Loan Default

July 6, 2025

[1]:

```python
#@title Load Dataset
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
path='/content/drive/MyDrive/Dataset/Loan_Default.csv'
df=pd.read_csv(path)
df.sample(10), df.columns.tolist()
```

[1]:

```
(            ID  year loan_limit             Gender approv_in_adv loan_type  \
 97238   122128  2019        ncf              Joint           pre     type3
 101175  126065  2019         cf               Male         nopre     type1
 26389    51279  2019         cf              Joint         nopre     type3
 64912    89802  2019         cf  Sex Not Available         nopre     type1
 138801  163691  2019         cf               Male         nopre     type2
 48866    73756  2019        NaN               Male         nopre     type1
 88688   113578  2019         cf  Sex Not Available         nopre     type2
 131363  156253  2019         cf               Male         nopre     type1
 56079    80969  2019         cf              Joint         nopre     type1
 102389  127279  2019        ncf  Sex Not Available         nopre     type1

        loan_purpose Credit_Worthiness open_credit business_or_commercial  …
\
 97238            p1                l1        nopc                  nob/c  …
 101175           p4                l1        nopc                  nob/c  …
 26389            p3                l1        nopc                  nob/c  …
 64912            p4                l1        nopc                  nob/c  …
 138801           p4                l1        nopc                    b/c  …
 48866            p1                l1        nopc                  nob/c  …
 88688            p4                l1        nopc                    b/c  …
 131363           p3                l1        nopc                  nob/c  …
 56079            p3                l1        nopc                  nob/c  …
 102389           p3                l1        nopc                  nob/c  …

         credit_type  Credit_Score  co-applicant_credit_type    age  \
 97238          CRIF           821                       EXP  35-44
```

```
101175          EXP           605                       CIB  45-54
26389           EXP           576                       EXP  65-74
64912           CIB           713                       CIB  55-64
138801         EQUI           693                       EXP  65-74
48866           CIB           590                       CIB  65-74
88688           CIB           780                       EXP  65-74
131363          CIB           727                       CIB  55-64
56079           CIB           531                       EXP  55-64
102389          EXP           789                       EXP  25-34

        submission_of_application         LTV Region Security_Type  Status  \
97238                     to_inst  101.706827  North        direct       0
101175                    to_inst   75.122549  North        direct       0
26389                     to_inst   75.887574  North        direct       0
64912                     to_inst   59.339080  south        direct       1
138801                    to_inst         NaN  North        direct       1
48866                    not_inst   78.882576  North        direct       1
88688                     to_inst   59.765625  south        direct       0
131363                    to_inst   68.208661  North        direct       0
56079                    not_inst   58.366142  south        direct       0
102389                    to_inst   74.441341  south        direct       0

       dtir1
97238   36.0
101175  44.0
26389   60.0
64912   46.0
138801   NaN
48866   23.0
88688   16.0
131363  42.0
56079   38.0
102389  44.0

[10 rows x 34 columns],
['ID',
 'year',
 'loan_limit',
 'Gender',
 'approv_in_adv',
 'loan_type',
 'loan_purpose',
 'Credit_Worthiness',
 'open_credit',
 'business_or_commercial',
 'loan_amount',
 'rate_of_interest',
```

```
 'Interest_rate_spread',
 'Upfront_charges',
 'term',
 'Neg_ammortization',
 'interest_only',
 'lump_sum_payment',
 'property_value',
 'construction_type',
 'occupancy_type',
 'Secured_by',
 'total_units',
 'income',
 'credit_type',
 'Credit_Score',
 'co-applicant_credit_type',
 'age',
 'submission_of_application',
 'LTV',
 'Region',
 'Security_Type',
 'Status',
 'dtir1'])
```

Column	Description
ID	Unique identifier for each loan application.
year	The year the loan was applied for.
loan_limit	Whether the loan was under a limit category like 'cf' (Conforming).
Gender	Applicant's gender or profile (`Male`, `Joint`, `Sex Not Available`).
approv_in_adv	Was the loan pre-approved? (`pre`, `nopre`).
loan_type	Type/category of the loan product (`type1`, `type2`, etc.).
loan_purpose	Reason for the loan (e.g., `p1`, `p4`). Encoded.
Credit_Worthiness	Applicant's credit status, usually based on a rule (`l1`, `l2`).
open_credit	Whether the applicant has open lines of credit (`nopc` = none open).
business_or_commercial	Whether loan is for business/commercial use (`b/c`, `nob/c`).
loan_amount	Total loan amount requested.
rate_of_interest	Interest rate on the loan.
Interest_rate_spread	Spread above the benchmark rate.
Upfront_charges	Any upfront costs or fees charged.
term	Duration of the loan in months or years.
Neg_ammortization	Whether negative amortization is allowed (`y`, `n`).
interest_only	Whether it's an interest-only loan initially.
lump_sum_payment	Whether lump-sum payments are part of the terms.
property_value	Assessed or declared value of the property.
construction_type	Type of construction involved (`ct1`, `ct2`, etc.).

Column	Description
occupancy_type	Whether owner-occupied, rental, etc.
Secured_by	Whether the loan is secured by real estate or other assets.
total_units	Number of housing units tied to the loan (e.g., duplex = 2).
income	Applicant's reported income.
credit_type	Credit score source agency (`EXP`, `EQUI`, `CRIF`, etc.).
Credit_Score	Numerical credit score of the applicant.
co-applicant_credit_type	Credit source for the co-applicant (if any).
age	Age group of applicant (e.g., `25-34`, `45-54`).
submission_of_application	Whether submitted online, in-person, etc.
LTV	Loan-to-Value ratio (loan amount / property value × 100).
Region	Geographical region (e.g., `North`, `south`).
Security_Type	Type of collateral (`direct`, etc.).
Status	**Target variable** – likely 1 = Defaulted, 0 = Repaid.
dtir1	Debt-to-Income Ratio – key feature for affordability analysis.

[2]:
```
#@title Column Summary
def column_summary(df):
    summary_data = []

    for col_name in df.columns:
        col_dtype = df[col_name].dtype
        num_of_nulls = df[col_name].isnull().sum()
        num_of_non_nulls = df[col_name].notnull().sum()
        num_of_distinct_values = df[col_name].nunique()

        if num_of_distinct_values <= 10:
            distinct_values_counts = df[col_name].value_counts().to_dict()
        else:
            top_10_values_counts = df[col_name].value_counts().head(10).
↪to_dict()
            distinct_values_counts = {k: v for k, v in␣
↪sorted(top_10_values_counts.items(), key=lambda item: item[1], reverse=True)}

        summary_data.append({
            'col_name': col_name,
            'col_dtype': col_dtype,
            'num_of_nulls': num_of_nulls,
            'num_of_non_nulls': num_of_non_nulls,
            'num_of_distinct_values': num_of_distinct_values,
            'distinct_values_counts': distinct_values_counts
        })

    summary_df = pd.DataFrame(summary_data)
    return summary_df
```

```
summary_df = column_summary(df)
display(summary_df)
```

```
                   col_name col_dtype  num_of_nulls  num_of_non_nulls  \
0                        ID     int64             0            148670
1                      year     int64             0            148670
2                loan_limit    object          3344            145326
3                    Gender    object             0            148670
4              approv_in_adv    object           908            147762
5                 loan_type    object             0            148670
6              loan_purpose    object           134            148536
7         Credit_Worthiness    object             0            148670
8                open_credit    object             0            148670
9     business_or_commercial    object             0            148670
10               loan_amount     int64             0            148670
11          rate_of_interest   float64         36439            112231
12      Interest_rate_spread   float64         36639            112031
13           Upfront_charges   float64         39642            109028
14                      term   float64            41            148629
15         Neg_ammortization    object           121            148549
16             interest_only    object             0            148670
17          lump_sum_payment    object             0            148670
18            property_value   float64         15098            133572
19         construction_type    object             0            148670
20            occupancy_type    object             0            148670
21                Secured_by    object             0            148670
22               total_units    object             0            148670
23                    income   float64          9150            139520
24               credit_type    object             0            148670
25              Credit_Score     int64             0            148670
26   co-applicant_credit_type    object             0            148670
27                       age    object           200            148470
28  submission_of_application    object           200            148470
29                       LTV   float64         15098            133572
30                    Region    object             0            148670
31             Security_Type    object             0            148670
32                    Status     int64             0            148670
33                     dtir1   float64         24121            124549

   num_of_distinct_values                          distinct_values_counts
0                  148670  {173559: 1, 24890: 1, 24891: 1, 24892: 1, 2489…
1                       1                                  {2019: 148670}
2                       2                      {'cf': 135348, 'ncf': 9978}
3                       4  {'Male': 42346, 'Joint': 41399, 'Sex Not Avail…
4                       2                   {'nopre': 124621, 'pre': 23141}
5                       3  {'type1': 113173, 'type2': 20762, 'type3': 14735}
```

```
6                          4  {'p3': 55934, 'p4': 54799, 'p1': 34529, 'p2': …
7                          2                        {'l1': 142344, 'l2': 6326}
8                          2                      {'nopc': 148114, 'opc': 556}
9                          2                   {'nob/c': 127908, 'b/c': 20762}
10                       211  {206500: 4610, 256500: 4079, 156500: 3967, 226…
11                       131  {3.99: 14455, 3.625: 8800, 3.875: 8592, 3.75: …
12                     22516  {-0.028: 77, -0.038: 64, -0.023: 60, -0.173: 5…
13                     58271  {0.0: 20770, 1250.0: 1184, 1150.0: 892, 795.0:…
14                        26  {360.0: 121685, 180.0: 12981, 240.0: 5859, 300…
15                         2            {'not_neg': 133420, 'neg_amm': 15129}
16                         2            {'not_int': 141560, 'int_only': 7110}
17                         2               {'not_lpsm': 145286, 'lpsm': 3384}
18                       385  {308000.0: 2792, 258000.0: 2763, 358000.0: 267…
19                         2                          {'sb': 148637, 'mh': 33}
20                         3           {'pr': 138201, 'ir': 7340, 'sr': 3129}
21                         2                      {'home': 148637, 'land': 33}
22                         4   {'1U': 146480, '2U': 1477, '3U': 393, '4U': 320}
23                      1001  {0.0: 1260, 3600.0: 1250, 4200.0: 1243, 4800.0…
24                         4  {'CIB': 48152, 'CRIF': 43901, 'EXP': 41319, 'E…
25                       401  {763: 415, 867: 413, 639: 411, 581: 408, 554: …
26                         2                      {'CIB': 74392, 'EXP': 74278}
27                         7  {'45-54': 34720, '35-44': 32818, '55-64': 3253…
28                         2            {'to_inst': 95814, 'not_inst': 52656}
29                      8484  {81.25: 530, 91.66666667: 499, 80.03875969: 38…
30                         4  {'North': 74722, 'south': 64016, 'central': 86…
31                         2               {'direct': 148637, 'Indriect': 33}
32                         2                              {0: 112031, 1: 36639}
33                        57  {37.0: 6848, 36.0: 6553, 44.0: 6500, 49.0: 630…
```

[3]:
```python
#@title Numeric Columns
# Select numeric columns (e.g., int64, float64)
numeric_columns = df.select_dtypes(include=['int64', 'float64']).columns
print("Numeric Columns:", numeric_columns)
```

```
Numeric Columns: Index(['ID', 'year', 'loan_amount', 'rate_of_interest',
'Interest_rate_spread',
       'Upfront_charges', 'term', 'property_value', 'income', 'Credit_Score',
       'LTV', 'Status', 'dtir1'],
      dtype='object')
```

[4]:
```python
#@title Categorical columms
# Select categorical columns
categorical_columns = df.select_dtypes(include=['object']).columns
print("Categorical Columns:", categorical_columns)
```

```
Categorical Columns: Index(['loan_limit', 'Gender', 'approv_in_adv',
'loan_type', 'loan_purpose',
       'Credit_Worthiness', 'open_credit', 'business_or_commercial',
```

```
       'Neg_ammortization', 'interest_only', 'lump_sum_payment',
       'construction_type', 'occupancy_type', 'Secured_by', 'total_units',
       'credit_type', 'co-applicant_credit_type', 'age',
       'submission_of_application', 'Region', 'Security_Type'],
      dtype='object')
```

[5]:
```
#@title Data Cleaning
# Create a copy of the dataset for cleaning
df_clean = df.copy()

# Normalize categorical text (strip + lowercase)
for col in categorical_columns:
    df_clean[col] = df_clean[col].astype(str).str.strip().str.lower()

print('Done ')
```

```
Done
```

[6]:
```
# Remove exact duplicate rows
df_clean.drop_duplicates()
print('Done ')
```

```
Done
```

[7]:
```
# Fix common known typos
df_clean['Security_Type'] = df_clean['Security_Type'].replace({'indriect':␣
  ↪'indirect'})
print('Done ')
```

```
Done
```

[8]:
```
# Imputing missing values
import numpy as np
from sklearn.impute import SimpleImputer

# Identify column types
cat_cols = df_clean.select_dtypes(include='object').columns.tolist()
num_cols = df_clean.select_dtypes(include=['float64', 'int64']).columns.tolist()

# Replace common string-based missing values with np.nan
df_clean[cat_cols] = df_clean[cat_cols].replace(['NaN', 'nan', '', 'missing'],␣
  ↪np.nan)

# Impute categorical columns with most frequent (mode)
if cat_cols:
    cat_imputer = SimpleImputer(strategy='most_frequent')
    df_clean[cat_cols] = pd.DataFrame(
        cat_imputer.fit_transform(df_clean[cat_cols]),
```

```
        columns=cat_cols,
        index=df_clean.index
    )

# Impute numeric columns with median
if num_cols:
    num_imputer = SimpleImputer(strategy='median')
    df_clean[num_cols] = pd.DataFrame(
        num_imputer.fit_transform(df_clean[num_cols]),
        columns=num_cols,
        index=df_clean.index
    )
    print('Done ')
```

Done

[9]:

```
# Create numerical midpoints for age ranges
age_map = {
    '25-34': 29.5,
    '35-44': 39.5,
    '45-54': 49.5,
    '55-64': 59.5,
    '65-74': 69.5,
    '>74': 79.5,
    '<25': 24
}

df_clean['age_midpoint'] = df_clean['age'].map(age_map)
print('Done ')
```

Done

[10]:

```
df_clean['Gender'] = df_clean['Gender'].replace({
    'male': 'Male',
    'female': 'Female',
    'sex not available': 'Unknown',
    'joint': 'Unknown'
})
print('Done ')
```

Done

[11]:

```
# Drop columns with extremely high cardinality or redundancy
drop_columns = ['ID', 'year','age']  # ID is unique, year is constant
df_clean.drop(columns=drop_columns, inplace=True)
print('Done ')
```

Done

[12]:
```python
#@title Column Summary of the cleaned dataset
summary_df = column_summary(df_clean)
display(summary_df)
```

```
                   col_name col_dtype  num_of_nulls  num_of_non_nulls  \
0                loan_limit    object             0            148670
1                    Gender    object             0            148670
2              approv_in_adv    object             0            148670
3                 loan_type    object             0            148670
4              loan_purpose    object             0            148670
5          Credit_Worthiness    object             0            148670
6               open_credit    object             0            148670
7    business_or_commercial    object             0            148670
8               loan_amount   float64             0            148670
9          rate_of_interest   float64             0            148670
10      Interest_rate_spread   float64             0            148670
11           Upfront_charges   float64             0            148670
12                      term   float64             0            148670
13         Neg_ammortization    object             0            148670
14             interest_only    object             0            148670
15          lump_sum_payment    object             0            148670
16            property_value   float64             0            148670
17         construction_type    object             0            148670
18            occupancy_type    object             0            148670
19                Secured_by    object             0            148670
20               total_units    object             0            148670
21                    income   float64             0            148670
22               credit_type    object             0            148670
23              Credit_Score   float64             0            148670
24   co-applicant_credit_type    object             0            148670
25  submission_of_application    object             0            148670
26                       LTV   float64             0            148670
27                    Region    object             0            148670
28             Security_Type    object             0            148670
29                    Status   float64             0            148670
30                     dtir1   float64             0            148670
31              age_midpoint   float64             0            148670

   num_of_distinct_values                             distinct_values_counts
0                       2                      {'cf': 138692, 'ncf': 9978}
1                       3  {'Unknown': 79058, 'Male': 42346, 'Female': 27…
2                       2                   {'nopre': 125529, 'pre': 23141}
3                       3  {'type1': 113173, 'type2': 20762, 'type3': 14735}
4                       4  {'p3': 56068, 'p4': 54799, 'p1': 34529, 'p2': …
5                       2                       {'l1': 142344, 'l2': 6326}
6                       2                    {'nopc': 148114, 'opc': 556}
7                       2                   {'nob/c': 127908, 'b/c': 20762}
```

```
8                          211  {206500.0: 4610, 256500.0: 4079, 156500.0: 396…
9                          131  {3.99: 50894, 3.625: 8800, 3.875: 8592, 3.75: …
10                       22516  {0.3904: 36650, -0.028: 77, -0.038: 64, -0.023…
11                       58272  {2596.45: 39642, 0.0: 20770, 1250.0: 1184, 115…
12                          26  {360.0: 121726, 180.0: 12981, 240.0: 5859, 300…
13                           2             {'not_neg': 133541, 'neg_amm': 15129}
14                           2             {'not_int': 141560, 'int_only': 7110}
15                           2                {'not_lpsm': 145286, 'lpsm': 3384}
16                         385  {418000.0: 16930, 308000.0: 2792, 258000.0: 27…
17                           2                          {'sb': 148637, 'mh': 33}
18                           2              {'pr': 138201, 'ir': 7340, 'sr': 3129}
19                           2                      {'home': 148637, 'land': 33}
20                           4   {'1u': 146480, '2u': 1477, '3u': 393, '4u': 320}
21                        1001  {5760.0: 10092, 0.0: 1260, 3600.0: 1250, 4200…
22                           4  {'cib': 48152, 'crif': 43901, 'exp': 41319, 'e…
23                         401  {763.0: 415, 867.0: 413, 639.0: 411, 581.0: 40…
24                           2                      {'cib': 74392, 'exp': 74278}
25                           2             {'to_inst': 96014, 'not_inst': 52656}
26                        8484  {75.13586957: 15255, 81.25: 530, 91.66666667: …
27                           4  {'north': 74722, 'south': 64016, 'central': 86…
28                           2                {'direct': 148637, 'indirect': 33}
29                           2                         {0.0: 112031, 1.0: 36639}
30                          57  {39.0: 28661, 37.0: 6848, 36.0: 6553, 44.0: 65…
31                           7  {49.5: 34920, 39.5: 32818, 59.5: 32534, 69.5: …
```

[13]:
```python
#@title Statistical Analysis
import scipy.stats as stats
from pandas import set_option

def distribution_statistics(df):
    results = []
    for column in df.select_dtypes(include=[np.number]).columns:
        mean = df[column].mean()
        median = df[column].median()
        mode = df[column].mode()[0] if not df[column].empty else np.nan
        std_dev = df[column].std()
        variance = df[column].var()
        range_val = df[column].max() - df[column].min()
        skewness_val = stats.skew(df[column], nan_policy='omit')
        kurtosis_val = stats.kurtosis(df[column], nan_policy='omit')

        results.append({
            'Parameter': column,
            'Mean': mean,
            'Median': median,
            'Mode': mode,
            'Standard Deviation': std_dev,
```

```
            'Variance': variance,
            'Range': range_val,
            'Skewness': skewness_val,
            'Kurtosis': kurtosis_val,
        })

    result_df = pd.DataFrame(results)
    return result_df

# Display the results
display(distribution_statistics(df_clean))
set_option('display.max_columns', 10)
set_option('display.float_format', lambda x: '%.2f' % x)
```

```
               Parameter           Mean         Median           Mode  \
0            loan_amount  331117.743997  296500.00000  206500.00000
1       rate_of_interest       4.031879       3.99000       3.99000
2   Interest_rate_spread       0.429024       0.39040       0.39040
3        Upfront_charges    3057.397919    2596.45000    2596.45000
4                   term     335.143438     360.00000     360.00000
5         property_value  489779.982512  418000.00000  418000.00000
6                 income    6883.647811    5760.00000    5760.00000
7           Credit_Score     699.789103     699.00000     763.00000
8                    LTV      72.989111      75.13587      75.13587
9                 Status       0.246445       0.00000       0.00000
10                 dtir1      37.938508      39.00000      39.00000
11          age_midpoint      50.914922      49.50000      49.50000

    Standard Deviation      Variance         Range    Skewness      Kurtosis
0        183909.310127  3.382263e+10  3.560000e+06    1.666981      9.127428
1             0.488348  2.384833e-01  8.000000e+00    0.528620      1.463512
2             0.445907  1.988328e-01  6.995000e+00    0.406870      0.760482
3          2797.972965  7.828653e+06  6.000000e+04    2.194908     10.028642
4            58.402488  3.410851e+03  2.640000e+02   -2.175268      3.175206
5        342022.063957  1.169791e+11  1.650000e+07    4.872281     81.450232
6          6300.067060  3.969084e+07  5.785800e+05   17.844818    940.403642
7           115.875857  1.342721e+04  4.000000e+02    0.004767     -1.202649
8            37.890714  1.435706e+03  7.830283e+03  127.159755  22217.442705
9             0.430942  1.857112e-01  1.000000e+00    1.176750     -0.615259
10            9.663417  9.338162e+01  5.600000e+01   -0.663850      1.068179
11           14.090924  1.985541e+02  5.550000e+01    0.140321     -0.828574
```

1. loan_amount, Upfront_charges, property_value

Right-skewed: Skewness > 1

High kurtosis: Heavy tails (e.g. property_value = 81.45!)

Recommendation: Apply log1p() transformation to reduce skew and normalize

2. income

Extremely right-skewed: Skew = 17.84

Very high kurtosis: 940.4 → extreme outliers

Recommendation: Log transform and possibly cap values at 99th percentile

3. term

Negative skew: -2.18 → most values around 360

Recommendation: Consider converting to categorical: 'standard' vs 'non-standard'

4. LTV

Extreme skew and kurtosis (127.16, 22,217.44)

Recommendation: Cap values at 100–120%, validate if >100% is meaningful

5. Credit_Score, dtir1, age_midpoint

Relatively normal distribution

[14]:
```
#@title Transforming some columns for better model perfomance

# Create a copy for transformations
df_transformed = df_clean.copy()

# 1. Log-transform right-skewed features
log_transform_cols = ['loan_amount', 'Upfront_charges', 'property_value',␣
↪'income']
for col in log_transform_cols:
    df_transformed[col] = df_transformed[col].apply(lambda x: np.log1p(x) if x␣
↪> 0 else 0)

# 2. Cap income at 99th percentile
income_cap = df_clean['income'].quantile(0.99)
df_transformed['income'] = np.clip(df_clean['income'], 0, income_cap)

# 3. Cap LTV at 120
df_transformed['LTV'] = np.clip(df_clean['LTV'], 0, 120)

# 4. Convert term to binary categorical: standard vs non-standard
df_transformed['term_group'] = df_clean['term'].apply(lambda x: 'standard' if x␣
↪== 360 else 'non-standard')

# Display preview
df_transformed[['loan_amount', 'Upfront_charges', 'property_value', 'income',␣
↪'LTV', 'term_group']].head()
```

[14]:

	loan_amount	Upfront_charges	property_value	income	LTV	term_group
0	11.67	7.86	11.68	1740.00	98.73	standard

```
1        12.24              7.86           12.94  4980.00 75.14   standard
2        12.92              6.39           13.14  9480.00 80.02   standard
3        13.03              7.86           13.40 11880.00 69.38   standard
4        13.45              0.00           13.54 10440.00 91.89   standard
```

[15]:

```
df_transformed
```

[15]:

```
       loan_limit   Gender approv_in_adv loan_type loan_purpose  …  \
0              cf  Unknown         nopre     type1           p1  …
1              cf     Male         nopre     type2           p1  …
2              cf     Male           pre     type1           p1  …
3              cf     Male         nopre     type1           p4  …
4              cf  Unknown           pre     type1           p1  …
…             …      …             …        …            …   …
148665         cf  Unknown         nopre     type1           p3  …
148666         cf     Male         nopre     type1           p1  …
148667         cf     Male         nopre     type1           p4  …
148668         cf   Female         nopre     type1           p4  …
148669         cf   Female         nopre     type1           p3  …

       Security_Type Status dtir1  age_midpoint    term_group
0             direct   1.00 45.00         29.50      standard
1             direct   1.00 39.00         59.50      standard
2             direct   0.00 46.00         39.50      standard
3             direct   0.00 42.00         49.50      standard
4             direct   0.00 39.00         29.50      standard
…                …    …    …             …            …
148665        direct   0.00 48.00         59.50  non-standard
148666        direct   0.00 15.00         29.50      standard
148667        direct   0.00 49.00         49.50  non-standard
148668        direct   0.00 29.00         59.50  non-standard
148669        direct   0.00 44.00         49.50  non-standard

[148670 rows x 33 columns]
```

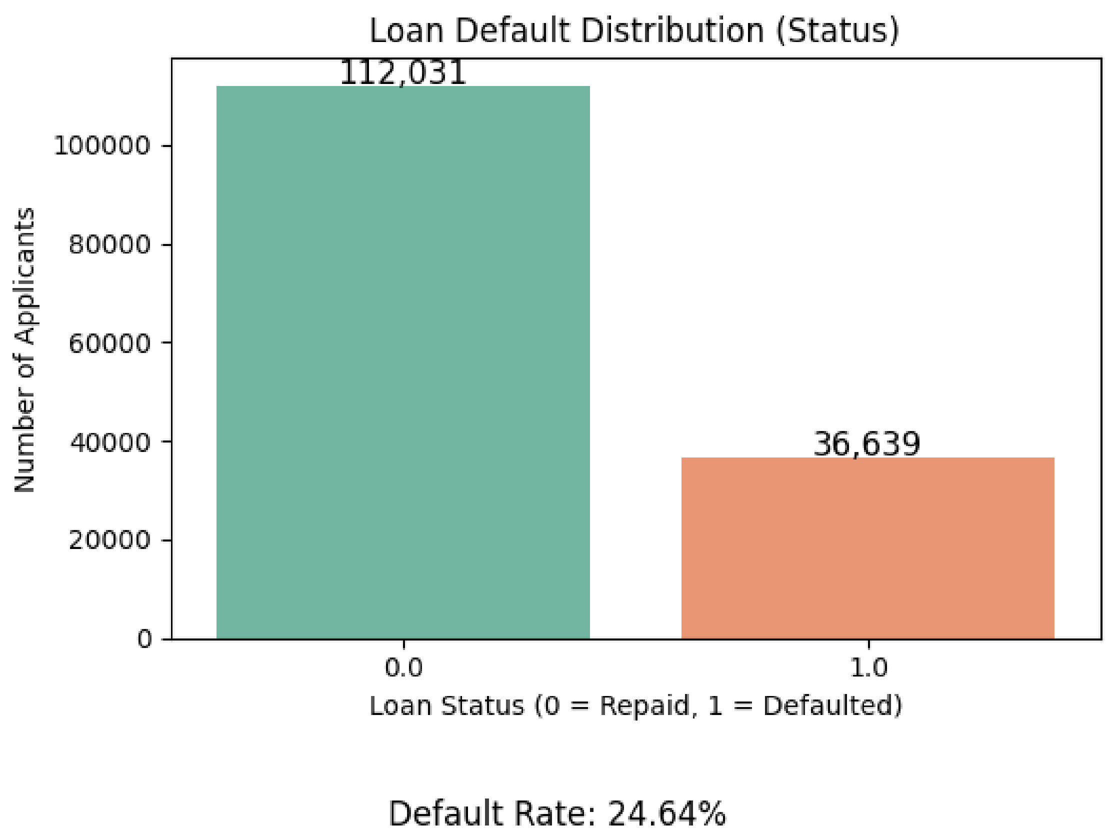
[16]:

```
#@title EDA
```

[17]:

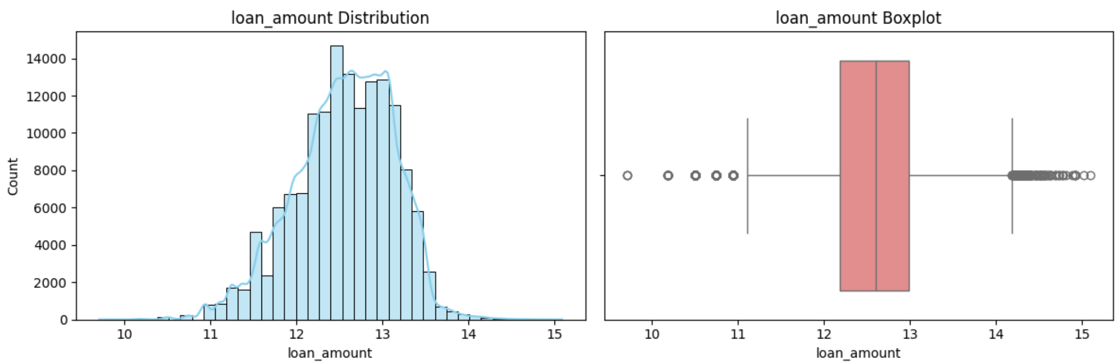
```
#@title Target Distribution
import matplotlib.pyplot as plt
import seaborn as sns

# Count values in Status
status_counts = df_transformed['Status'].value_counts()
default_rate = df_transformed['Status'].mean() * 100

# Plot
plt.figure(figsize=(6, 4))
```

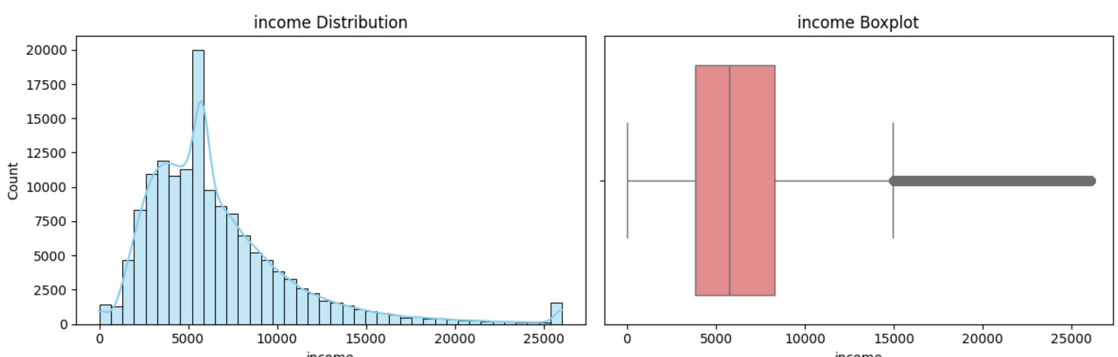
```
sns.countplot(x='Status', data=df_transformed, palette='Set2')
plt.title('Loan Default Distribution (Status)')
plt.xlabel('Loan Status (0 = Repaid, 1 = Defaulted)')
plt.ylabel('Number of Applicants')

# Add value labels
for i, count in enumerate(status_counts):
    plt.text(i, count + 500, f"{count:,}", ha='center', fontsize=12)

# Show
plt.figtext(0.5, -0.1, f"Default Rate: {default_rate:.2f}%", ha="center",␣
 ↪fontsize=12)
plt.tight_layout()
plt.show()
```

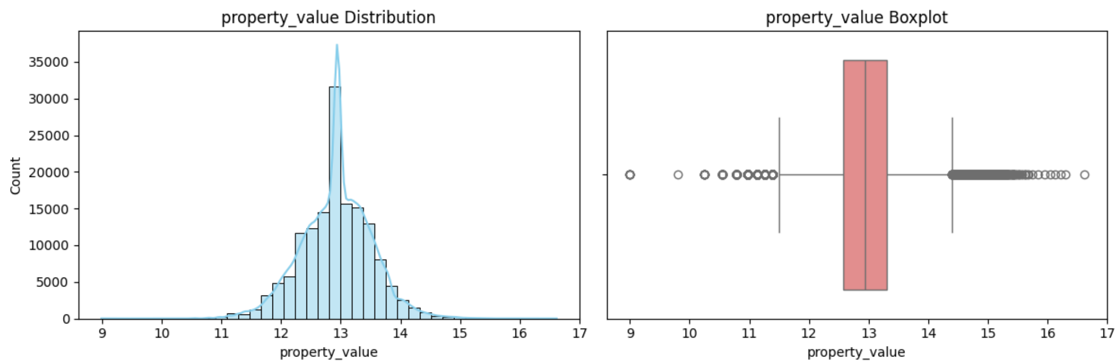


[18]:
```
#@title Univariate Distribution Analysis
# List of numerical features to explore
num_cols = ['loan_amount', 'income', 'property_value', 'Credit_Score', 'LTV',␣
 ↪'dtir1', 'age_midpoint']
```

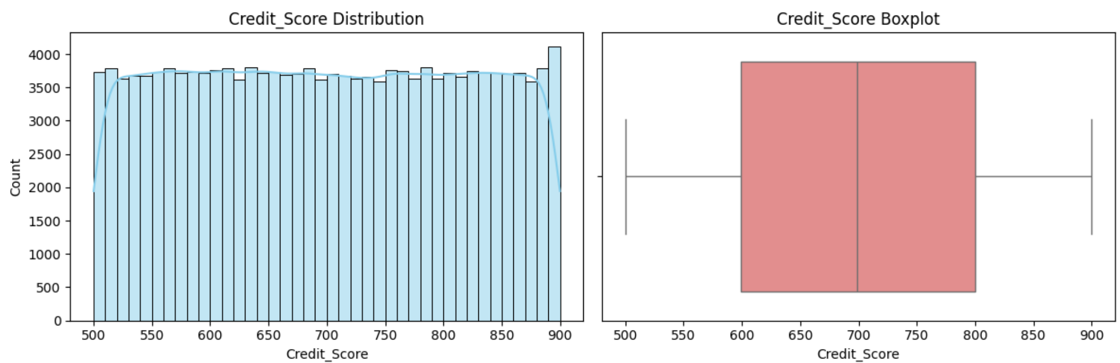
```python
# Plot histogram and boxplot for each feature
for col in num_cols:
    fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 4))

    # Histogram with KDE
    sns.histplot(df_transformed[col], bins=40, kde=True, ax=axes[0], color='skyblue')
    axes[0].set_title(f'{col} Distribution')

    # Boxplot
    sns.boxplot(x=df_transformed[col], ax=axes[1], color='lightcoral')
    axes[1].set_title(f'{col} Boxplot')

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



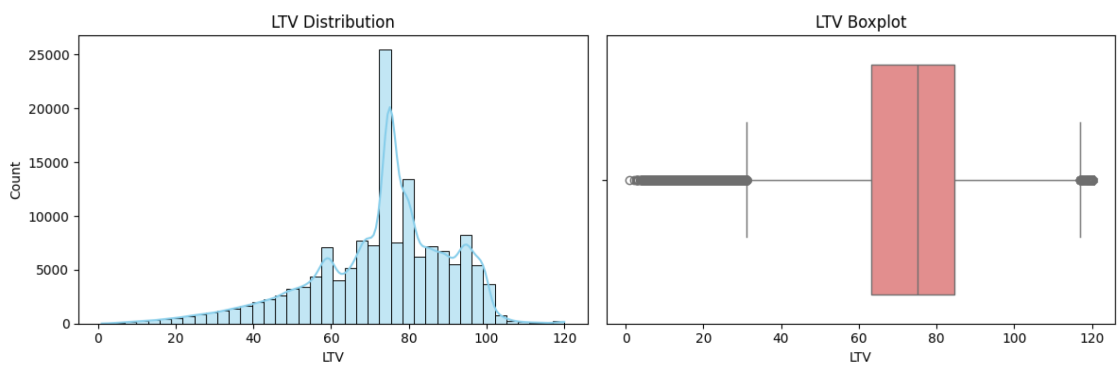




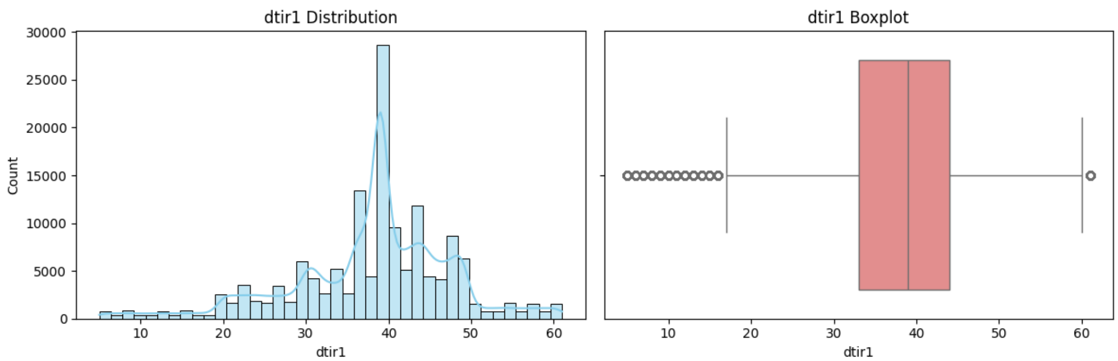
property_value Distribution
property_value Boxplot
Count
property_value
property_value

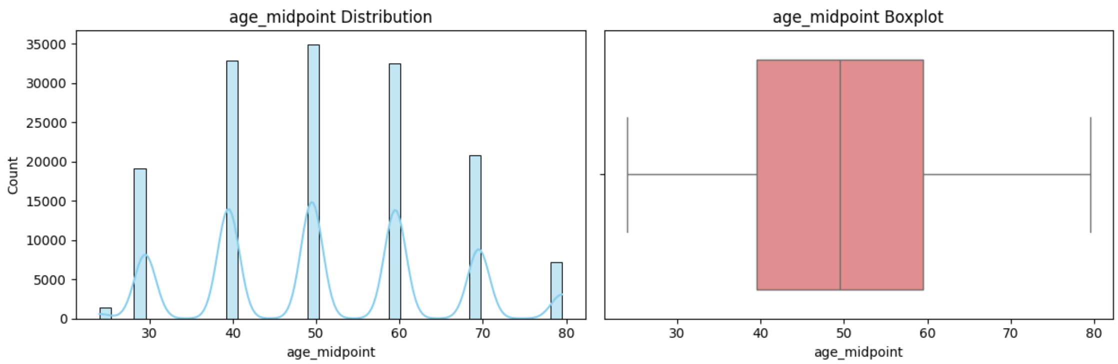


Credit_Score Distribution
Credit_Score Boxplot
Count
Credit_Score
Credit_Score



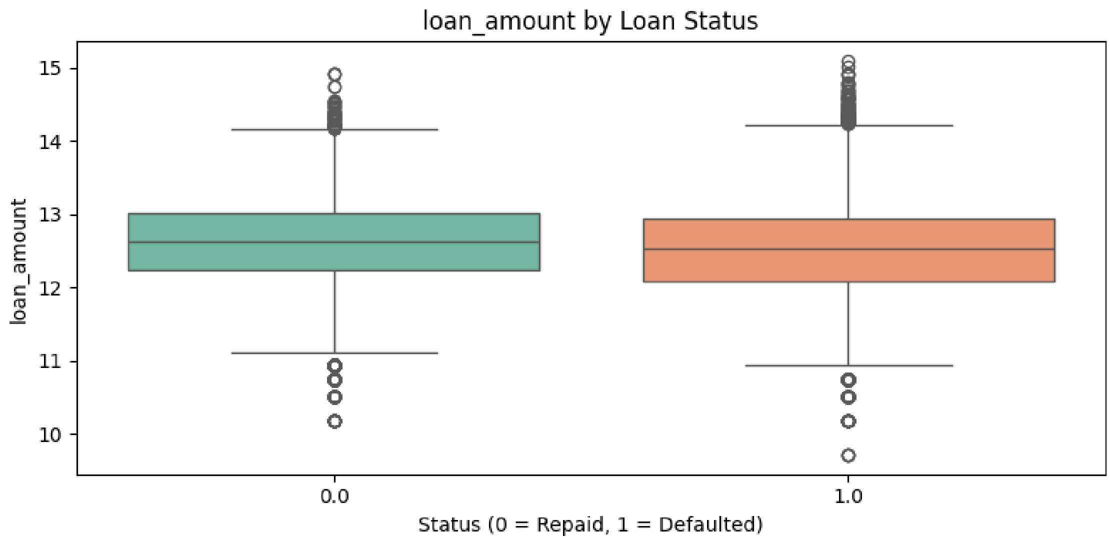
LTV Distribution
LTV Boxplot
Count
LTV
LTV

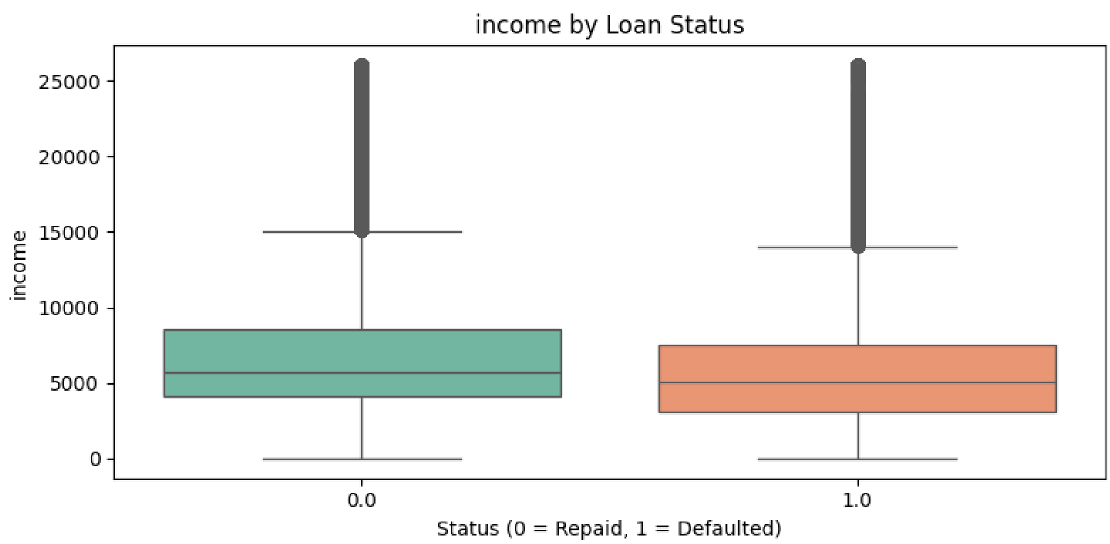


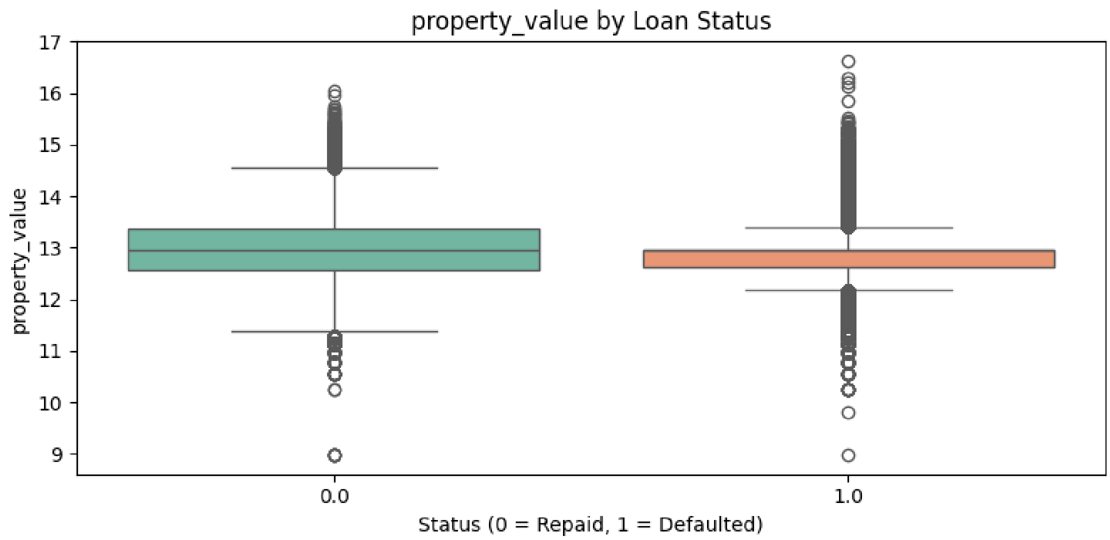


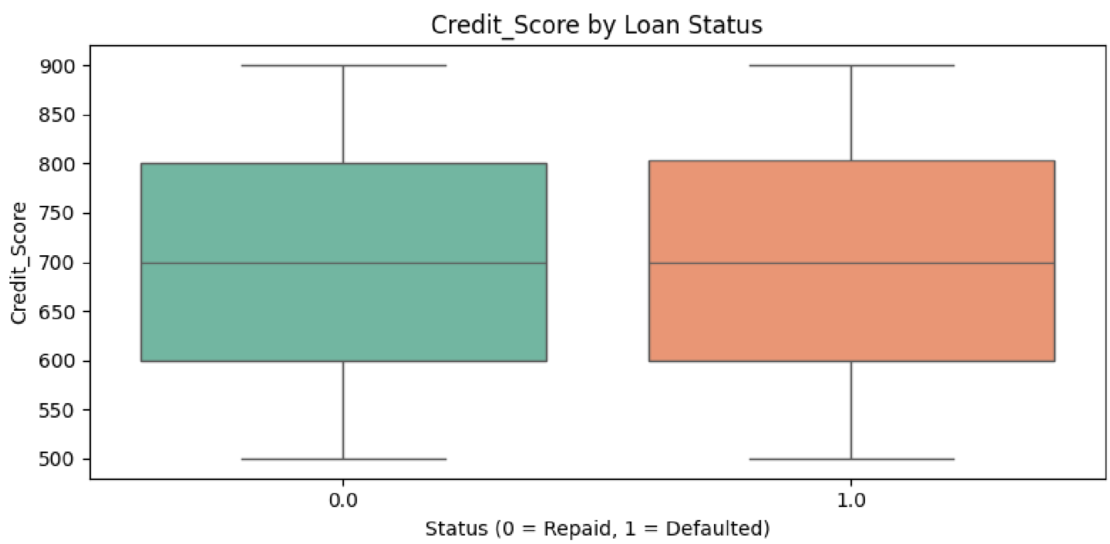
[19]:
```
#@title Bivariate Analysis
```

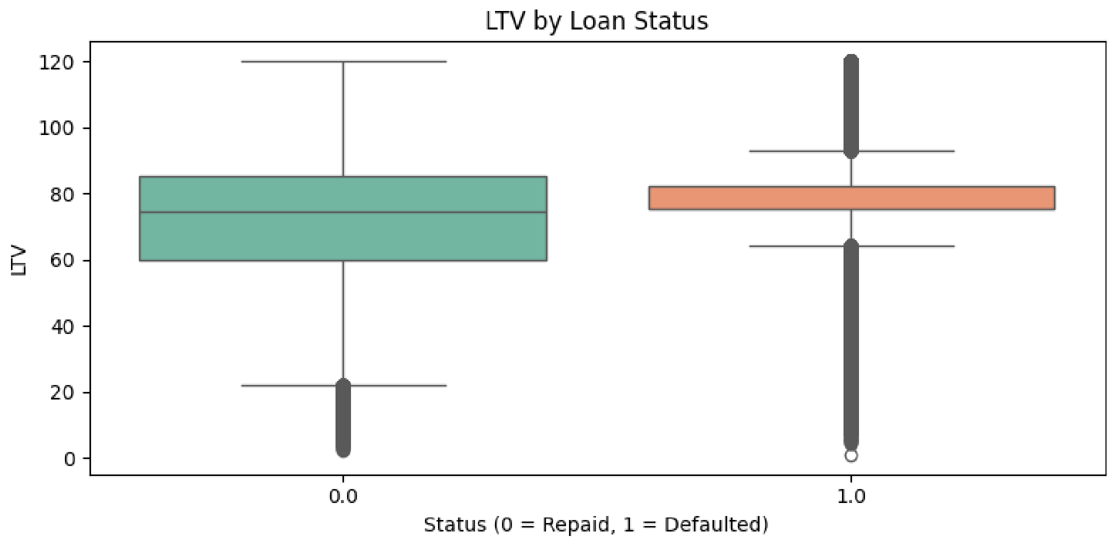
[20]:
```
#@title Feature vs Status (Target)

# List of key numerical features
num_features = ['loan_amount', 'income', 'property_value', 'Credit_Score',␣
↪'LTV', 'dtir1', 'age_midpoint']

# Boxplots grouped by loan status
import seaborn as sns
import matplotlib.pyplot as plt

for col in num_features:
    plt.figure(figsize=(8, 4))
    sns.boxplot(x='Status', y=col, data=df_transformed, palette='Set2')
    plt.title(f'{col} by Loan Status')
    plt.xlabel('Status (0 = Repaid, 1 = Defaulted)')
    plt.tight_layout()
    plt.show()
```

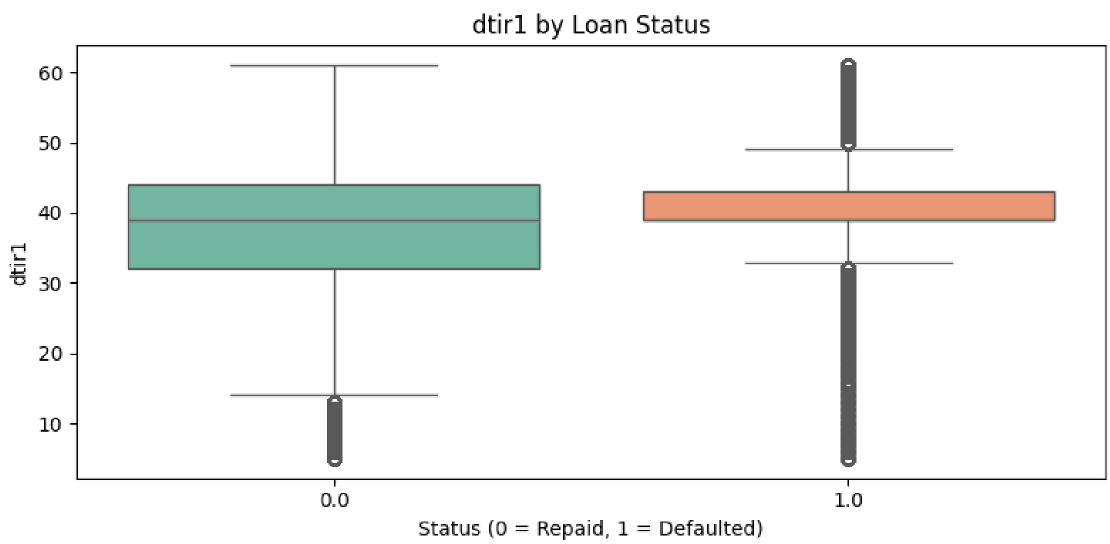

loan_amount by Loan Status
loan_amount
15
14
13
12
11
10
0.0
1.0
Status (0 = Repaid, 1 = Defaulted)

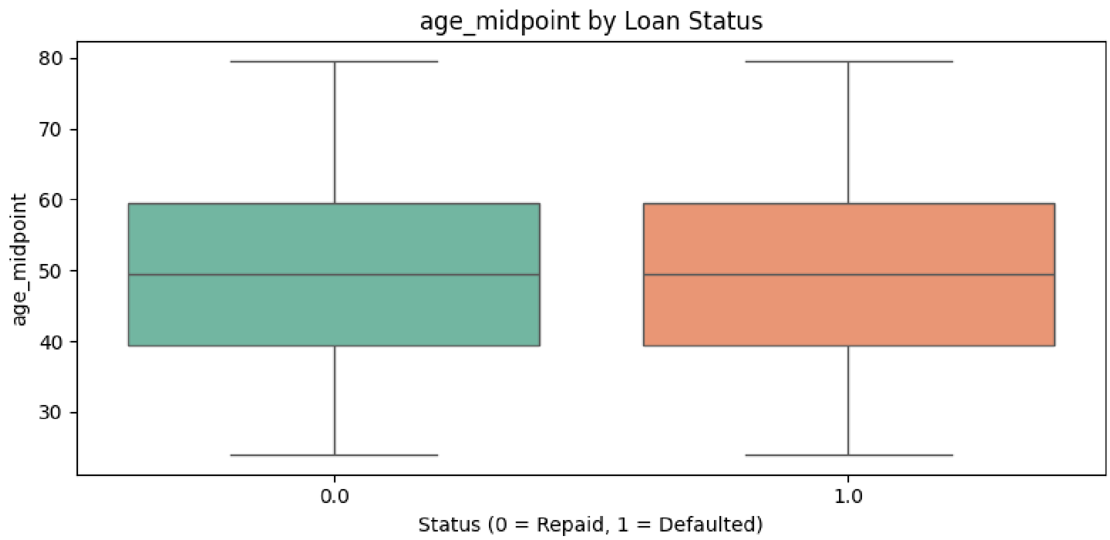

income by Loan Status
income
25000
20000
15000
10000
5000
0
0.0
1.0
Status (0 = Repaid, 1 = Defaulted)


property_value by Loan Status
17
16
15
14
13
12
11
10
9
property_value
0.0
1.0
Status (0 = Repaid, 1 = Defaulted)

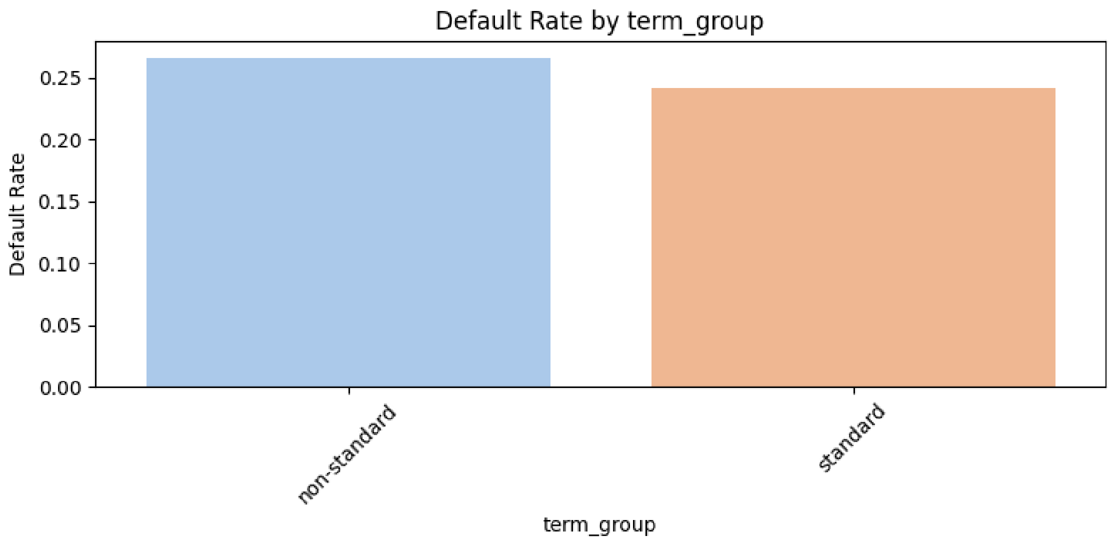

Credit_Score by Loan Status
900
850
800
750
700
650
600
550
500
Credit_Score
0.0
1.0
Status (0 = Repaid, 1 = Defaulted)

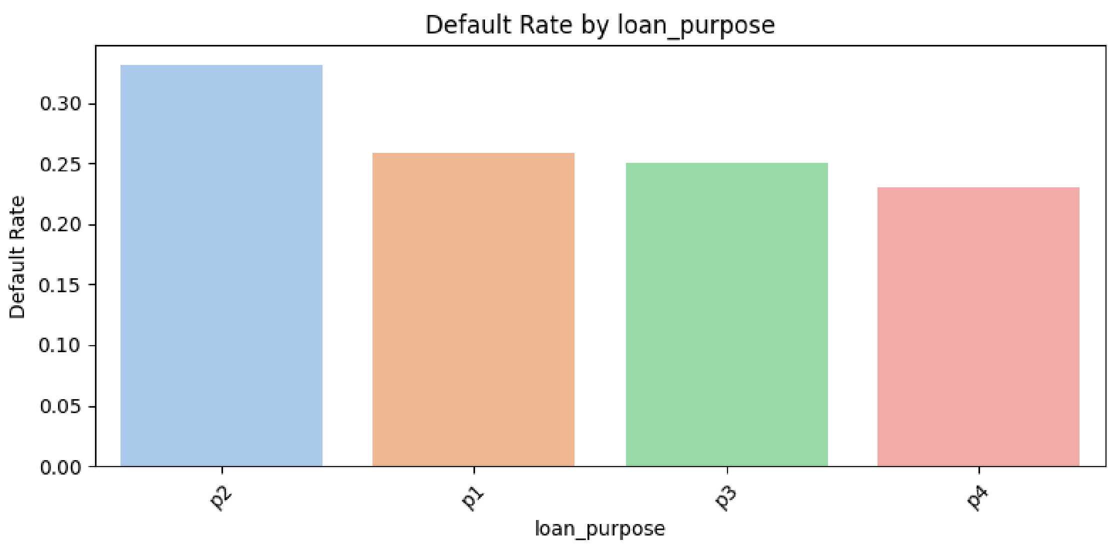

LTV by Loan Status
LTV
120
100
80
60
40
20
0
0.0
1.0
Status (0 = Repaid, 1 = Defaulted)

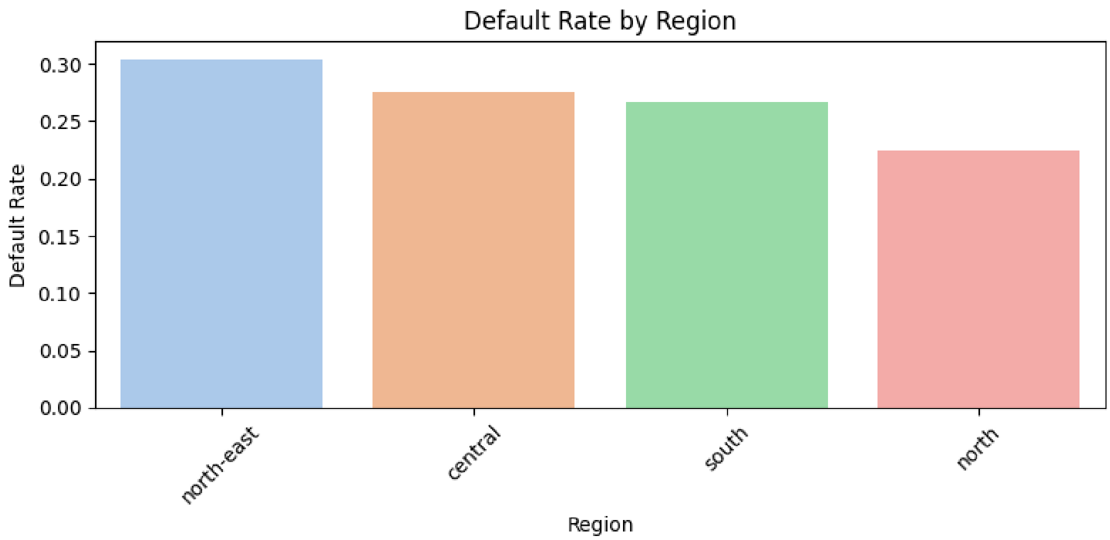

dtir1 by Loan Status
dtir1
60
50
40
30
20
10
0.0
1.0
Status (0 = Repaid, 1 = Defaulted)

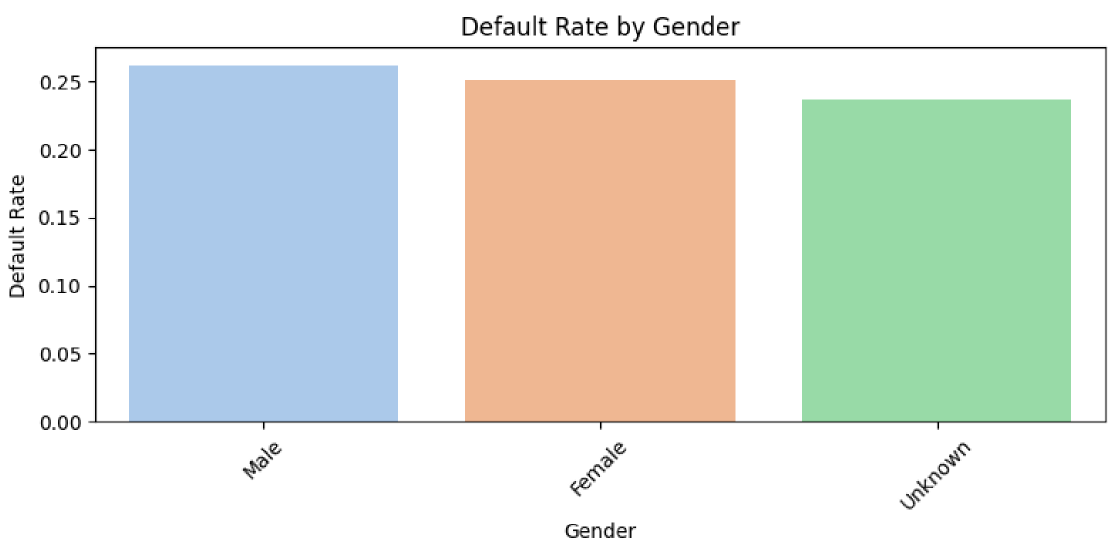


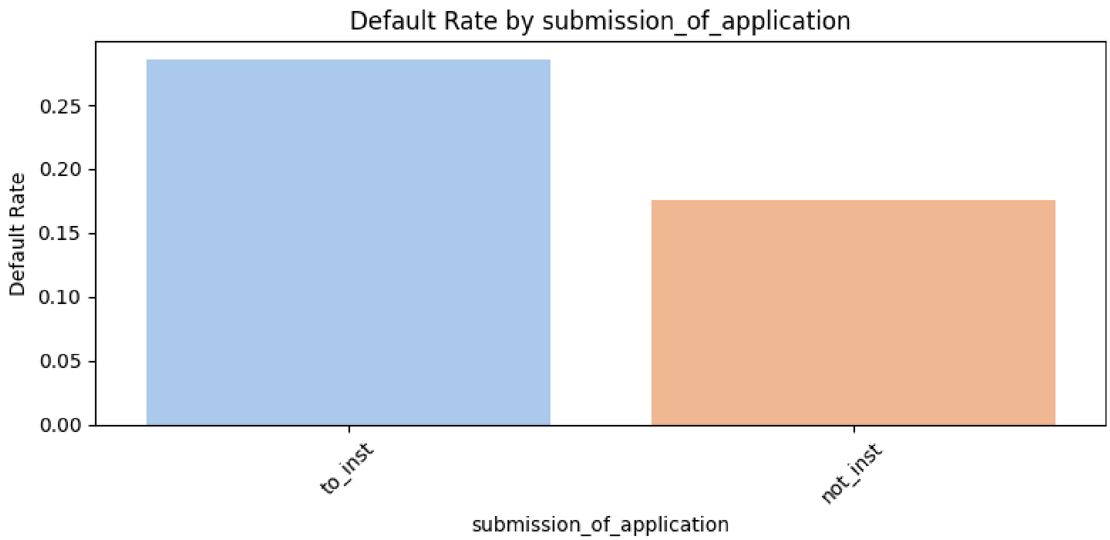
[21]:
```
# List of important categorical features
cat_features = ['term_group', 'loan_purpose', 'Region', 'Gender',
                'submission_of_application', 'interest_only',␣
 ↪'Neg_ammortization']

for col in cat_features:
    plt.figure(figsize=(8, 4))
    rate_df = df_transformed.groupby(col)['Status'].mean().reset_index().
 ↪sort_values('Status', ascending=False)
    sns.barplot(x=col, y='Status', data=rate_df, palette='pastel')
    plt.title(f'Default Rate by {col}')
    plt.ylabel('Default Rate')
    plt.xlabel(col)
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```

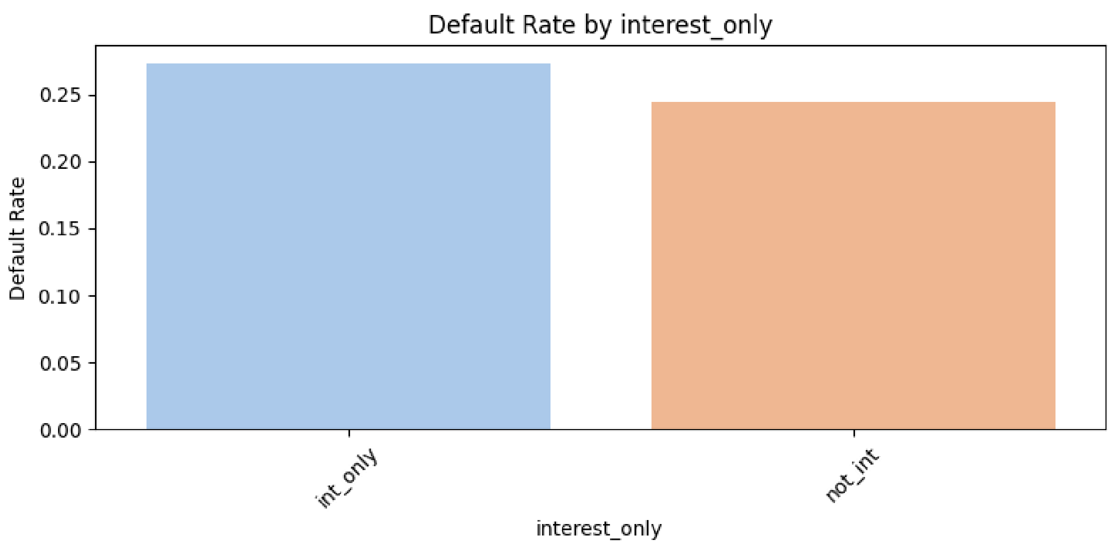

Default Rate by term_group
Default Rate
0.25
0.20
0.15
0.10
0.05
0.00
non-standard
standard
term_group

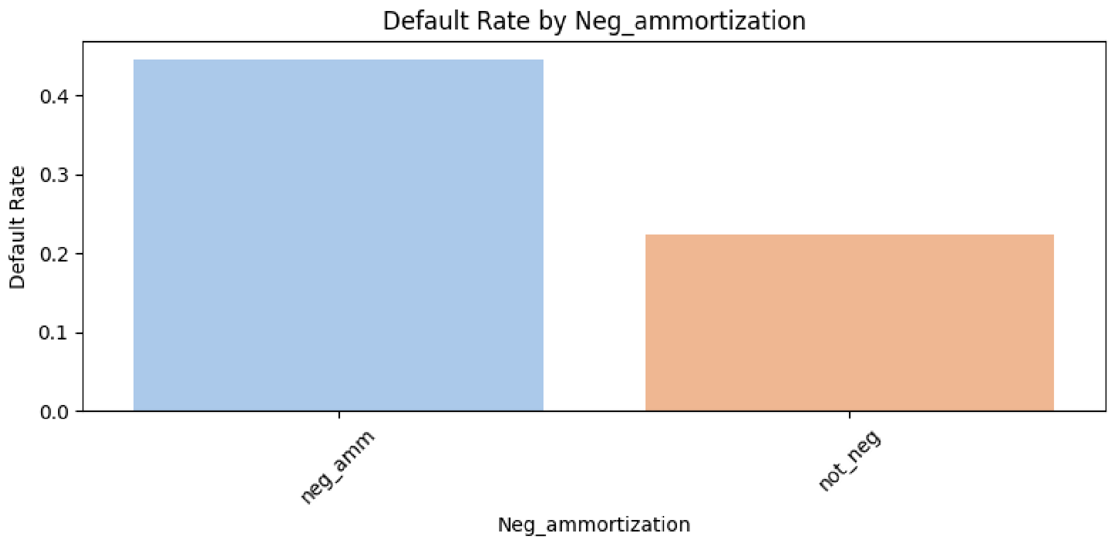

Default Rate by loan_purpose
Default Rate
0.30
0.25
0.20
0.15
0.10
0.05
0.00
p2
p1
p3
p4
loan_purpose


Default Rate by Region
Default Rate
0.00
0.05
0.10
0.15
0.20
0.25
0.30
north-east
central
south
north
Region

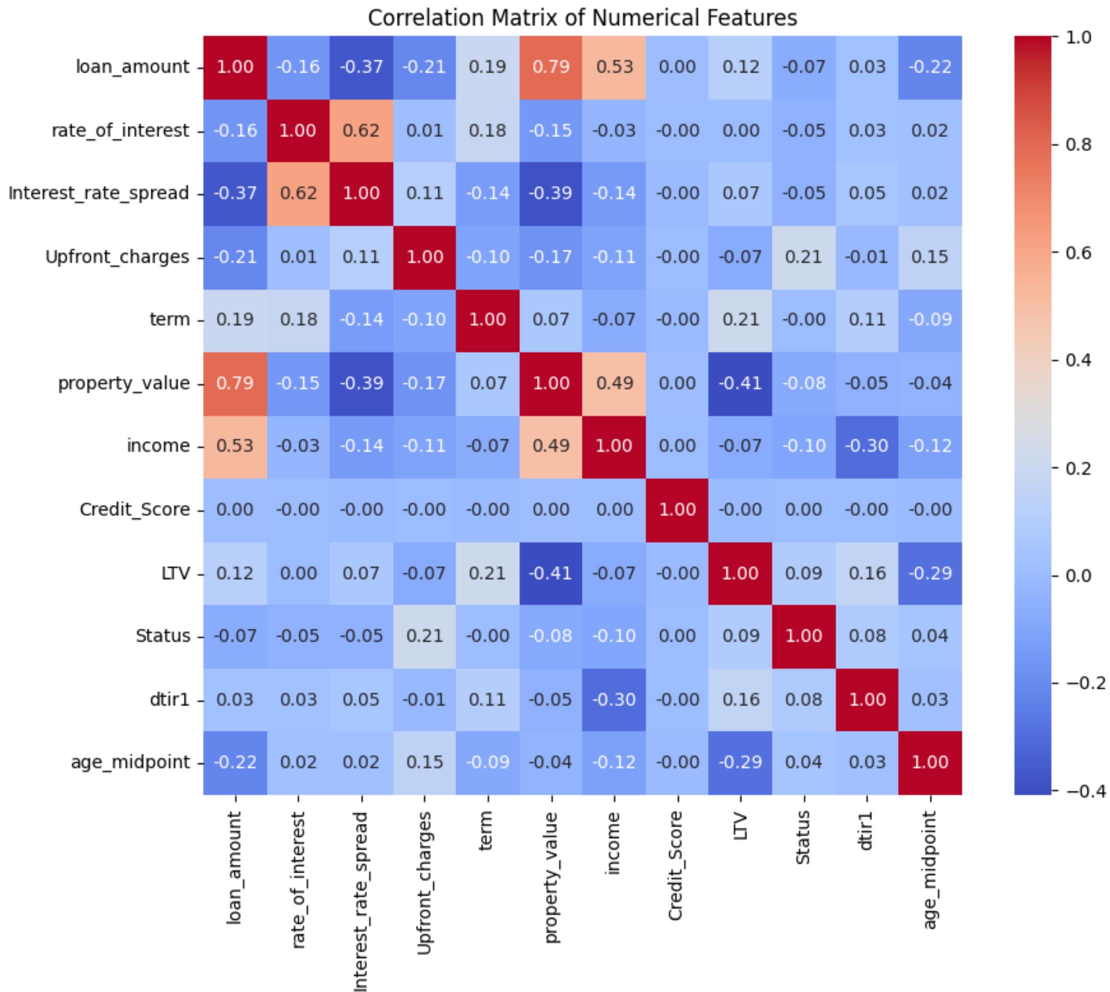

Default Rate by Gender
Default Rate
0.00
0.05
0.10
0.15
0.20
0.25
Male
Female
Unknown
Gender


Default Rate by submission_of_application
Default Rate
0.00
0.05
0.10
0.15
0.20
0.25
to_inst
not_inst
submission_of_application


Default Rate by interest_only
Default Rate
0.00
0.05
0.10
0.15
0.20
0.25
int_only
not_int
interest_only



[22]:
```
#@title Correlations
# Only numerical columns
numeric_data = df_transformed.select_dtypes(include=['int64', 'float64'])

# Correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm', fmt='.2f',␣
↪square=True)
plt.title('Correlation Matrix of Numerical Features')
plt.tight_layout()
plt.show()
```



The correlation matrix of numerical features highlights the relationships between variables:

- Strong Positive Correlations: Loan amount has a strong positive correlation with property value (0.79) and income (0.53). Age midpoint shows a strong positive correlation with dti ratio (0.22).
- Moderate Positive Correlations: Rate of interest correlates with interest rate spread (0.62) and upfront charges (0.11). Property value correlates with income (0.49).
- Strong Negative Correlations: Age midpoint has a notable negative correlation with LTV (-0.22). Dti ratio shows a strong negative correlation with income (-0.30).
- Weak or No Correlations: Credit Score shows minimal correlation with other features (all near 0), indicating independence. Status and LTV have weak correlations with most variables.

Key insights include the interdependence of loan amount with property value and income, and the inverse relationship between age midpoint and LTV.

[23]:
```python
#@title Reducinging Dimensionality with Feature Selection
from sklearn.feature_selection import RFE
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import LabelEncoder

# Copy transformed dataset
df_selected = df_transformed.copy()

# Drop rows with missing target, if any
df_selected = df_selected[df_selected['Status'].notnull()]

# Separate features and target
X = df_selected.drop(columns=['Status'])
y = df_selected['Status']

# Encode all categorical variables using LabelEncoder for RFE (basic encoding)
X_encoded = X.copy()
for col in X_encoded.select_dtypes(include='object').columns:
    X_encoded[col] = LabelEncoder().fit_transform(X_encoded[col])

# Initialize model and RFE
estimator = RandomForestClassifier(random_state=42)
rfe = RFE(estimator=estimator, n_features_to_select=15)  # Select top 15␣
 ↪features

# Fit RFE
rfe.fit(X_encoded, y)

# Extract selected features
selected_features = X_encoded.columns[rfe.support_].tolist()
selected_features
```

[23]:
```
['business_or_commercial',
 'loan_amount',
 'rate_of_interest',
 'Interest_rate_spread',
 'Upfront_charges',
 'term',
 'Neg_ammortization',
 'lump_sum_payment',
 'property_value',
 'income',
 'credit_type',
 'co-applicant_credit_type',
 'submission_of_application',
 'LTV',
 'dtir1']
```

[24]:
```
#@title Comparing model perfomance when trained with the selected features and␣
↪all the features
# Prepare feature sets

# Target variable
y = df_transformed['Status']

# Feature set 1: All features (drop target column only)
X_all = df_transformed.drop(columns=['Status'])

# Feature set 2: Selected features from RFE
selected_features = [
    'business_or_commercial', 'loan_amount', 'rate_of_interest',
    'Interest_rate_spread', 'Upfront_charges', 'term',
    'Neg_ammortization', 'lump_sum_payment', 'property_value',
    'income', 'credit_type', 'co-applicant_credit_type',
    'submission_of_application', 'LTV', 'dtir1'
]
X_selected = df_transformed[selected_features]

# Confirm shapes
X_all.shape, X_selected.shape
```

[24]: ((148670, 32), (148670, 15))

[25]:
```
#@title Building pipeline to Train the models

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.metrics import classification_report, roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from imblearn.pipeline import Pipeline as ImbPipeline
from imblearn.over_sampling import SMOTE
import numpy as np

def train_models_with_gridsearch(X, y):
    # Identify column types
    cat_cols = X.select_dtypes(include='object').columns.tolist()
    num_cols = X.select_dtypes(include=['int64', 'float64']).columns.tolist()

    # Preprocessor
    preprocessor = ColumnTransformer([
```

```
        ('num', StandardScaler(), num_cols),
        ('cat', OneHotEncoder(handle_unknown='ignore'), cat_cols)
    ])

    # Train-test split
    X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
↪test_size=0.2, random_state=42)

    # Models and hyperparameter grids
    models = {
        'LogisticRegression': {
            'model': LogisticRegression(max_iter=1000, class_weight='balanced'),
            'params': {'model__C': [0.01, 0.1, 1, 10]}
        },
        'RandomForest': {
            'model': RandomForestClassifier(random_state=42),
            'params': {'model__n_estimators': [100, 200], 'model__max_depth':␣
↪[None, 10, 20]}
        },
        'XGBoost': {
            'model': XGBClassifier(use_label_encoder=False,␣
↪eval_metric='logloss', random_state=42),
            'params': {'model__n_estimators': [100, 200],␣
↪'model__learning_rate': [0.05, 0.1]}
        },
        'KNN': {
            'model': KNeighborsClassifier(),
            'params': {'model__n_neighbors': [3, 5, 7]}
        }
    }

    best_models = []

    for name, mp in models.items():
        print(f" Training {name}...")
        pipe = ImbPipeline(steps=[
            ('preprocessor', preprocessor),
            ('smote', SMOTE(random_state=42)),
            ('model', mp['model'])
        ])

        grid = GridSearchCV(pipe, mp['params'], cv=3, scoring='f1', n_jobs=-1)
        grid.fit(X_train, y_train)

        # Predict and evaluate
        y_pred = grid.predict(X_test)
```

```
        y_proba = grid.predict_proba(X_test)[:, 1] if hasattr(grid,␣
 ↪"predict_proba") else np.zeros_like(y_pred)

        print(f"  Best Params: {grid.best_params_}")
        print(classification_report(y_test, y_pred))
        print(f"ROC-AUC: {roc_auc_score(y_test, y_proba):.4f}\n")

        best_models.append((name, grid.best_estimator_, roc_auc_score(y_test,␣
 ↪y_proba)))

    return best_models


'''This function is now ready to use with either X_all or X_selected and y,
You can call it like: train_models_with_gridsearch(X_all, y)
# or: train_models_with_gridsearch(X_selected, y)'''
```

[25]:
```
'This function is now ready to use with either X_all or X_selected and y,\nYou
can call it like: train_models_with_gridsearch(X_all, y)\n# or:
train_models_with_gridsearch(X_selected, y)'
```

[26]:
```
#@title Function to Visualize model performace
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc, confusion_matrix,␣
 ↪ConfusionMatrixDisplay

def plot_model_evaluations(best_models, X, y):
    # Split and preprocess again for prediction
    X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
 ↪test_size=0.2, random_state=42)

    for name, model, _ in best_models:
        print(f"\n  Plotting results for: {name}")

        # Predict probabilities and labels
        y_proba = model.predict_proba(X_test)[:, 1]
        y_pred = model.predict(X_test)

        # ROC Curve
        fpr, tpr, _ = roc_curve(y_test, y_proba)
        roc_auc = auc(fpr, tpr)

        plt.figure(figsize=(12, 4))

        # ROC-AUC plot
        plt.subplot(1, 2, 1)
```

```
        plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC =␣
↪{roc_auc:.2f})')
        plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
        plt.title(f'{name} - ROC Curve')
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.legend(loc='lower right')

        # Confusion Matrix plot
        plt.subplot(1, 2, 2)
        cm = confusion_matrix(y_test, y_pred)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm)
        disp.plot(cmap='Blues', ax=plt.gca())
        plt.title(f'{name} - Confusion Matrix')

        plt.tight_layout()
        plt.show()

'''This function is now ready to use with either best_model, X_all or␣
↪X_selected and y,
You can call it like: plot_model_evaluations(best_models_slected, X_selected, y)
# or: plot_model_evaluations(best_models_all, X_all, y) '''
```

[26]:
```
'This function is now ready to use with either best_model, X_all or X_selected
and y,\nYou can call it like: plot_model_evaluations(best_models_slected,
X_selected, y)\n# or: plot_model_evaluations(best_models_all, X_all, y) '
```

[27]:
```
#@title Function to Check if the models generalizes well
from sklearn.metrics import accuracy_score, f1_score, roc_auc_score

def evaluate_generalization(best_models, X, y):
    X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
↪test_size=0.2, random_state=42)

    print(f"{'Model':<20}{'Train F1':<10}{'Test F1':<10}{'Train ROC':<10}{'Test␣
↪ROC':<10}{'Conclusion'}")
    print("-" * 70)

    for name, model, _ in best_models:
        # Train predictions
        y_train_pred = model.predict(X_train)
        y_train_proba = model.predict_proba(X_train)[:, 1]

        # Test predictions
        y_test_pred = model.predict(X_test)
        y_test_proba = model.predict_proba(X_test)[:, 1]
```

```
        # Metrics
        f1_train = f1_score(y_train, y_train_pred)
        f1_test = f1_score(y_test, y_test_pred)
        roc_train = roc_auc_score(y_train, y_train_proba)
        roc_test = roc_auc_score(y_test, y_test_proba)

        # Evaluate generalization
        if f1_train - f1_test > 0.1 and roc_train - roc_test > 0.1:
            conclusion = "  Overfitting"
        elif f1_train < 0.5 and f1_test < 0.5:
            conclusion = "  Underfitting"
        elif abs(f1_train - f1_test) < 0.05 and abs(roc_train - roc_test) < 0.
 ↪05:
            conclusion = "  Generalizes Well"
        else:
            conclusion = "  Mixed"

        print(f"{name:<20}{f1_train:<10.2f}{f1_test:<10.2f}{roc_train:<10.
 ↪2f}{roc_test:<10.2f}{conclusion}")

'''This function is now ready to use with either best_model, X_all or␣
 ↪X_selected and y,
You can call it like: evaluate_generalization(best_models_slected, X_selected,␣
 ↪y)
# or: evaluate_generalization(best_models_all, X_all, y)'''
```

[27]:
```
'This function is now ready to use with either best_model, X_all or X_selected
and y,\nYou can call it like: evaluate_generalization(best_models_slected,
X_selected, y)\n# or: evaluate_generalization(best_models_all, X_all, y)'
```

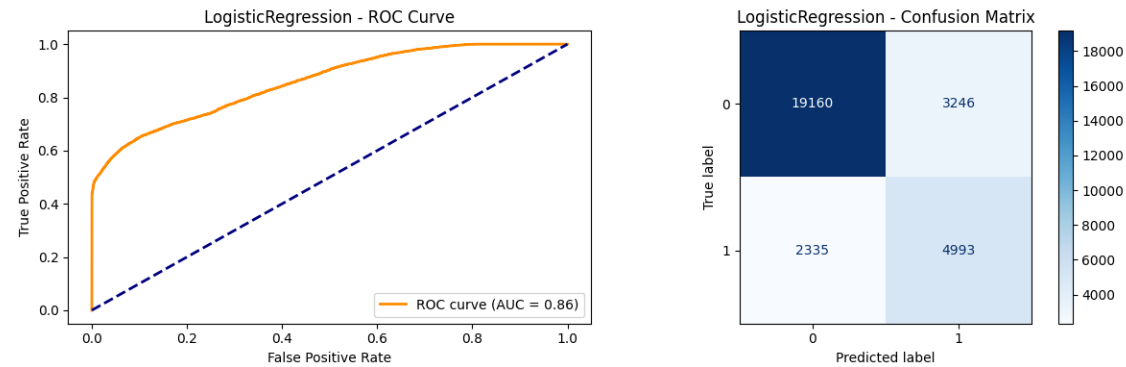
[28]:
```
#@title Training models with selected features and checking performace
best_models_slected = train_models_with_gridsearch(X_selected, y)
```

```
 Training LogisticRegression…
 Best Params: {'model__C': 10}
              precision    recall  f1-score   support

         0.0       0.89      0.86      0.87     22406
         1.0       0.61      0.68      0.64      7328

    accuracy                           0.81     29734
   macro avg       0.75      0.77      0.76     29734
weighted avg       0.82      0.81      0.82     29734

ROC-AUC: 0.8579

 Training RandomForest…
```

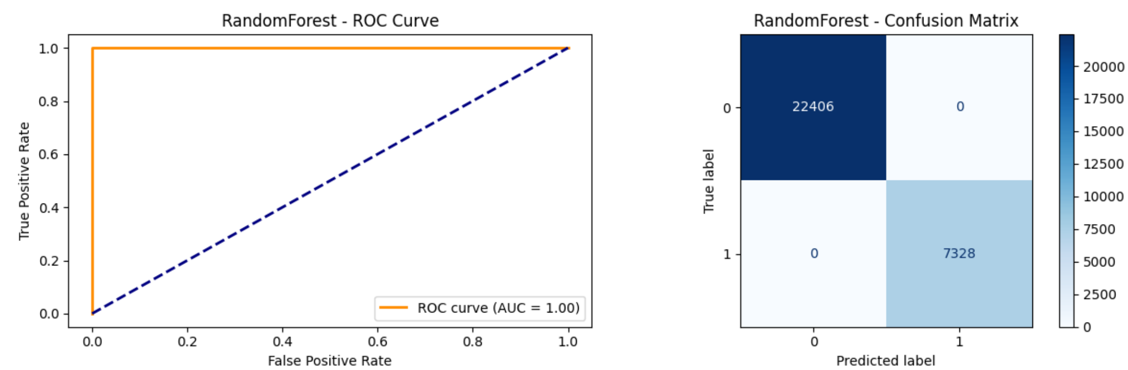
```
  Best Params: {'model__max_depth': 20, 'model__n_estimators': 200}
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00     22406
         1.0       1.00      1.00      1.00      7328

    accuracy                           1.00     29734
   macro avg       1.00      1.00      1.00     29734
weighted avg       1.00      1.00      1.00     29734

ROC-AUC: 1.0000

  Training XGBoost…
  Best Params: {'model__learning_rate': 0.05, 'model__n_estimators': 200}
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00     22406
         1.0       1.00      1.00      1.00      7328

    accuracy                           1.00     29734
   macro avg       1.00      1.00      1.00     29734
weighted avg       1.00      1.00      1.00     29734

ROC-AUC: 1.0000

  Training KNN…
  Best Params: {'model__n_neighbors': 3}
              precision    recall  f1-score   support

         0.0       0.99      0.91      0.95     22406
         1.0       0.78      0.96      0.86      7328

    accuracy                           0.93     29734
   macro avg       0.89      0.94      0.91     29734
weighted avg       0.94      0.93      0.93     29734

ROC-AUC: 0.9651
```

[29]:
```python
#@title Visualizing model performance when trained with the selected features
plot_model_evaluations(best_models_slected, X_selected, y)
```

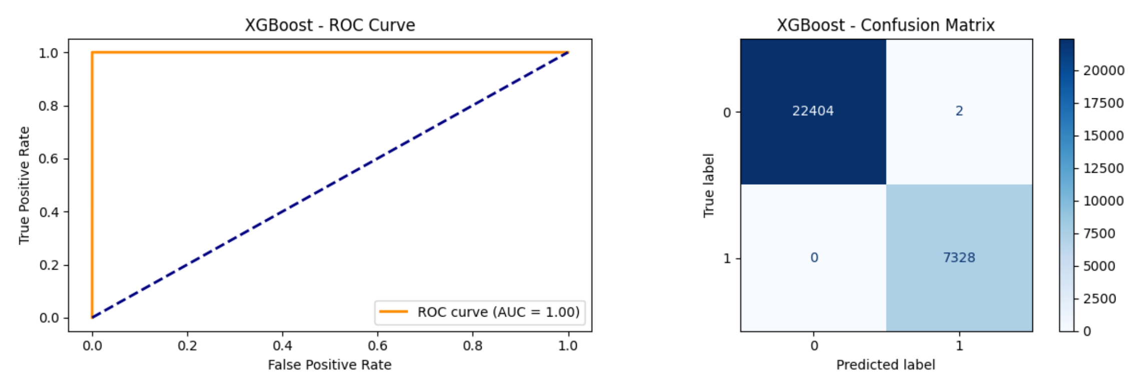
```
  Plotting results for: LogisticRegression
```



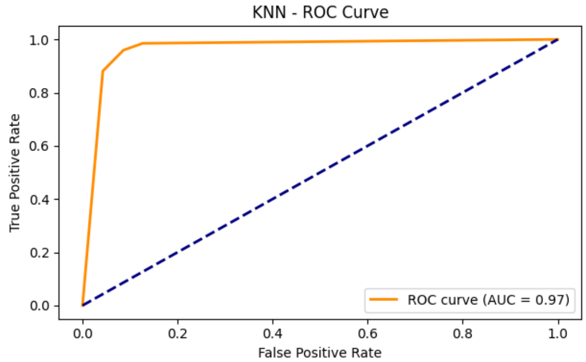
Plotting results for: RandomForest

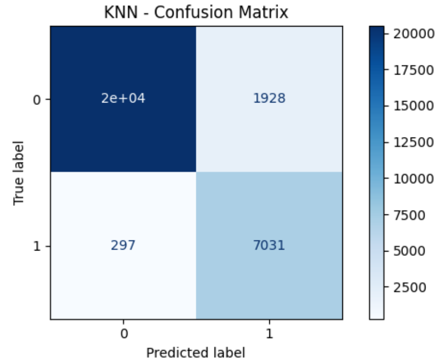


Plotting results for: XGBoost



Plotting results for: KNN





[30]:
```
#@title Checking if the models generalizes well when trained with the selected
 ↪features
evaluate_generalization(best_models_slected, X_selected, y)
```

```
Model                Train F1  Test F1   Train ROC Test ROC  Conclusion
----------------------------------------------------------------------
LogisticRegression   0.63      0.64      0.85      0.86        Generalizes Well
RandomForest         1.00      1.00      1.00      1.00        Generalizes Well
XGBoost              1.00      1.00      1.00      1.00        Generalizes Well
KNN                  0.93      0.86      1.00      0.97        Mixed
```

The generalization evaluation results using selected features are:

- **LogisticRegression**: Train F1 0.63, Test F1 0.64, Train ROC 0.85, Test ROC 0.86 - Generalizes Well (slight improvement in test scores, indicating good generalization).
- **RandomForest**: Train F1 1.00, Test F1 1.00, Train ROC 1.00, Test ROC 1.00 - Generalizes Well (perfect scores, showing strong generalization).
- **XGBoost**: Train F1 1.00, Test F1 1.00, Train ROC 1.00, Test ROC 1.00 - Generalizes Well (perfect scores, indicating robust generalization).
- **KNN**: Train F1 0.93, Test F1 0.86, Train ROC 1.00, Test ROC 0.97 - Mixed (improved test scores compared to all features, but still a noticeable gap, suggesting limited generalization).

Overall, using selected features improves generalization for LogisticRegression and KNN, while RandomForest and XGBoost maintain perfect generalization. KNN still shows mixed results with a performance drop on the test set.

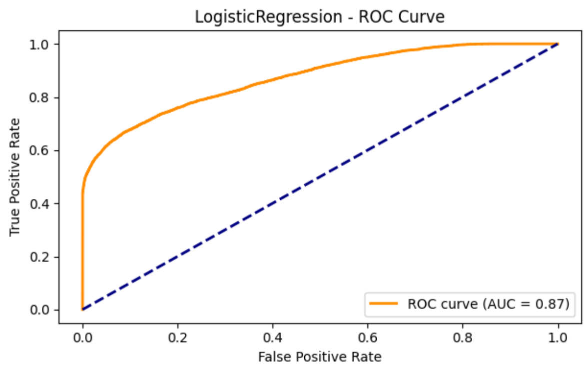
[31]:
```
#@title Training models with all features and checking performace
best_models_all = train_models_with_gridsearch(X_all, y)
```

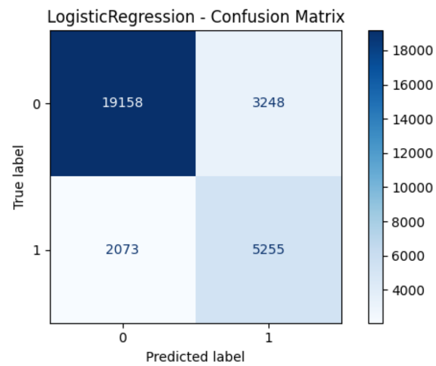
```
Training LogisticRegression…
Best Params: {'model__C': 1}
              precision    recall  f1-score   support

         0.0       0.90      0.86      0.88     22406
```

```
         1.0       0.62      0.72      0.66      7328

    accuracy                           0.82     29734
   macro avg       0.76      0.79      0.77     29734
weighted avg       0.83      0.82      0.83     29734

ROC-AUC: 0.8722

 Training RandomForest…
 Best Params: {'model__max_depth': 20, 'model__n_estimators': 200}
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00     22406
         1.0       1.00      1.00      1.00      7328

    accuracy                           1.00     29734
   macro avg       1.00      1.00      1.00     29734
weighted avg       1.00      1.00      1.00     29734

ROC-AUC: 1.0000

 Training XGBoost…
 Best Params: {'model__learning_rate': 0.05, 'model__n_estimators': 100}
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00     22406
         1.0       1.00      1.00      1.00      7328

    accuracy                           1.00     29734
   macro avg       1.00      1.00      1.00     29734
weighted avg       1.00      1.00      1.00     29734

ROC-AUC: 1.0000

 Training KNN…
 Best Params: {'model__n_neighbors': 3}
              precision    recall  f1-score   support

         0.0       0.95      0.88      0.91     22406
         1.0       0.70      0.87      0.78      7328

    accuracy                           0.88     29734
   macro avg       0.83      0.88      0.85     29734
weighted avg       0.89      0.88      0.88     29734

ROC-AUC: 0.9236
```

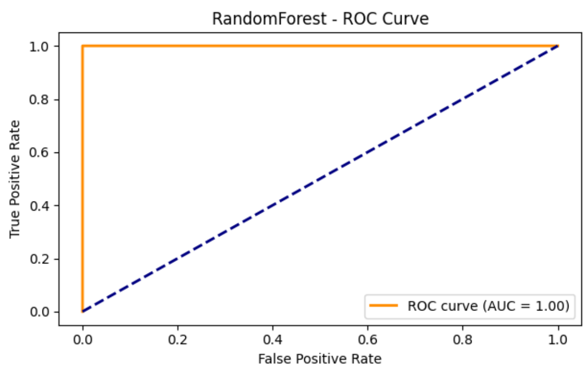
```
[32]: #@title Visualizing model performance when trained with the all features
plot_model_evaluations(best_models_all, X_all, y)
```

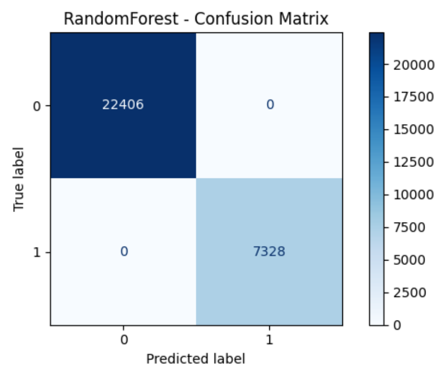
```
Plotting results for: LogisticRegression
```



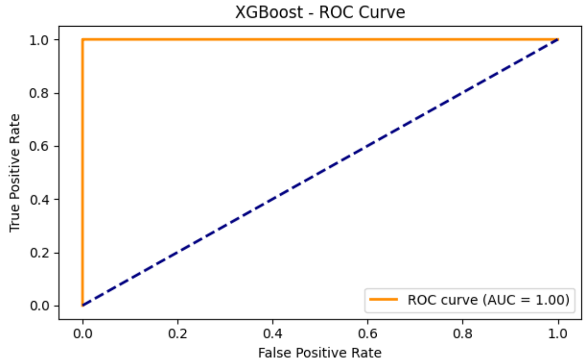


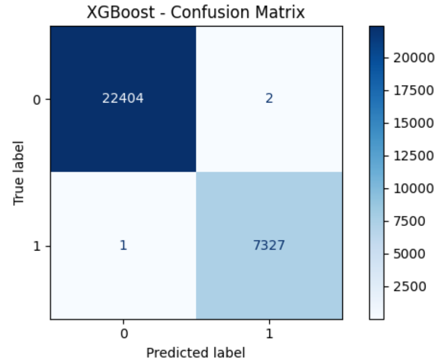

```
Plotting results for: RandomForest
```



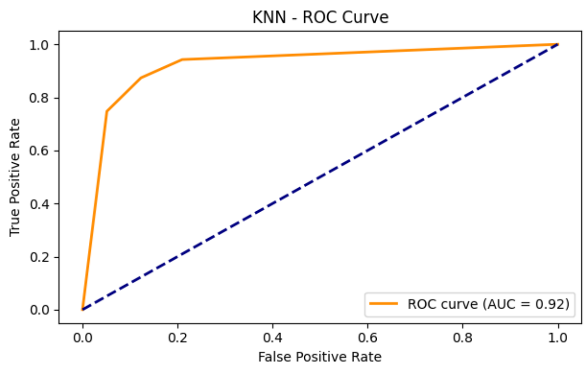


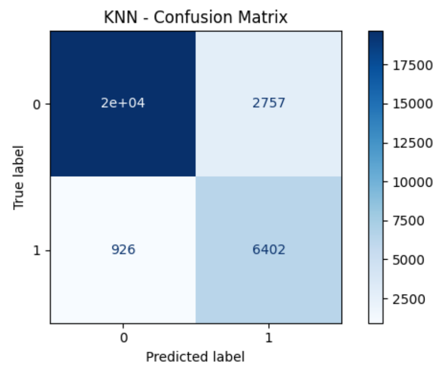

```
Plotting results for: XGBoost
```






```
Plotting results for: KNN
```





[33]:
```
#@title Checking if the models generalizes well when trained with the all␣
↪features
evaluate_generalization(best_models_all, X_all, y)
```

```
Model               Train F1   Test F1    Train ROC Test ROC  Conclusion
----------------------------------------------------------------------
LogisticRegression  0.66       0.66       0.87      0.87        Generalizes Well
RandomForest        1.00       1.00       1.00      1.00        Generalizes Well
XGBoost             1.00       1.00       1.00      1.00        Generalizes Well
KNN                 0.90       0.78       1.00      0.92        Mixed
```

The generalization evaluation results using all features are:

- **LogisticRegression**: Train F1 0.66, Test F1 0.66, Train ROC 0.87, Test ROC 0.87 - Generalizes Well (consistent performance across train and test sets).
- **RandomForest**: Train F1 1.00, Test F1 1.00, Train ROC 1.00, Test ROC 1.00 - Generalizes Well (perfect scores, indicating strong generalization).

- **XGBoost**: Train F1 1.00, Test F1 1.00, Train ROC 1.00, Test ROC 1.00 - Generalizes Well (perfect scores, showing robust generalization).
- **KNN**: Train F1 0.90, Test F1 0.78, Train ROC 1.00, Test ROC 0.92 - Mixed (noticeable drop in F1 and ROC from train to test, suggesting limited generalization).

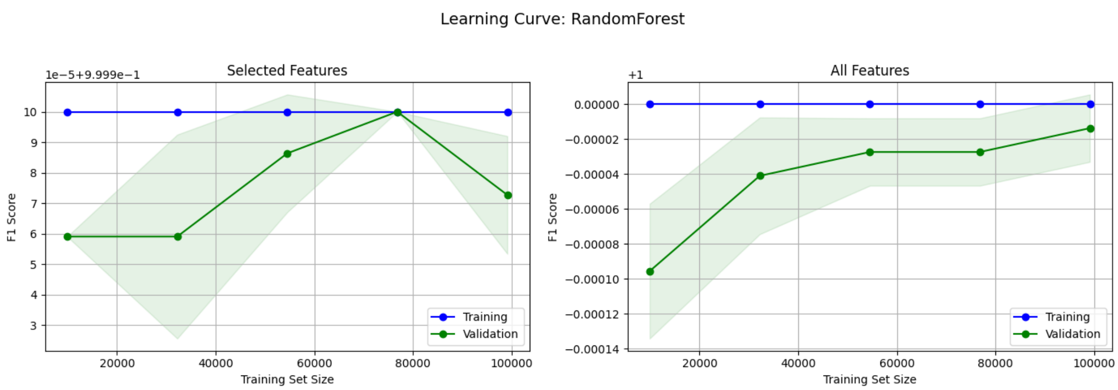
Overall, LogisticRegression, RandomForest, and XGBoost generalize well, while KNN shows mixed results with a performance drop on the test set.

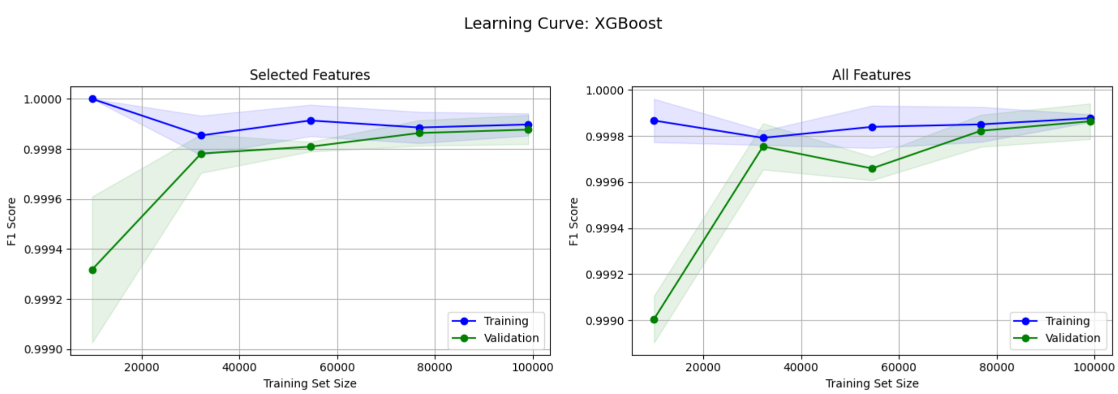
[34]:
```
#@title Function to visualize Learning Curve
from sklearn.model_selection import learning_curve

def compare_learning_curves(models_selected, models_all, X_selected, X_all, y,␣
↪scoring='f1', cv=3, step=5):
    """
    Plots learning curves for each model using selected and all features.
    """
    for (name_sel, model_sel, _), (name_all, model_all, _) in␣
↪zip(models_selected, models_all):
        assert name_sel == name_all, "Model mismatch between selected and all␣
↪features"

        # Compute learning curve for selected features
        train_sizes_sel, train_scores_sel, val_scores_sel = learning_curve(
            model_sel, X_selected, y, cv=cv, scoring=scoring, n_jobs=-1,
            train_sizes=np.linspace(0.1, 1.0, step), shuffle=True,␣
↪random_state=42
        )

        # Compute learning curve for all features
        train_sizes_all, train_scores_all, val_scores_all = learning_curve(
            model_all, X_all, y, cv=cv, scoring=scoring, n_jobs=-1,
            train_sizes=np.linspace(0.1, 1.0, step), shuffle=True,␣
↪random_state=42
        )

        # Mean scores
        train_mean_sel = train_scores_sel.mean(axis=1)
        val_mean_sel = val_scores_sel.mean(axis=1)
        train_mean_all = train_scores_all.mean(axis=1)
        val_mean_all = val_scores_all.mean(axis=1)

        # Plotting
        plt.figure(figsize=(14, 5))
        plt.suptitle(f"Learning Curve: {name_sel}", fontsize=14)

        # Selected Features
        plt.subplot(1, 2, 1)
```

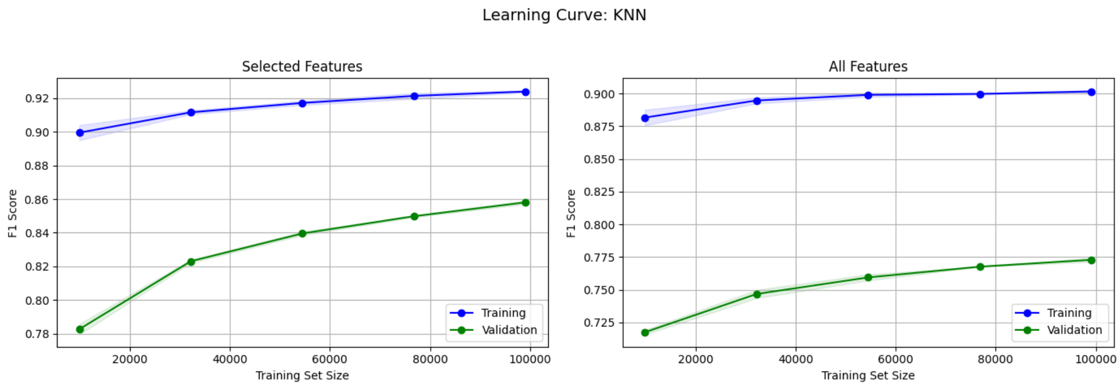
```
    plt.plot(train_sizes_sel, train_mean_sel, 'o-', color='blue',␣
↪label='Training')
    plt.plot(train_sizes_sel, val_mean_sel, 'o-', color='green',␣
↪label='Validation')
    plt.fill_between(train_sizes_sel, train_mean_sel - train_scores_sel.
↪std(1),
                     train_mean_sel + train_scores_sel.std(1), alpha=0.1,␣
↪color='blue')
    plt.fill_between(train_sizes_sel, val_mean_sel - val_scores_sel.std(1),
                     val_mean_sel + val_scores_sel.std(1), alpha=0.1,␣
↪color='green')
    plt.title("Selected Features")
    plt.xlabel("Training Set Size")
    plt.ylabel(f"{scoring.title()} Score")
    plt.grid(True)
    plt.legend()

    # All Features
    plt.subplot(1, 2, 2)
    plt.plot(train_sizes_all, train_mean_all, 'o-', color='blue',␣
↪label='Training')
    plt.plot(train_sizes_all, val_mean_all, 'o-', color='green',␣
↪label='Validation')
    plt.fill_between(train_sizes_all, train_mean_all - train_scores_all.
↪std(1),
                     train_mean_all + train_scores_all.std(1), alpha=0.1,␣
↪color='blue')
    plt.fill_between(train_sizes_all, val_mean_all - val_scores_all.std(1),
                     val_mean_all + val_scores_all.std(1), alpha=0.1,␣
↪color='green')
    plt.title("All Features")
    plt.xlabel("Training Set Size")
    plt.ylabel(f"{scoring.title()} Score")
    plt.grid(True)
    plt.legend()

    plt.tight_layout(rect=[0, 0.03, 1, 0.95])
    plt.show()
```

[35]:
```
compare_learning_curves(best_models_slected, best_models_all, X_selected,␣
↪X_all, y)
```


Learning Curve: LogisticRegression
Selected Features
All Features
F1 Score
Training Set Size
Training
Validation


Learning Curve: RandomForest
Selected Features
All Features
1e−5+9.999e−1
+1
F1 Score
Training Set Size
Training
Validation


Learning Curve: XGBoost
Selected Features
All Features
F1 Score
Training Set Size
Training
Validation



Based on the learning curves for Logistic Regression, Random Forest, XGBoost, and KNN models, the overall conclusion is as follows:

- **Logistic Regression**: The selected features model generalizes well with a small gap between training and validation scores (both around 0.634), while the all features model shows a wider gap and potential overfitting (training ~0.657, validation ~0.657).
- **Random Forest**: The selected features model exhibits a large gap (training ~10, validation ~9) suggesting underfitting or instability, while the all features model performs more consistently (training ~0.0000, validation ~-0.0002).
- **XGBoost**: Both models show high performance with converging scores (selected: training ~0.9996, validation ~0.9996; all: training ~0.9990, validation ~0.9998), with all features slightly outperforming.
- **KNN**: The selected features model generalizes better (training ~0.92, validation ~0.86), while the all features model shows a larger gap (training ~0.90, validation ~0.775), indicating overfitting.

Overall, models with selected features tend to generalize better across most algorithms, except for XGBoost where all features slightly edge out. The choice of features and model type significantly impacts performance and generalization.

[40]:
```
# Convert the notebook
!jupyter nbconvert --to pdf "/content/drive/MyDrive/Colab Notebooks/Loan␣
↪Default.ipynb"
```

```
[NbConvertApp] Converting notebook /content/drive/MyDrive/Colab Notebooks/Loan
Default.ipynb to pdf
[NbConvertApp] ERROR | Error while converting '/content/drive/MyDrive/Colab
Notebooks/Loan Default.ipynb'
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-packages/nbconvert/nbconvertapp.py", line
487, in export_single_notebook
    output, resources = self.exporter.from_filename(
                        ^^^^^^^^^^^^^^^^^^^^^^^^^^^^

  File "/usr/local/lib/python3.11/dist-
packages/nbconvert/exporters/templateexporter.py", line 390, in from_filename
```

```
    return super().from_filename(filename, resources, **kw)  #
type:ignore[return-value]
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/nbconvert/exporters/exporter.py", line 201, in from_filename
    return self.from_file(f, resources=resources, **kw)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/nbconvert/exporters/templateexporter.py", line 396, in from_file
    return super().from_file(file_stream, resources, **kw)  #
type:ignore[return-value]
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/nbconvert/exporters/exporter.py", line 220, in from_file
    return self.from_notebook_node(
           ^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-packages/nbconvert/exporters/pdf.py",
line 184, in from_notebook_node
    latex, resources = super().from_notebook_node(nb, resources=resources, **kw)
                       ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-packages/nbconvert/exporters/latex.py",
line 92, in from_notebook_node
    return super().from_notebook_node(nb, resources, **kw)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/nbconvert/exporters/templateexporter.py", line 429, in
from_notebook_node
    output = self.template.render(nb=nb_copy, resources=resources)
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-packages/jinja2/environment.py", line
1295, in render
    self.environment.handle_exception()
  File "/usr/local/lib/python3.11/dist-packages/jinja2/environment.py", line
942, in handle_exception
    raise rewrite_traceback_stack(source=source)
  File "/usr/local/share/jupyter/nbconvert/templates/latex/index.tex.j2", line
8, in top-level template code
    ((* extends cell_style *))
    ^^^^^^^^^^^^^^^^^^^^^^^^^
  File
"/usr/local/share/jupyter/nbconvert/templates/latex/style_jupyter.tex.j2", line
176, in top-level template code
    \prompt{(((prompt)))}{(((prompt_color)))}{(((execution_count)))}{(((extra_sp
ace)))}
    ^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/share/jupyter/nbconvert/templates/latex/base.tex.j2", line 7,
in top-level template code
    ((*- extends 'document_contents.tex.j2' -*))
```

```
    ^^^^^^^^^^^^^^^^^^^^^^^^^
  File
"/usr/local/share/jupyter/nbconvert/templates/latex/document_contents.tex.j2",
line 51, in top-level template code
    ((*- block figure scoped -*))
    ^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/share/jupyter/nbconvert/templates/latex/display_priority.j2",
line 5, in top-level template code
    ((*- extends 'null.j2' -*))
    ^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/share/jupyter/nbconvert/templates/latex/null.j2", line 30, in
top-level template code
    ((*- block body -*))
  File "/usr/local/share/jupyter/nbconvert/templates/latex/base.tex.j2", line
241, in block 'body'
    ((( super() )))
  File "/usr/local/share/jupyter/nbconvert/templates/latex/null.j2", line 32, in
block 'body'
    ((*- block any_cell scoped -*))
    ^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/share/jupyter/nbconvert/templates/latex/null.j2", line 85, in
block 'any_cell'
    ((*- block markdowncell scoped-*)) ((*- endblock markdowncell -*))
    ^^^^^^^^^^^^^^^^^^^^^^^^^
  File
"/usr/local/share/jupyter/nbconvert/templates/latex/document_contents.tex.j2",
line 68, in block 'markdowncell'
    ((( cell.source | citation2latex | strip_files_prefix |
convert_pandoc('markdown+tex_math_double_backslash', 'json',extra_args=[]) |
resolve_references | convert_explicitly_relative_paths |
convert_pandoc('json','latex'))))
    ^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-packages/nbconvert/filters/pandoc.py",
line 36, in convert_pandoc
    return pandoc(source, from_format, to_format, extra_args=extra_args)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-packages/nbconvert/utils/pandoc.py", line
50, in pandoc
    check_pandoc_version()
  File "/usr/local/lib/python3.11/dist-packages/nbconvert/utils/pandoc.py", line
98, in check_pandoc_version
    v = get_pandoc_version()
        ^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-packages/nbconvert/utils/pandoc.py", line
75, in get_pandoc_version
    raise PandocMissing()
nbconvert.utils.pandoc.PandocMissing: Pandoc wasn't found.
Please check that pandoc is installed:
```

https://pandoc.org/installing.html