'],
          dtype='object')
```

Visualize the results above.

```
threshold.sort_values(ascending=False).head(20).plot(kind='barh', figsize=(10,6))
plt.xlabel('Percentage of Top 20 missing values')
plt.show()
```



Column Dropping — Post-Loan and Irrelevant Features

Based on EDA and business understanding, we drop columns that fall into the following categories:

- **Post-loan outcome features**: These contain information that would not be available at the time of loan approval and can lead to data leakage (e.g., `total_pymnt`, `recoveries`, `last_fico_range_low`)
- **High-missing-value fields**: Particularly those related to joint applications or hardship/settlement programs
- **Administrative or user-entered fields**: Such as IDs and free-text descriptions

```
columns_to_drop = ['member_id', 'orig_projected_additional_accrued_interest',
       'hardship_end_date', 'hardship_reason', 'hardship_status',
       'hardship_type', 'hardship_start_date', 'hardship_loan_status',
       'hardship_dpd', 'hardship_length', 'payment_plan_start_date',
       'hardship_amount', 'hardship_payoff_balance_amount',
       'hardship_last_payment_amount', 'deferral_term', 'settlement_date',
       'settlement_amount', 'settlement_percentage', 'settlement_term',
       'settlement_status', 'debt_settlement_flag_date',
       'sec_app_mths_since_last_major_derog', 'sec_app_revol_util',
       'revol_bal_joint', 'sec_app_fico_range_low',
       'sec_app_collections_12_mths_ex_med', 'sec_app_fico_range_high',
       'sec_app_inq_last_6mths', 'sec_app_earliest_cr_line',
       'sec_app_chargeoff_within_12_mths', 'sec_app_num_rev_accts',
       'sec_app_open_acc', 'sec_app_mort_acc', 'sec_app_open_act_il',
       'verification_status_joint', 'dti_joint', 'annual_inc_joint', 'desc',
       'out_prncp', 'out_prncp_inv', 'total_pymnt', 'total_pymnt_inv',
       'total_rec_prncp', 'total_rec_int', 'total_rec_late_fee',
       'recoveries', 'collection_recovery_fee', 'last_pymnt_amnt',
       'last_credit_pull_d', 'last_fico_range_high', 'last_fico_range_low'
       ]

dataset.drop(columns=columns_to_drop, inplace=True)
```

Removing Demographic Variables

To prevent bias and ensure fairness in loan approval prediction, we remove geographic and demographic variables such as `addr_state` and `zip_code` . These features, while potentially predictive, could introduce unethical or discriminatory bias into the model.

```
columns_to_drop = [ 'zip_code', 'addr_state', 'emp_title']
```

```
dataset.drop(columns=columns_to_drop, inplace=True)
```

Removing Joint Application and Secondary Applicant Columns

In this step, we remove all columns related to **joint loan applications** and **secondary (co-) applicants**, including:

- `annual_inc_joint`, `dti_joint`, `verification_status_joint`
- All columns prefixed with `sec_app_` (e.g., `sec_app_fico_range_high`, `sec_app_open_acc`, etc.)

These fields are only populated for joint loans and are typically `NaN` for individual borrowers. Since our machine learning model focuses solely on **individual loan applications**, keeping these columns would:

- Introduce unnecessary sparsity and noise
- Complicate preprocessing due to large amounts of missing data
- Add features not relevant to the majority of loan records

By dropping these variables, we simplify the dataset and ensure our model is trained on consistent, reliable inputs relevant to single applicants only.

```
columns_to_drop = [
    'annual_inc_joint', 'dti_joint', 'verification_status_joint',
    'revol_bal_joint',
    'sec_app_fico_range_low', 'sec_app_fico_range_high',
    'sec_app_earliest_cr_line', 'sec_app_inq_last_6mths',
    'sec_app_mort_acc', 'sec_app_open_acc', 'sec_app_revol_util',
    'sec_app_open_act_il', 'sec_app_num_rev_accts',
    'sec_app_chargeoff_within_12_mths', 'sec_app_collections_12_mths_ex_med',
    'sec_app_mths_since_last_major_derog'
]

dataset.drop(columns=columns_to_drop, inplace=True, errors='ignore')
```

Review of Categorical Variables (Object-Type Columns)

In this section, we examine object-type (categorical) columns in the dataset to determine which are useful for training a machine learning model to predict loan default. Our goal is to retain only relevant features that are:

- Known before the loan is granted (to avoid data leakage),
- Potentially predictive or informative,
- Reasonably clean or transformable.

```
dataset.dtypes.value_counts()
```

	count
float64	76
object	21

dtype: int64

```
non_float_cols = dataset.dtypes[dataset.dtypes != 'float64'].index
print(non_float_cols)
print(len(non_float_cols))
```

```
Index(['id', 'term', 'grade', 'sub_grade', 'emp_length', 'home_ownership',
       'verification_status', 'issue_d', 'loan_status', 'pymnt_plan', 'url',
       'purpose', 'title', 'earliest_cr_line', 'initial_list_status',
       'last_pymnt_d', 'next_pymnt_d', 'application_type', 'hardship_flag',
       'disbursement_method', 'debt_settlement_flag'],
      dtype='object')
21
```

Column Name	Description
term	Duration of the loan (e.g., 36 or 60 months)
grade	Credit grade assigned by Lending Club
sub_grade	Finer granularity of credit grade
home_ownership	Housing status of the borrower (e.g., RENT, OWN)
verification_status	Status of income verification
purpose	Purpose for which the loan was requested
application_type	Whether the loan is individual or joint
loan_status	**Target variable** – final loan outcome (will be converted later to binary)

Based on the list of Categorical Variables here are some variables to keep (Directly usable for modeling). While the remaining categorical/object columns are to be dropped.

```
drop_columns = [
    'id', 'pymnt_plan', 'url', 'title', 'issue_d',
    'last_pymnt_d', 'next_pymnt_d', 'hardship_flag',
    'debt_settlement_flag'
    ]

dataset.drop(columns=drop_columns, inplace=True)
```

```
len(list(dataset.columns))
```

```
88
```

Current dataset has now **88** columns from the initial 151 columns.

Handling Missing Values in Credit History Timing Columns

Some features in the dataset represent the number of months since a borrower last experienced a negative credit event, such as a delinquency or derogatory remark. These include:

- `mths_since_last_record`
- `mths_since_recent_bc_dlq`
- `mths_since_last_major_derog`
- `mths_since_recent_revol_delinq`
- `mths_since_last_delinq`

In many cases, missing values in these columns do **not** indicate bad data but rather the **absence of the event** — for example, the borrower never had a delinquency or public record.

To preserve this distinction, we fill the missing values with **-1**, which semantically means "**no such event has occurred**". This avoids misrepresenting the absence of an event as having occurred recently (which would be implied by filling with `0`).

This approach is particularly effective for tree-based models like Random Forest or XGBoost, which can naturally separate `-1` as its own category during training.

```
total_rows = dataset.shape[0]
missing_values = dataset.isnull().sum()
missing_percentage = (missing_values / total_rows) * 100

missing_df = pd.DataFrame({
    'Column Name': missing_values.index,
    'Number of Missing Values': missing_values.values,
    'Percentage of Missing Values': missing_percentage.values
})

missing_df = missing_df[missing_df['Percentage of Missing Values'] > 0]
missing_df = missing_df.sort_values(by='Number of Missing Values', ascending=False)
missing_df
```

	Column Name	Number of Missing Values	Percentage of Missing Values
21	mths_since_last_record	1901545	84.113069
62	mths_since_recent_bc_dlq	1741000	77.011511
29	mths_since_last_major_derog	1679926	74.309960
64	mths_since_recent_revol_delinq	1520342	67.250910
20	mths_since_last_delinq	1158535	51.246715
...	...	...	...
27	initial_list_status	33	0.001460
31	application_type	33	0.001460
30	policy_code	33	0.001460
24	revol_bal	33	0.001460
87	disbursement_method	33	0.001460

88 rows × 3 columns

Checking columns with months.

```
mths_columns = [col for col in dataset.columns if 'mths' in col.lower()]
print(f"Columns with 'mths' in name: ({len(mths_columns)} found)")
print(mths_columns)
```

```
Columns with 'mths' in name: (12 found)
['inq_last_6mths', 'mths_since_last_delinq', 'mths_since_last_record', 'collections_12_mths_ex_med', 'mths_since_last_major_derog', 'mth
```

Checking which of these columns have missing values.

```
mths_with_na = [col for col in mths_columns if dataset[col].isna().sum() > 0]
print(f"'mths' columns with missing values: ({len(mths_with_na)} found)")
print(mths_with_na)
```

```
'mths' columns with missing values: (12 found)
['inq_last_6mths', 'mths_since_last_delinq', 'mths_since_last_record', 'collections_12_mths_ex_med', 'mths_since_last_major_derog', 'mth
```

Fill the columns with -1 as it indicates `No Record`. Columns with date or temporal data for values in particular isn't always right be filled with median or mode as it might distort behavioral pattern.

```
cols_to_fill = [
    'mths_since_last_record',
    'mths_since_recent_bc_dlq',
    'mths_since_last_major_derog',
    'mths_since_recent_revol_delinq',
    'mths_since_last_delinq',
    'mths_since_rcnt_il',
    'mths_since_recent_bc',
    'mths_since_recent_inq'
]

dataset[cols_to_fill] = dataset[cols_to_fill].fillna(-1)
```

```
fill_with_zero = ['collections_12_mths_ex_med', 'chargeoff_within_12_mths']

dataset[fill_with_zero] = dataset[fill_with_zero].fillna(0)
```

Note on `acc_open_past_24mths` and `inq_last_6mths`:

- `acc_open_past_24mths`: This column is not filled unless null. This column shows the number of accounts opened in past 2 years. Shouldn't have many missing values. If null → maybe fill with median.
- `inq_last_6mths`: This column is **retained without any filling** because it records the **number of recent credit inquiries**, which is known at the time of loan application. It usually has no missing values. If any nulls are found later, they should be investigated rather than imputed blindly.

Identifying Remaining Columns with Missing Values

After several rounds of cleaning and targeted imputation, we now perform a final check for any remaining columns with missing values.

This step helps ensure:

- All important columns are properly handled before modeling
- No unexpected nulls remain that could disrupt encoding or training
- We make informed decisions on whether to **impute**, **drop**, or **transform** the remaining columns

The output below shows each column that still has missing values, along with the **count** and **percentage** of missing entries.

```
missing_info = dataset.isnull().sum()
missing_info = missing_info[missing_info > 0].sort_values(ascending=False)

missing_df = pd.DataFrame({
    'Missing Values': missing_info,
    'Percent Missing': (missing_info / len(dataset)) * 100
})

missing_df
```

	Missing Values	Percent Missing
il_util	1068883	47.281042
all_util	866381	38.323555
total_cu_tl	866163	38.313912
open_acc_6m	866163	38.313912
inq_last_12m	866163	38.313912
...	...	...
fico_range_low	33	0.001460
application_type	33	0.001460
policy_code	33	0.001460
fico_range_high	33	0.001460
disbursement_method	33	0.001460

78 rows × 2 columns

We start filling columns that are important such as `term`, `grade` , etc. with either **Unknown** or using **mode**. For columns with numerical values we could use the **median**.
Note: Review your data first before implementing this steps as it might require different approach or solution.

```
dataset['annual_inc'] = dataset['annual_inc'].fillna(dataset['annual_inc'].median())
dataset['dti'] = dataset['dti'].fillna(dataset['dti'].median())
dataset['fico_range_low'] = dataset['fico_range_low'].fillna(dataset['fico_range_low'].median())
dataset['fico_range_high'] = dataset['fico_range_high'].fillna(dataset['fico_range_high'].median())

dataset['emp_length'] = dataset['emp_length'].fillna('Unknown')
dataset['term'] = dataset['term'].fillna(dataset['term'].mode()[0])
dataset['grade'] = dataset['grade'].fillna(dataset['grade'].mode()[0])
dataset['sub_grade'] = dataset['sub_grade'].fillna(dataset['sub_grade'].mode()[0])
dataset['purpose'] = dataset['purpose'].fillna('Unknown')
dataset['home_ownership'] = dataset['home_ownership'].fillna('Unknown')

dataset['revol_util'] = dataset['revol_util'].fillna(-1)

dataset = dataset[~dataset['loan_amnt'].isnull()]
dataset = dataset[~dataset['installment'].isnull()]
```

Check remaining columns.

```
remaining_nulls = dataset.isnull().sum()
remaining_nulls = remaining_nulls[remaining_nulls > 0]
print("Remaining columns with nulls:", remaining_nulls)
```

```
Remaining columns with nulls: delinq_2yrs                       29
earliest_cr_line                29
inq_last_6mths                  30
open_acc                        29
pub_rec                         29
total_acc                       29
acc_now_delinq                  29
tot_coll_amt                 70276
tot_cur_bal                  70276
open_acc_6m                 866130
open_act_il                 866129
open_il_12m                 866129
open_il_24m                 866129
total_bal_il                866129
il_util                    1068850
open_rv_12m                 866129
open_rv_24m                 866129
max_bal_bc                  866129
all_util                    866348
total_rev_hi_lim             70276
inq_fi                      866129
total_cu_tl                 866130
inq_last_12m                866130
acc_open_past_24mths         50030
avg_cur_bal                  70346
bc_open_to_buy               74935
bc_util                      76071
delinq_amnt                     29
mo_sin_old_il_acct          139071
mo_sin_old_rev_tl_op         70277
mo_sin_rcnt_rev_tl_op        70277
mo_sin_rcnt_tl               70276
mort_acc                     50030
num_accts_ever_120_pd        70276
num_actv_bc_tl               70276
num_actv_rev_tl              70276
num_bc_sats                  58590
num_bc_tl                    70276
num_il_tl                    70276
num_op_rev_tl                70276
num_rev_accts                70277
num_rev_tl_bal_gt_0          70276
num_sats                     58590
num_tl_120dpd_2m            153657
num_tl_30dpd                 70276
num_tl_90g_dpd_24m           70276
num_tl_op_past_12m           70276
pct_tl_nvr_dlq               70431
percent_bc_gt_75             75379
pub_rec_bankruptcies          1365
tax_liens                      105
tot_hi_cred_lim              70276
total_bal_ex_mort            50030
total_bc_limit               50030
total_il_high_credit_limit   70276
dtype: int64
```

Drop rows with low missing/null values. And fill the rest with -1 for "Unknown"

```
low_null_cols = [
    'delinq_2yrs', 'earliest_cr_line', 'inq_last_6mths', 'open_acc', 'pub_rec',
    'total_acc', 'acc_now_delinq', 'total_rev_hi_lim', 'delinq_amnt',
    'mo_sin_old_rev_tl_op', 'mo_sin_rcnt_rev_tl_op', 'mo_sin_rcnt_tl',
    'num_accts_ever_120_pd', 'num_actv_bc_tl', 'num_actv_rev_tl', 'num_bc_tl',
    'num_il_tl', 'num_op_rev_tl', 'num_rev_accts', 'num_rev_tl_bal_gt_0',
    'num_tl_30dpd', 'num_tl_90g_dpd_24m', 'num_tl_op_past_12m',
    'pct_tl_nvr_dlq', 'pub_rec_bankruptcies', 'tax_liens', 'tot_hi_cred_lim',
    'total_il_high_credit_limit', 'num_tl_120dpd_2m'
]
dataset = dataset.dropna(subset=low_null_cols)

fill_with_neg1 = [
    'tot_coll_amt', 'tot_cur_bal', 'avg_cur_bal', 'bc_open_to_buy', 'bc_util',
    'mort_acc', 'total_bc_limit', 'total_bal_ex_mort', 'mo_sin_old_il_acct', 'percent_bc_gt_75'
]
dataset[fill_with_neg1] = dataset[fill_with_neg1].fillna(-1)

high_missing_cols = [
    'open_acc_6m', 'open_act_il', 'open_il_12m', 'open_il_24m', 'total_bal_il',
    'il_util', 'open_rv_12m', 'open_rv_24m', 'max_bal_bc', 'all_util',
```

```
    'inq_fi', 'total_cu_tl', 'inq_last_12m'
]
dataset[high_missing_cols] = dataset[high_missing_cols].fillna(-1)
```

Encoding Categorical Variables

Now that we've completed the data cleaning process, the next essential step in preparing our dataset for machine learning is to **encode categorical variables**.

Most machine learning models require input data to be in **numerical format**. However, our dataset contains several columns with **categorical (non-numeric) values**, such as:

- `emp_length` — Employment length
- `purpose` — Purpose of the loan
- `grade` and `sub_grade` — Credit grade tiers
- `home_ownership` — Home ownership status
- `term` — Loan term duration
- And others

To ensure that the model can interpret these variables correctly, we will convert them into numeric format using appropriate encoding techniques:

- ✅ **Ordinal Encoding** for features with an inherent order (e.g., `grade`, `sub_grade`, `emp_length`)
- ✅ **One-Hot Encoding** for features with no natural order (e.g., `purpose`, `home_ownership`, `application_type`)

> ⚠️ **Note:** Encoding must be done *before* feature selection or training, as most machine learning algorithms and statistical methods can only process numerical input.

In the next code cell, we will identify which columns are categorical and determine the best encoding strategy for each.

```
categorical_cols = dataset.select_dtypes(include=['object']).columns.tolist()

print("Categorical columns detected:")
for col in categorical_cols:
    print(f"- {col}")
```

```
Categorical columns detected:
- term
- grade
- sub_grade
- emp_length
- home_ownership
- verification_status
- loan_status
- purpose
- earliest_cr_line
- initial_list_status
- application_type
- disbursement_method
```

```
for col in categorical_cols:
    print(f"\n Column: {col}")
    print(dataset[col].unique())
```

```
 Column: term
[' 36 months' ' 60 months']

 Column: grade
['C' 'B' 'F' 'A' 'E' 'D' 'G']

 Column: sub_grade
['C4' 'C1' 'B4' 'C5' 'F1' 'C3' 'B2' 'B1' 'A2' 'B5' 'C2' 'E2' 'A4' 'A1'
 'D4' 'F3' 'D1' 'B3' 'E4' 'D3' 'D2' 'D5' 'A5' 'E3' 'F2' 'F5' 'E5' 'A3'
 'G2' 'G1' 'E1' 'G3' 'G4' 'F4' 'G5']

 Column: emp_length
['10+ years' '3 years' '4 years' '6 years' '1 year' '7 years' '8 years'
 '5 years' '2 years' '9 years' '< 1 year' 'Unknown']

 Column: home_ownership
['MORTGAGE' 'RENT' 'OWN' 'ANY' 'NONE' 'OTHER']

 Column: verification_status
```

```
['Not Verified' 'Source Verified' 'Verified']

 Column: loan_status
['Fully Paid' 'Current' 'Charged Off' 'In Grace Period'
 'Late (31-120 days)' 'Late (16-30 days)' 'Default']

 Column: purpose
['debt_consolidation' 'small_business' 'home_improvement' 'major_purchase'
 'credit_card' 'other' 'house' 'vacation' 'car' 'medical' 'moving'
 'renewable_energy' 'wedding' 'educational']

 Column: earliest_cr_line
['Aug-2003' 'Dec-1999' 'Aug-2000' 'Sep-2008' 'Jun-1998' 'Oct-1987'
 'Jun-1990' 'Feb-1999' 'Apr-2002' 'Nov-1994' 'Apr-1995' 'Feb-1988'
 'Jun-1996' 'Jun-2005' 'May-1984' 'Dec-2001' 'Nov-1993' 'Sep-2001'
 'May-2004' 'Jun-1991' 'May-2000' 'Oct-2011' 'May-1994' 'Jul-2011'
 'May-1991' 'May-2001' 'Jun-2002' 'Dec-1985' 'Apr-2007' 'Feb-2002'
 'Jun-2001' 'Jun-1997' 'Oct-1996' 'Jan-2005' 'Jul-2001' 'Aug-2004'
 'Jun-2007' 'Jul-2004' 'Apr-2001' 'Oct-2004' 'May-1992' 'Oct-1999'
 'Nov-2001' 'Oct-2005' 'Jan-2001' 'Sep-2004' 'Sep-1993' 'Nov-2005'
 'Feb-1989' 'Sep-2006' 'Oct-1982' 'Oct-2002' 'Feb-1990' 'Aug-1987'
 'Oct-1998' 'Aug-2001' 'Feb-2004' 'Aug-2009' 'Mar-2002' 'Nov-1999'
 'Jun-2006' 'Jan-1999' 'Jun-2000' 'Jan-2007' 'Dec-1998' 'Aug-1997'
 'Dec-1987' 'Feb-1996' 'Apr-1990' 'Jun-2004' 'Jun-1995' 'Dec-2002'
 'Aug-1986' 'Nov-2002' 'Oct-2006' 'Sep-2000' 'Feb-2012' 'Apr-2005'
 'Sep-1994' 'Apr-1993' 'Sep-2007' 'Jan-1998' 'May-2008' 'Mar-2001'
 'Apr-1994' 'Apr-2003' 'Jan-2002' 'Jan-2011' 'Nov-2000' 'Sep-2002'
 'May-2002' 'Nov-2003' 'Sep-2003' 'Aug-2008' 'Dec-1997' 'May-2006'
 'Jan-1996' 'Nov-2009' 'Oct-1994' 'May-1985' 'Jun-1999' 'Aug-1999'
 'Nov-2006' 'Nov-1996' 'Feb-2000' 'Jan-1957' 'Aug-1974' 'Feb-2010'
 'Dec-1983' 'Jan-1993' 'Mar-2004' 'Aug-1998' 'Dec-2006' 'Nov-1991'
 'Apr-2006' 'Oct-2008' 'Nov-2004' 'Feb-1995' 'Oct-1991' 'Sep-1983'
 'Jan-2008' 'Jul-1995' 'Aug-1989' 'Oct-2000' 'Dec-2000' 'Sep-1989'
 'May-1998' 'Aug-2011' 'Sep-1984' 'Apr-2004' 'Oct-2003' 'May-2012'
 'Jan-2004' 'Jun-1981' 'Jul-1993' 'Dec-2009' 'Oct-1989' 'Jul-1998'
 'Jul-1994' 'Sep-2010' 'Mar-2000' 'Nov-1985' 'Sep-1990' 'Mar-1997'
 'Mar-1993' 'May-1993' 'Jun-1986' 'Oct-1993' 'Nov-1998' 'May-1999'
```

Processing `earliest_cr_line` into Credit History Length

Based on initial observation, we start our encoding process by transforming the column `earliest_cr_line`, which contains date strings like `'Jan-2005'`, `'Dec-1999'`, etc. This column represents the borrower's **earliest recorded credit line**, and is a valuable indicator of their **credit history length** — an important factor in assessing financial risk.

However, since the values are in string format, they must first be **converted into proper datetime objects**. Once converted, we compute a new feature: `credit_history_length`, which represents the **number of years** between the earliest credit line and a fixed reference point in time.

> ⚠️ Note: Instead of using the current year (e.g., 2025), we use **2018** as the reference year — the endpoint of this dataset's time coverage — to avoid introducing data leakage from the future.

This new column gives us a clean, numerical representation of a borrower's credit age, which can now be used safely in model training. After creating this new column, we drop the original `earliest_cr_line` column since it's no longer needed in its raw form.

```python
dataset['earliest_cr_line'] = pd.to_datetime(dataset['earliest_cr_line'], format='%b-%Y', errors='coerce')

reference_year = 2018
dataset['credit_history_length'] = reference_year - dataset['earliest_cr_line'].dt.year

dataset.drop('earliest_cr_line', axis=1, inplace=True)
```

Performing Encoding Categorical Variables (Ordinal and Nominal)

After identifying all categorical features in the dataset, we now prepare them for machine learning by converting them into numerical format. Most ML models cannot directly interpret string-based categories, so encoding is essential.

We divide the categorical variables into two types:

🔷 Ordinal Variables (with inherent order)

These features have a clear, ranked structure, so we will apply **Label Encoding or Ordinal Encoding**:

- `term`: Loan duration, where `'36 months' < '60 months'`
- `grade`: Credit score grade from `'A'` (best) to `'G'` (worst)
- `sub_grade`: Fine-grained version of grade (e.g., `A1 < A2 < ... < G5`)
- `emp_length`: Length of employment (e.g., `'< 1 year' < '1 year' < ... < '10+ years'`)

🟧 Nominal Variables (no natural order)

These features have no rank or hierarchy, so we apply **One-Hot Encoding**:

- `home_ownership` : Types of housing (Rent, Mortgage, etc.)
- `verification_status` : Loan info verification status
- `purpose` : Reason for the loan
- `initial_list_status` : Internal LC listing code
- `application_type` : Individual or Joint App
- `disbursement_method` : Method of disbursing funds

> 🔄 `loan_status` : This is our **target variable** and will not be encoded here. We will process it separately when we begin model training.

In the next steps, we will first encode the ordinal variables using custom mapping, and then apply one-hot encoding to the nominal ones.

```
dataset['term'] = dataset['term'].str.strip()

term_mapping = {
    '36 months': 0,
    '60 months': 1
}
dataset['term'] = dataset['term'].map(term_mapping)

grade_order = ['A', 'B', 'C', 'D', 'E', 'F', 'G']
grade_mapping = {grade: i for i, grade in enumerate(grade_order)}
dataset['grade'] = dataset['grade'].map(grade_mapping)

subgrades = sorted(dataset['sub_grade'].dropna().unique(), key=lambda x: (x[0], int(x[1:])))
subgrade_mapping = {subgrade: idx for idx, subgrade in enumerate(subgrades)}
dataset['sub_grade'] = dataset['sub_grade'].map(subgrade_mapping)

dataset['emp_length'] = dataset['emp_length'].str.strip()

emp_length_mapping = {
    '< 1 year': 0,
    '1 year': 1,
    '2 years': 2,
    '3 years': 3,
    '4 years': 4,
    '5 years': 5,
    '6 years': 6,
    '7 years': 7,
    '8 years': 8,
    '9 years': 9,
    '10+ years': 10,
    'Unknown': -1
}
dataset['emp_length'] = dataset['emp_length'].map(emp_length_mapping)


nominal_cols = [
    'home_ownership',
    'verification_status',
    'purpose',
    'initial_list_status',
    'application_type',
    'disbursement_method'
]

dataset = pd.get_dummies(dataset, columns=nominal_cols, prefix=nominal_cols, drop_first=True)
```

Encoding the Target Variable: `loan_status`

As the final part of our categorical encoding process, we now prepare the **target variable** — `loan_status` — which indicates whether a loan was repaid successfully or resulted in a default.

The original values in `loan_status` include multiple statuses such as:

- `Fully Paid`
- `Current`

- `Charged Off`
- `Default`
- `Late (31-120 days)`
- `Late (16-30 days)`
- `In Grace Period`, etc.

✅ Problem Framing: Binary Classification

For this project, we simplify the problem as a **binary classification task**:

- `1` = The borrower **defaulted** (e.g., `Charged Off`, `Default`, or Lates)
- `0` = The loan was **fully paid**
- Other ambiguous statuses like `Current` and `In Grace Period` are **excluded** to avoid uncertainty and ensure data clarity

This approach allows us to build a focused model that answers the question:

> *"Will this borrower default on their loan?"*

We will now filter the dataset to keep only the relevant statuses and encode the target accordingly.

```
default_statuses = ['Charged Off', 'Default', 'Late (31-120 days)', 'Late (16-30 days)']

dataset = dataset[dataset['loan_status'].isin(['Fully Paid'] + default_statuses)]

dataset['loan_status'] = dataset['loan_status'].apply(lambda x: 1 if x in default_statuses else 0)
```

Feature Selection: Identifying Important Predictors

With data cleaning and encoding complete, we now move into **feature selection**, the process of identifying which features (columns) are most relevant for predicting the target variable, `loan_status`.

Not all features contribute equally to a machine learning model. Some may be redundant, weakly related, or introduce noise. By removing these less useful features, we can:

- Improve model accuracy and efficiency
- Reduce overfitting and training time
- Make the model easier to interpret

What We'll Do:

In this section, we'll begin feature selection by examining how **numerical features** correlate with the target variable. This gives us a quick idea of which features are **most linearly related** to loan default outcomes.

> Note: Not all important features are strongly correlated. Correlation is just one tool — later we can use **model-based methods** (e.g., Random Forest feature importance) for deeper analysis.

Next, we'll generate a correlation matrix and visually explore which features have meaningful relationships with `loan_status`.

Creating a Correlation Matrix

Correlation Matrix, a technique used to measure the linear relationship between each numeric feature and the target variable `loan_status`. This helps us identify features that are **strongly** (positively or negatively) **related** to the target and **remove features** with very weak linear relationships, which are unlikely to help in prediction. We considered a feature as weak if its absolute correlation with `loan_status` was less than **0.05** (|r| < 0.05).

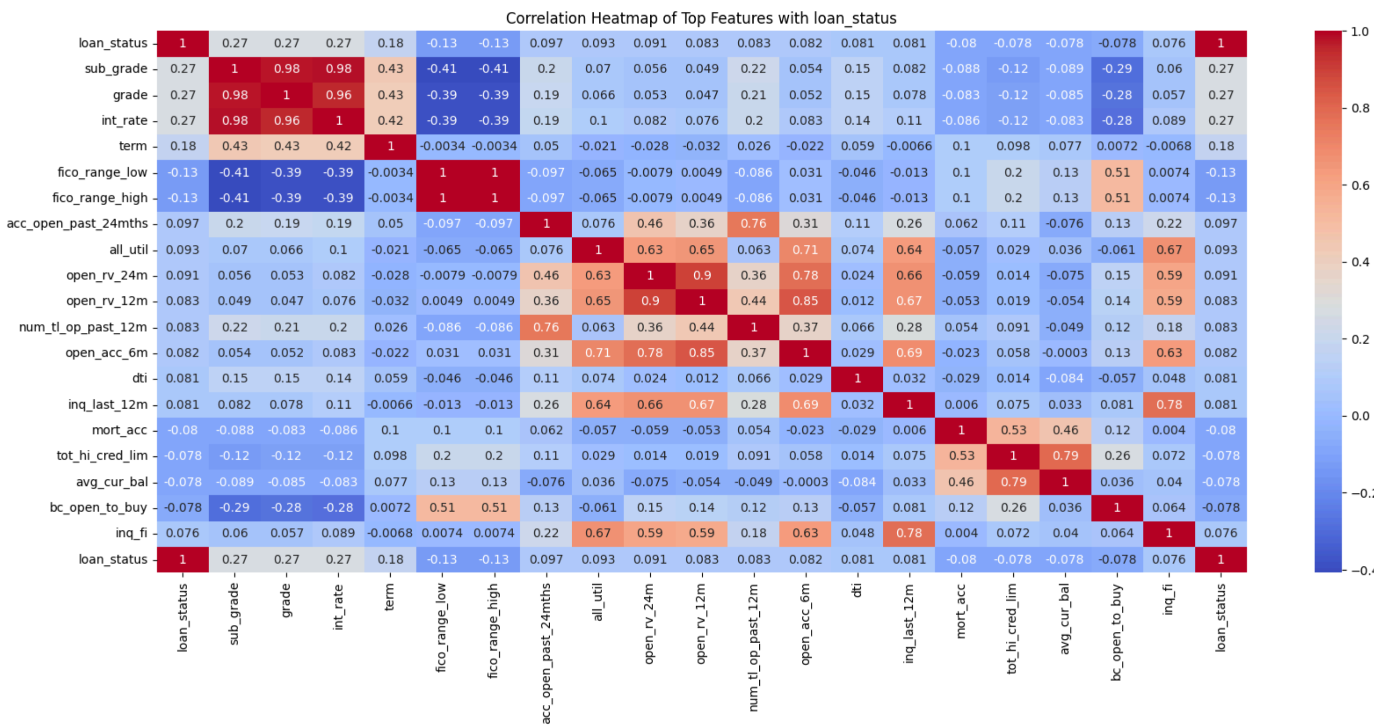
```
correlation_matrix = dataset.corr(numeric_only=True)
correlation_with_target = correlation_matrix['loan_status'].sort_values(key=abs, ascending=False)
top_features = correlation_with_target.head(20)
print("Top 20 features most correlated with loan_status:\n")
print(top_features)
```

```
Top 20 features most correlated with loan_status:

loan_status              1.000000
sub_grade                0.272642
grade                    0.266139
int_rate                 0.265919
term                     0.184330
```

```
fico_range_low         -0.125041
fico_range_high        -0.125039
acc_open_past_24mths    0.097373
all_util                0.093317
open_rv_24m             0.090813
open_rv_12m             0.083230
num_tl_op_past_12m      0.082527
open_acc_6m             0.081793
dti                     0.081450
inq_last_12m            0.081036
mort_acc               -0.079793
tot_hi_cred_lim        -0.078276
avg_cur_bal            -0.078190
bc_open_to_buy         -0.077516
inq_fi                  0.075871
Name: loan_status, dtype: float64
```

Visualize the results.

```
plt.figure(figsize=(20, 8))
sns.heatmap(dataset[top_features.index.tolist() + ['loan_status']].corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap of Top Features with loan_status")
plt.show()
```



Model-Based (Random Forest Importance)

After the correlation check, we used a Random Forest Classifier to calculate the model-based feature importances. This step captures **non-linear** and **interaction effects** that correlation cannot detect. Feature importance in Random Forests shows how much a model relies on a feature to make predictions. Features with importance less than 0.005 were considered weak contributors.

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
```

```
import pandas as pd

X = dataset.drop('loan_status', axis=1)
y = dataset['loan_status']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

importances = pd.Series(rf.feature_importances_, index=X.columns)
importances_sorted = importances.sort_values(ascending=False)

print("Top 20 Features by Random Forest Importance:\n")
print(importances_sorted.head(20))
```

```
Top 20 Features by Random Forest Importance:

int_rate                      0.032509
dti                           0.027170
sub_grade                     0.027031
mo_sin_old_rev_tl_op          0.023329
tot_hi_cred_lim               0.022995
avg_cur_bal                   0.022972
annual_inc                    0.022222
grade                         0.022191
installment                   0.022061
mo_sin_old_il_acct            0.021936
bc_open_to_buy                0.021730
tot_cur_bal                   0.021479
revol_util                    0.021438
revol_bal                     0.021310
total_rev_hi_lim              0.021288
bc_util                       0.021225
total_bc_limit                0.021138
total_bal_ex_mort             0.020378
total_il_high_credit_limit    0.018709
mths_since_recent_bc          0.018156
dtype: float64
```

Dropping Low-Value Features (Both Filters)

After evaluating features using both methods, we removed columns that were flagged by both the correlation analysis and the Random Forest model. We retained features that passed at least one of the two importance checks, ensuring we do not mistakenly discard non-linear patterns missed by the correlation matrix.

```
correlation_matrix = dataset.corr(numeric_only=True)
correlations = correlation_matrix['loan_status'].drop('loan_status')
abs_correlations = correlations.abs()

feature_summary = pd.DataFrame({
    'Correlation': correlations,
    'AbsCorrelation': abs_correlations,
    'RF_Importance': importances
})

to_drop = feature_summary[
    (feature_summary['AbsCorrelation'] < 0.05) &
    (feature_summary['RF_Importance'] < 0.005)
].sort_values(by='AbsCorrelation')

print("Features weak in both correlation and model importance:\n")
print(to_drop)
```

```
Features weak in both correlation and model importance:

                                   Correlation  AbsCorrelation  \
purpose_major_purchase               -0.000233        0.000233
purpose_educational                  -0.000467        0.000467
home_ownership_OTHER                 -0.000540        0.000540
num_tl_120dpd_2m                      0.000595        0.000595
home_ownership_NONE                  -0.000864        0.000864
purpose_vacation                     -0.001332        0.001332
num_tl_30dpd                          0.002036        0.002036
purpose_renewable_energy              0.002161        0.002161
delinq_amnt                           0.002238        0.002238
chargeoff_within_12_mths              0.002541        0.002541
```

```
acc_now_delinq                        0.002618        0.002618
purpose_wedding                      -0.004448        0.004448
purpose_house                         0.005732        0.005732
purpose_medical                       0.006296        0.006296
home_ownership_OWN                    0.007031        0.007031
purpose_moving                        0.008936        0.008936
num_tl_90g_dpd_24m                    0.009267        0.009267
tax_liens                             0.009738        0.009738
purpose_other                         0.010775        0.010775
disbursement_method_DirectPay         0.010940        0.010940
initial_list_status_w                 0.011877        0.011877
purpose_home_improvement             -0.012346        0.012346
num_accts_ever_120_pd                 0.013932        0.013932
collections_12_mths_ex_med            0.014700        0.014700
delinq_2yrs                           0.018948        0.018948
verification_status_Source Verified   0.023880        0.023880
pub_rec_bankruptcies                  0.024808        0.024808
pub_rec                               0.024886        0.024886
purpose_small_business                0.027195        0.027195
purpose_debt_consolidation            0.030447        0.030447
total_cu_tl                           0.034894        0.034894
application_type_Joint App            0.038043        0.038043
purpose_credit_card                  -0.042503        0.042503

                                    RF_Importance
purpose_major_purchase                   0.000932
purpose_educational                      0.000000
home_ownership_OTHER                     0.000010
num_tl_120dpd_2m                         0.000060
home_ownership_NONE                      0.000005
purpose_vacation                         0.000454
num_tl_30dpd                             0.000223
purpose_renewable_energy                 0.000075
delinq_amnt                              0.000399
chargeoff_within_12_mths                 0.000514
acc_now_delinq                           0.000296
purpose_wedding                          0.000061
purpose_house                            0.000377
purpose_medical                          0.000737
home_ownership_OWN                       0.001824
purpose_moving                           0.000467
num_tl_90g_dpd_24m                       0.001815
tax_liens                                0.001663
purpose_other                            0.001586
```

```python
drop_features = to_drop.index.tolist()
dataset.drop(columns=drop_features, inplace=True)

print(f"Dropped {len(drop_features)} low-value features.")
```

```
Dropped 33 low-value features.
```

```python
dataset.info()
```

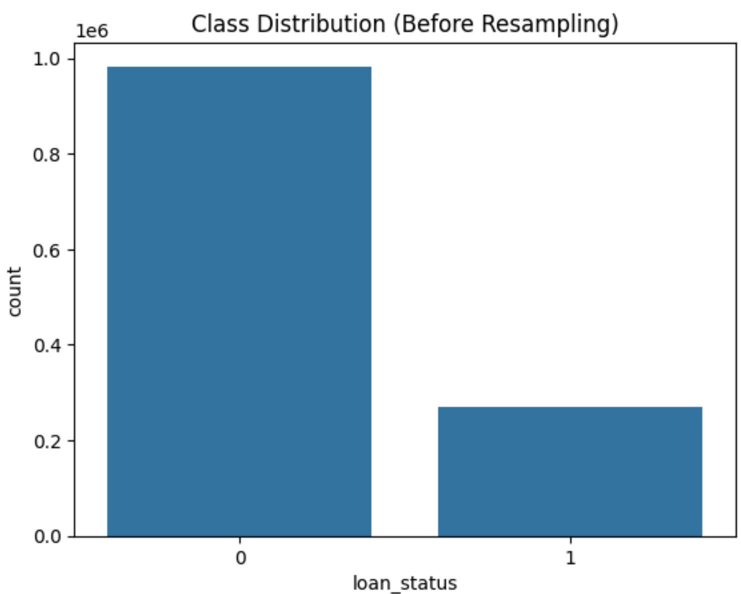
```
<class 'pandas.core.frame.DataFrame'>
Index: 1251976 entries, 0 to 2260697
Data columns (total 72 columns):
 #   Column                         Non-Null Count    Dtype
---  ------                         --------------    -----
 0   loan_amnt                      1251976 non-null  float64
 1   funded_amnt                    1251976 non-null  float64
 2   funded_amnt_inv                1251976 non-null  float64
 3   term                           1251976 non-null  int64
 4   int_rate                       1251976 non-null  float64
 5   installment                    1251976 non-null  float64
 6   grade                          1251976 non-null  int64
 7   sub_grade                      1251976 non-null  int64
 8   emp_length                     1251976 non-null  int64
 9   annual_inc                     1251976 non-null  float64
 10  loan_status                    1251976 non-null  int64
 11  dti                            1251976 non-null  float64
 12  fico_range_low                 1251976 non-null  float64
 13  fico_range_high                1251976 non-null  float64
 14  inq_last_6mths                 1251976 non-null  float64
 15  mths_since_last_delinq         1251976 non-null  float64
 16  mths_since_last_record         1251976 non-null  float64
 17  open_acc                       1251976 non-null  float64
 18  revol_bal                      1251976 non-null  float64
 19  revol_util                     1251976 non-null  float64
 20  total_acc                      1251976 non-null  float64
 21  mths_since_last_major_derog    1251976 non-null  float64
 22  policy_code                    1251976 non-null  float64
```

```
 23  tot_coll_amt                 1251976 non-null  float64
 24  tot_cur_bal                  1251976 non-null  float64
 25  open_acc_6m                  1251976 non-null  float64
 26  open_act_il                  1251976 non-null  float64
 27  open_il_12m                  1251976 non-null  float64
 28  open_il_24m                  1251976 non-null  float64
 29  mths_since_rcnt_il           1251976 non-null  float64
 30  total_bal_il                 1251976 non-null  float64
 31  il_util                      1251976 non-null  float64
 32  open_rv_12m                  1251976 non-null  float64
 33  open_rv_24m                  1251976 non-null  float64
 34  max_bal_bc                   1251976 non-null  float64
 35  all_util                     1251976 non-null  float64
 36  total_rev_hi_lim             1251976 non-null  float64
 37  inq_fi                       1251976 non-null  float64
 38  inq_last_12m                 1251976 non-null  float64
 39  acc_open_past_24mths         1251976 non-null  float64
 40  avg_cur_bal                  1251976 non-null  float64
 41  bc_open_to_buy               1251976 non-null  float64
 42  bc_util                      1251976 non-null  float64
 43  mo_sin_old_il_acct           1251976 non-null  float64
 44  mo_sin_old_rev_tl_op         1251976 non-null  float64
 45  mo_sin_rcnt_rev_tl_op        1251976 non-null  float64
 46  mo_sin_rcnt_tl               1251976 non-null  float64
 47  mort_acc                     1251976 non-null  float64
 48  mths_since_recent_bc         1251976 non-null  float64
 49  mths_since_recent_bc_dlq     1251976 non-null  float64
 50  mths_since_recent_inq        1251976 non-null  float64
 51  mths_since_recent_revol_delinq 1251976 non-null  float64
```

Data Splitting

```
from sklearn.model_selection import train_test_split

X = dataset.drop('loan_status', axis=1)
y = dataset['loan_status']
```

```
sns.countplot(x='loan_status', data=dataset)
plt.title('Class Distribution (Before Resampling)')
plt.show()
```




```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

We implement SMOTE as the classes are not balanced.

```
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

```
print("Before SMOTE:")
print(y_train.value_counts())
print(y_train.value_counts(normalize=True))

print("\nAfter SMOTE:")
print(pd.Series(y_train_resampled).value_counts())
print(pd.Series(y_train_resampled).value_counts(normalize=True))
```

```
Before SMOTE:
loan_status
0    687910
1    188473
Name: count, dtype: int64
loan_status
0    0.784942
1    0.215058
Name: proportion, dtype: float64

After SMOTE:
loan_status
0    687910
1    687910
Name: count, dtype: int64
loan_status
0    0.5
1    0.5
Name: proportion, dtype: float64
```

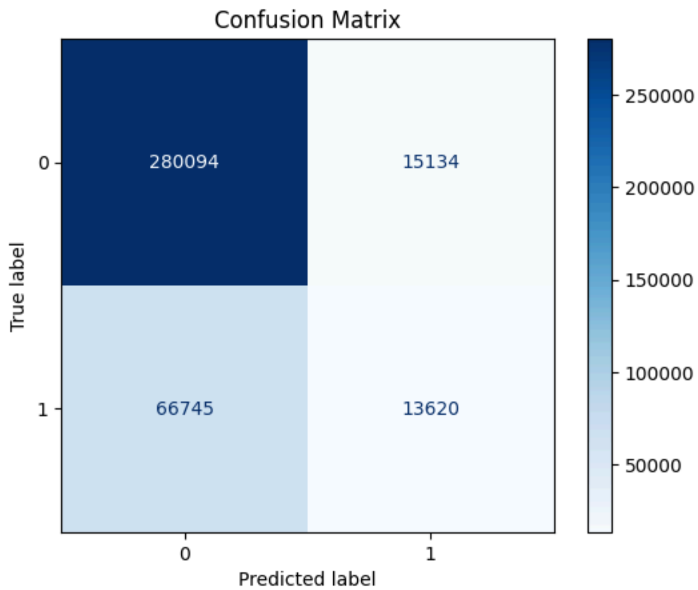
Model Training

Initial Training using Random Forest

On this section of this notebook we finally perform model training using the data that we preprocessed. We simply call `RandomForestClassifier` and set its parameters such as the `random_state`. We display the results then after the model training.

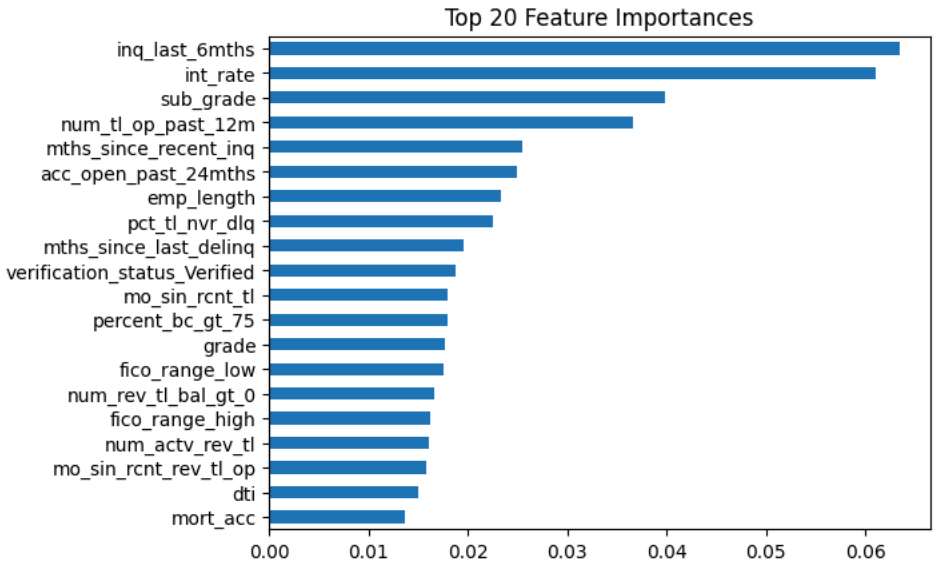
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix

rf = RandomForestClassifier(random_state=42)
rf.fit(X_train_resampled, y_train_resampled)

from sklearn.metrics import (
    classification_report,
    confusion_matrix,
    accuracy_score,
    roc_auc_score,
    ConfusionMatrixDisplay
)
import matplotlib.pyplot as plt

y_pred = rf.predict(X_test)
y_proba = rf.predict_proba(X_test)[:, 1]

print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))

print("\nClassification Report:")
print(classification_report(y_test, y_pred))

print("Accuracy:", accuracy_score(y_test, y_pred))

print("ROC-AUC:", roc_auc_score(y_test, y_proba))

disp = ConfusionMatrixDisplay.from_estimator(rf, X_test, y_test, cmap='Blues')
plt.title("Confusion Matrix")
plt.show()
```

```
Confusion Matrix:
[[280094  15134]
 [ 66745  13620]]

Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.95      0.87    295228
           1       0.47      0.17      0.25     80365

    accuracy                           0.78    375593
   macro avg       0.64      0.56      0.56    375593
weighted avg       0.74      0.78      0.74    375593

Accuracy: 0.7820007295130633
ROC-AUC: 0.7071223513520097
```



Check which feature Random Forest relied the most.

```
import pandas as pd
import matplotlib.pyplot as plt

feature_importances = pd.Series(rf.feature_importances_, index=X_train.columns)
top_features = feature_importances.sort_values(ascending=False).head(20)

top_features.plot(kind='barh')
plt.gca().invert_yaxis()
plt.title("Top 20 Feature Importances")
plt.show()
```



Use and Compare other models in terms of performance.

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingClassifier
from lightgbm import LGBMClassifier
from xgboost import XGBClassifier
from sklearn.metrics import roc_auc_score

models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Gradient Boosting": GradientBoostingClassifier(),
    "LightGBM": LGBMClassifier(),
    "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric='logloss')
}

for name, model in models.items():
    model.fit(X_train_resampled, y_train_resampled)
    y_pred = model.predict(X_test)
    y_proba = model.predict_proba(X_test)[:, 1]
    auc = roc_auc_score(y_test, y_proba)
    print(f"{name} ROC-AUC: {auc:.4f}")
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
Logistic Regression ROC-AUC: 0.6578
Gradient Boosting ROC-AUC: 0.6983
[LightGBM] [Info] Number of positive: 687910, number of negative: 687910
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.499918 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 15930
[LightGBM] [Info] Number of data points in the train set: 1375820, number of used features: 70
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
LightGBM ROC-AUC: 0.7245
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning: [19:26:59] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
XGBoost ROC-AUC: 0.7281
```

Use XGBoost with an improved ROC-AUC compared to Random Forest.

```
from xgboost import XGBClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score
```

```
xgb = XGBClassifier(eval_metric='logloss', use_label_encoder=False, random_state=42)
xgb.fit(X_train_resampled, y_train_resampled)

y_pred = xgb.predict(X_test)
y_proba = xgb.predict_proba(X_test)[:, 1]

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
print("ROC-AUC:", roc_auc_score(y_test, y_proba))
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning: [03:45:04] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
[[285500   9728]
 [ 68438  11927]]
              precision    recall  f1-score   support

           0       0.81      0.97      0.88    295228
           1       0.55      0.15      0.23     80365

    accuracy                           0.79    375593
   macro avg       0.68      0.56      0.56    375593
weighted avg       0.75      0.79      0.74    375593

ROC-AUC: 0.7281066743037125
```

```
import shap

explainer = shap.TreeExplainer(xgb)
shap_values = explainer.shap_values(X_test[:1000])

shap.summary_plot(shap_values, X_test[:1000])
```


High