turbo-aug-23-24-clustering

February 24, 2025

1 PROJECT TITLE: Borrower Segmentation and Credit Risk Profiling Using Clustering Techniques

1.1 PROJECT OVERVIEW

This project leverages unsupervised clustering methods to segment borrowers based on their loan repayment behavior and overall credit profile. By applying data wrangling, feature engineering, and K-Means clustering, the analysis uncovers inherent patterns in repayment performance and differentiates clients into distinct risk groups. Key objectives include:

- Client Segmentation: Grouping borrowers based on metrics such as payment consistency, delay frequency, and recovery trends to reveal varying levels of risk.
- Segment Characterization: Profiling each cluster to identify defining financial and behavioral attributes, such as outstanding balances, fee structures, and revenue generation.
- Feature Importance Analysis: Employing techniques like Random Forest and PCA to determine which variables—such as loan age, days interest calculated, and revenue per loan—are most influential in driving credit risk.

These insights support targeted risk management strategies, inform tailored lending approaches, and enhance overall credit portfolio decision-making.

1.2 PROJECT OBJECTIVE

The primary objective of this clustering analysis is to segment borrowers based on their loan repayment behavior and overall credit profile. By grouping clients into distinct clusters, the analysis aims to uncover inherent patterns in repayment performance, identify key characteristics of each borrower class, and determine the most influential features driving creditworthiness. These insights will enable targeted risk management, inform tailored lending strategies, and enhance credit portfolio decision-making.

1.2.1 Key Analysis Areas

a) Client Segmentation by Repayment Behavior - Objective: To group clients into distinct segments based on historical repayment data and behavior patterns. - **Description:** This analysis will employ clustering techniques to classify borrowers according to metrics such as payment consistency, delay frequency, and recovery trends. The resulting segments will reflect varying levels of risk and repayment discipline, providing a foundation for further analysis.

b) Characterization of Borrower Segments - Objective: To identify and profile the key financial and behavioral characteristics within each borrower segment. - **Description:** Post-clustering, each segment will be analyzed to determine its defining attributes—such as outstanding balances, interest rates, and revenue contributions. This profiling will help in understanding the risk profile and performance trends within and across clusters.

c) Feature Importance Analysis for Credit Profiling - Objective: To determine which features most significantly influence the clustering outcome and, by extension, the creditworthiness of borrowers. **- Description:** Using methods such as Random Forest and PCA, the model will rank feature importance, highlighting the critical variables (e.g., age, days of interest calculated, revenue per loan) that drive borrower segmentation. This will provide actionable insights into the primary factors that differentiate high-risk from low-risk clients.

1.2.2 Data Features

-loan_id: Unique identifier for the loan.

-agent_id: Identifier for the agent handling the loan.

-loan_amount: The total amount of the loan.

-loan_balance: The remaining balance of the loan.

-amount_paid: The total amount paid back so far.

-outstanding_principle: The remaining principal amount that has not been paid.

-outstanding_daily_interest: The daily interest that has not been paid.

-outstanding_setup_fees: The setup fees that have not been paid.

-outstanding_penalty_fees: The penalty fees that have not been paid.

-interest_earned: The interest earned on the loan.

-principle_repayment: The total amount repaid toward the principal of the loan.

-setup_fees_repayment: The total amount repaid toward the setup fees.

-daily_interest_repayment: The daily interest that has been repaid.

-penalty_fees_repayment: The penalty fees that have been repaid.

-status_id: Status of the loan.

-defaulted: Indicates if the loan has defaulted.

-eligible_amount: The amount eligible for repayment.

-created_at: The date the loan was created.

-due_date: The due date for the loan repayment.

-last_repayment_date: The date of the last repayment.

-days_interest_calculated: The number of days interest has been calculated.

-age: The age of the loan in days.

-is_npl: Binary indicator designating whether a loan is classified as non-performing.

-**created_month:** Month and year extracted from the loan creation date to facilitate time series analysis.

-**due_month:** Month and year extracted from the loan due date to enable monthly trend analysis.

-**last_repayment_month:** Month and year extracted from the date of the last repayment for temporal repayment pattern analysis.

-**days_since_last_repayment:** The number of days elapsed since the most recent repayment, indicating recent borrower activity.

-**days_past_due:** The number of days a payment is overdue, computed as the difference between the current date and the due date (with negative values adjusted to zero).

-**aging_bucket:** Categorical grouping of loans based on days past due (e.g., '0-30', '31-60', '61-90', '>90') used for risk stratification.

-**collection_rate:** The percentage of the eligible amount that has been repaid, reflecting repayment efficiency.

-**revenue_earned:** Aggregate revenue derived from interest, penalty fees, and daily interest repayment.

-**outstanding_revenue:** Sum of the remaining principal, daily interest, setup fees, and penalty fees yet to be repaid.

-**revenue_per_loan:** Ratio of total revenue earned to the initial loan amount, representing the revenue yield per loan.

1.2.3 Methodology

-**Data Wrangling and preparation:** Data will be loaded, cleaned and prepared for modeling ensuring accuracy and regularity across the whole data range.

-**Modeling (Clustering Analysis):** After standardization and appropriate scaling of the data, it will be subjected to K-means clustering algorithm.

-**Visualization and Interpration of Clusters:** Graphical representations will be created to visualize the clusters as well as key characteristics distinguishing varying clusters.

1.3 DATA UNDERSTANDING

1.3.1 Imports & Parsing

[1]:
```
# Import required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.cm as cm
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, calinski_harabasz_score,␣
↪silhouette_samples
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn.pipeline import make_pipeline
from sklearn.decomposition import PCA
from sklearn.preprocessing import MinMaxScaler
import warnings

# Ensures plots are generated within the notebook
%matplotlib inline
```

[2]:
```
# NB: Filepath can be adjusted depending on current working environment
filepath = 'C:/Users/Hp/Documents/WORK/TURBO GROUP/model_data_1.xlsx'

# Read the file into the working environment
df = pd.read_excel(filepath, parse_dates=True, date_format='%d/%b/%Y')
```

1.3.2 Data Wrangling

[3]:
```
# Sample the dataframe for visual inspection
df.sample(n=10, random_state=42)
```

[3]:
```
                                 loan_id           agent_id  loan_amount  \
23474   b3ce91fc402c12b906bb281c5c58507f  201000000000491296         6000
42631   ba984c7af699fa5cb8a99fa594831bf1  201000000000365504        21043
22663   006be45872682c50a031e78f228e5a10  201000000000359392         1350
166172  43fa8e2d74d942ec47a0e3a70cf39f82  201000000000567008         5000
1499    867af5aa4a4ae7525afac07ffe445a0f  201000000000742688         8850
149455  99b4c6417c08b35759d8ebed19768a6c  201000000000493408         6223
9245    40a4706d527493a69c9d1670e2167225  201000000000536384        16084
246914  e2c567b8eca6a2f9c3d71bb5e7ee7124  201000000000806208         9000
91839   7108b379aaed0007f2b295c69b624376  201000000000592096         8500
217049  0fc355d48a531ac28209bd77f6f2b6c6  201000000000742400        35000

        loan_balance  amount_paid  outstanding_principle  \
23474           0.00      6030.00                    0.0
42631           0.00     21148.22                    0.0
22663           0.00      1356.75                    0.0
166172          0.00      5124.36                    0.0
1499            0.00      8947.72                    0.0
149455          0.24      6507.00                    0.0
9245            0.00     16164.42                    0.0
246914          0.00      9989.00                    0.0
91839           0.00      9307.50                    0.0
217049      38681.00     14035.00                20965.0

        outstanding_daily_interest  outstanding_setup_fees  \
23474                         0.00                    0.00
```

```
42631                      0.00                    0.00
22663                      0.00                    0.00
166172                     0.00                    0.64
1499                       0.00                    0.00
149455                     0.22                    0.00
9245                       0.00                    0.00
246914                     0.00                    0.00
91839                      0.00                    0.00
217049                 12370.00                  875.00

        outstanding_penalty_fees  interest_earned  …  created_month  \
23474                       0.00            30.00  …        2023-09
42631                       0.00           105.22  …        2023-10
22663                       0.00             6.75  …        2023-09
166172                      0.00           124.36  …        2024-04
1499                        0.00            97.72  …        2023-08
149455                      0.02           284.00  …        2024-03
9245                        0.00            80.42  …        2023-08
246914                      0.00           989.00  …        2024-04
91839                       0.00           807.50  …        2024-02
217049                   4471.00             0.00  …        2024-10

        due_month  last_repayment_month  days_since_last_repayment  \
23474         NaN               2023-09                        426
42631         NaN               2023-10                        396
22663         NaN               2023-09                        427
166172    2024-06               2024-08                        114
1499          NaN               2023-08                        460
149455    2024-07               2024-10                         54
9245          NaN               2023-08                        476
246914    2024-11               2024-07                        137
91839     2024-09               2024-09                         87
217049    2024-06               2024-07                        119

        days_past_due  aging_bucket  collection_rate revenue_earned  \
23474             NaN           >90        12.060000          30.00
42631             NaN           >90         5.496556         105.22
22663             NaN           >90         0.365129           6.75
166172          175.0           >90        10.248720         124.36
1499              NaN           >90        16.081886         151.19
149455          146.0           >90        13.014000         412.00
9245              NaN           >90         5.003163          80.42
246914           20.0          0-30        19.277413        1753.00
91839            87.0         61-90        18.615000        1402.50
217049          163.0           >90        28.070000           0.00

       outstanding_revenue revenue_per_loan
```

```
23474                   0.00         0.005000
42631                   0.00         0.005000
22663                   0.00         0.005000
166172                  0.64         0.024872
1499                    0.00         0.017084
149455                  0.24         0.066206
9245                    0.00         0.005000
246914                  0.00         0.194778
91839                   0.00         0.165000
217049              38681.00         0.000000

[10 rows x 33 columns]
```

[4]:

```
# Visually inspect for columns with NaN values

# Separate rows with and without NaN values
rows_with_nan = df[df.isna().any(axis=1)]
rows_without_nan = df[~df.isna().any(axis=1)]

# Sample from each subset
sample_with_nan = rows_with_nan.sample(n=5, random_state=42)  # Ensure␣
↪reproducibility
sample_without_nan = rows_without_nan.sample(n=5, random_state=42)

# Combine the samples
sampled_df = pd.concat([sample_with_nan, sample_without_nan])

#print(sampled_df)
sampled_df
```

[4]:

```
                                 loan_id            agent_id  loan_amount  \
14050   5481ec85e1604bf617653bbe36931b85  201000000000496096         1000
57481   df8273c5a9f4464c85492fc8bb99f6fb  201000000000360608        36380
43337   ca7e5d99020254c98855412ff9f74ede  201000000000483008         1319
185689  47eb727a1a347d84e5bb8977f9c0fec6  201000000000336512        49812
82526   7c8a5c24748561e4a2b776d4dc356ede  201000000000524096        18500
215931  88fd2cb588eae0f73081c6646c6150cb  201000000000525600         8500
272765  f8a67717278d4f08d4319c7527308a85  201000000000787104        78547
199227  e9e40c4c69bfbb311e16819c0fc45d00  201000000000727616        30500
263782  2fdcc57e6385a0c7c27f5b32f01e3774  201000000000484800        18981
84274   8d717ad7772133de7317f42d876849c1  201000000000697312       127000

        loan_balance  amount_paid  outstanding_principle  \
14050            0.0      1005.00                    0.0
57481            0.0     36561.90                    0.0
43337            0.0      1325.59                    0.0
185689       75701.0         0.00                49812.0
```

```
82526           0.0     18592.50                    0.0
215931          0.0      9624.00                    0.0
272765          0.0     87612.00                    0.0
199227          0.0     33519.00                    0.0
263782          0.0     20859.00                    0.0
84274           0.0    130200.46                    0.0

        outstanding_daily_interest  outstanding_setup_fees  \
14050                          0.0                     0.0
57481                          0.0                     0.0
43337                          0.0                     0.0
185689                     17762.0                  1245.0
82526                          0.0                     0.0
215931                         0.0                     0.0
272765                         0.0                     0.0
199227                         0.0                     0.0
263782                         0.0                     0.0
84274                          0.0                     0.0

        outstanding_penalty_fees  interest_earned  …  created_month  \
14050                        0.0             5.00  …        2023-09
57481                        0.0           181.90  …        2023-11
43337                        0.0             6.59  …        2023-10
185689                    6882.0             0.00  …        2024-05
82526                        0.0            92.50  …        2023-12
215931                       0.0          1124.00  …        2024-08
272765                       0.0          9065.00  …        2024-07
199227                       0.0          3019.00  …        2024-05
263782                       0.0          1878.00  …        2024-07
84274                        0.0          3200.46  …        2023-12

        due_month  last_repayment_month  days_since_last_repayment  \
14050         NaN               2023-09                        438
57481         NaN               2023-11                        375
43337         NaN               2023-10                        396
185689    2024-05               2024-05                        193
82526         NaN               2023-12                        343
215931    2024-06               2024-06                        161
272765    2024-07               2024-03                        264
199227    2024-03               2024-04                        235
263782    2024-07               2024-07                        126
84274     2023-12               2023-12                        339

        days_past_due  aging_bucket  collection_rate revenue_earned  \
14050             NaN           >90         0.319396           5.00
57481             NaN           >90        16.848393         181.90
43337             NaN           >90         0.180239           6.59
```

```
185689          186.0           >90        0.000000           NaN
82526             NaN           >90        7.497051         92.50
215931          165.0           >90       19.248000       2035.00
272765          119.0           >90       98.402857      16166.00
199227          266.0           >90        7.516351       5275.00
263782          126.0           >90       41.718000       3281.00
84274           340.0           >90      111.915446       5765.92

       outstanding_revenue revenue_per_loan
14050                  0.0         0.005000
57481                  0.0         0.005000
43337                  0.0         0.004996
185689             75701.0              NaN
82526                  0.0         0.005000
215931                 0.0         0.239412
272765                 0.0         0.205813
199227                 0.0         0.172951
263782                 0.0         0.172857
84274                  0.0         0.045401

[10 rows x 33 columns]
```

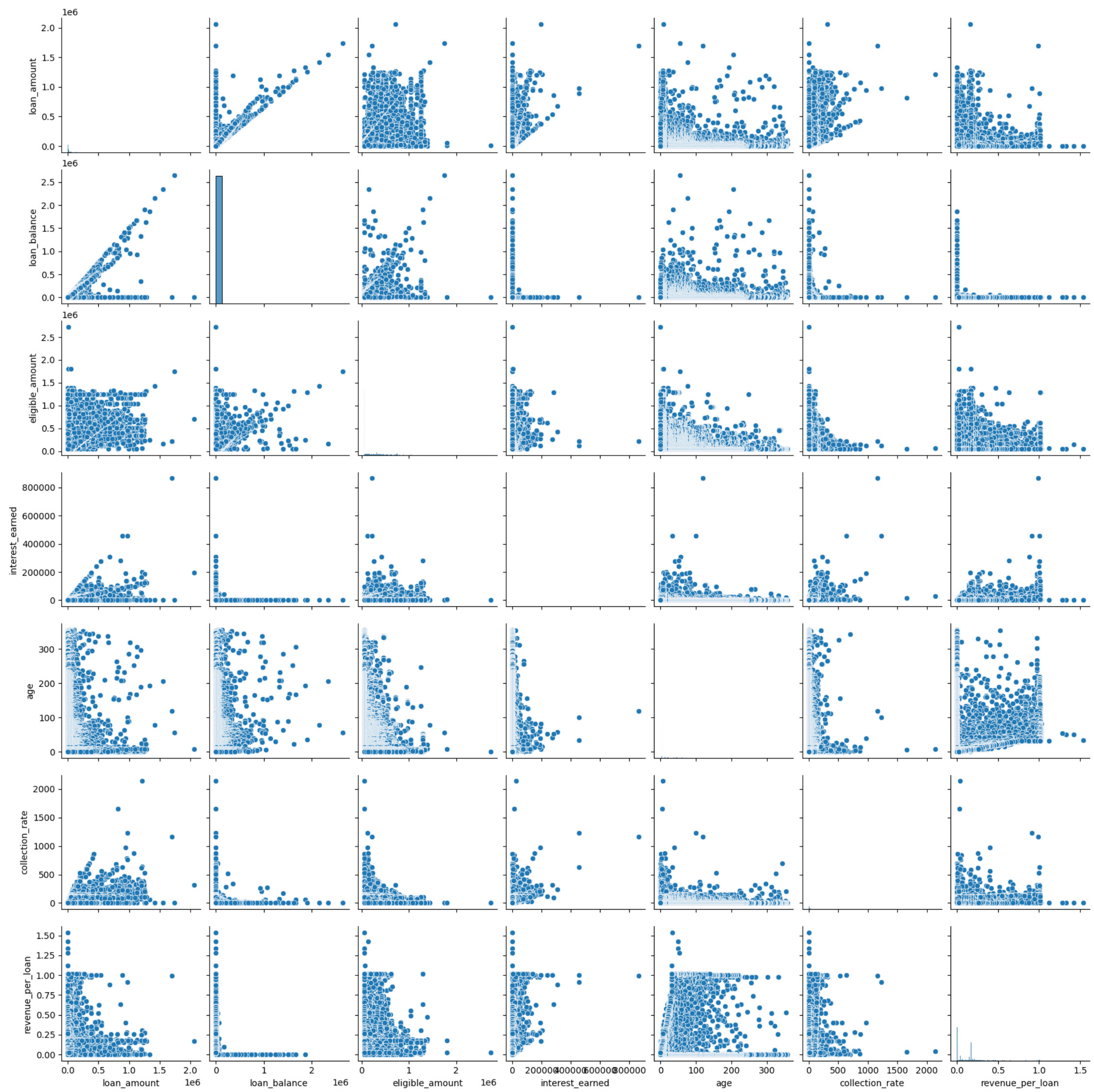
[5]:
```python
# Statistical summary of the numerical columns in the dataframe
df.describe()
```

[5]:
```
           agent_id   loan_amount  loan_balance   amount_paid  \
count  2.884460e+05  2.884460e+05  2.884460e+05  2.884460e+05
mean   2.010000e+17  2.394264e+04  2.408474e+03  2.338799e+04
min    2.010000e+17  1.000000e+00  0.000000e+00  0.000000e+00
25%    2.010000e+17  3.500000e+03  0.000000e+00  2.768000e+03
50%    2.010000e+17  9.946000e+03  0.000000e+00  8.839470e+03
75%    2.010000e+17  2.250000e+04  0.000000e+00  2.211000e+04
max    2.010000e+17  2.065000e+06  2.646558e+06  2.567576e+06
std    1.413122e+05  5.840495e+04  2.442308e+04  5.850679e+04

       outstanding_principle  outstanding_daily_interest  \
count           2.884460e+05               288446.000000
mean            1.820662e+03                  415.676313
min            -1.030000e+05                -2334.000000
25%             0.000000e+00                    0.000000
50%             0.000000e+00                    0.000000
75%             0.000000e+00                    0.000000
max             1.741500e+06               620924.000000
std             1.751825e+04                 5349.097861

       outstanding_setup_fees  outstanding_penalty_fees  interest_earned  \
count           288446.000000             288446.000000    288446.000000
```

```
mean                47.308286                 123.252379      1266.009303
min               -925.000000                   0.000000         0.000000
25%                  0.000000                   0.000000        52.500000
50%                  0.000000                   0.000000       288.000000
75%                  0.000000                   0.000000      1079.000000
max              43538.000000             240596.000000    865866.000000
std                436.738347               1972.549331      4490.971691

       principle_repayment  …            last_repayment_date  \
count         2.697850e+05  …                         288446
mean          2.365215e+04  …  2024-03-08 20:17:56.333178368
min           2.000000e-02  …            2023-01-09 00:00:00
25%           3.469000e+03  …            2023-11-29 00:00:00
50%           9.649000e+03  …            2024-04-03 00:00:00
75%           2.200000e+04  …            2024-06-23 00:00:00
max           2.065000e+06  …            2024-12-07 00:00:00
std           5.778920e+04  …                            NaN

       days_interest_calculated            age         is_npl  \
count             288446.000000  288446.000000  288446.000000
mean                   6.801814       9.795598       0.052426
min                    0.000000       0.000000       0.000000
25%                    0.000000       1.000000       0.000000
50%                    7.000000       7.000000       0.000000
75%                    7.000000       8.000000       0.000000
max                  171.000000     356.000000       1.000000
std                    7.589373      22.309433       0.222884

       days_since_last_repayment  days_past_due collection_rate  \
count              288446.000000  203590.000000   288446.000000
mean                  263.305558     185.172626       18.466052
min                     0.000000       0.000000        0.000000
25%                   157.000000     131.000000        2.481383
50%                   238.000000     184.000000        8.489266
75%                   364.000000     253.000000       22.550000
max                   688.000000     688.000000     2140.659418
std                   143.683535      84.259027       27.992265

      revenue_earned outstanding_revenue  revenue_per_loan
count   2.697850e+05        2.884460e+05     269785.000000
mean    2.335622e+03        2.406899e+03          0.124602
min     0.000000e+00       -1.035150e+05          0.000000
25%     9.700000e+01        0.000000e+00          0.005000
50%     5.000000e+02        0.000000e+00          0.129250
75%     1.952000e+03        0.000000e+00          0.172874
max     1.689189e+06        2.646558e+06          1.540000
std     8.626842e+03        2.442476e+04          0.161615
```

```
[8 rows x 28 columns]
```

[6]:
```python
# Generate a list of features to visualize using the pairplot
pair_features = ['loan_amount', 'loan_balance', 'eligible_amount',
 'interest_earned', 'age', 'collection_rate', 'revenue_per_loan']
# Generate the pairplot
sns.pairplot(df[pair_features], diag_kind='auto')
plt.show();
```



[7]:
```python
# Obtain metadata of the dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 288446 entries, 0 to 288445
Data columns (total 33 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
 0   loan_id                      288446 non-null  object
 1   agent_id                     288446 non-null  int64
 2   loan_amount                  288446 non-null  int64
 3   loan_balance                 288446 non-null  float64
 4   amount_paid                  288446 non-null  float64
 5   outstanding_principle        288446 non-null  float64
 6   outstanding_daily_interest   288446 non-null  float64
 7   outstanding_setup_fees       288446 non-null  float64
 8   outstanding_penalty_fees     288446 non-null  float64
 9   interest_earned              288446 non-null  float64
 10  principle_repayment          269785 non-null  float64
 11  setup_fees_repayment         269785 non-null  float64
 12  daily_interest_repayment     269785 non-null  float64
 13  penalty_fees_repayment       269785 non-null  float64
 14  status_id                    288446 non-null  int64
 15  defaulted                    288446 non-null  int64
 16  eligible_amount              288446 non-null  float64
 17  created_at                   288446 non-null  datetime64[ns]
 18  due_date                     203590 non-null  datetime64[ns]
 19  last_repayment_date          288446 non-null  datetime64[ns]
 20  days_interest_calculated     288446 non-null  int64
 21  age                          288446 non-null  int64
 22  is_npl                       288446 non-null  int64
 23  created_month                288446 non-null  object
 24  due_month                    203590 non-null  object
 25  last_repayment_month         288446 non-null  object
 26  days_since_last_repayment    288446 non-null  int64
 27  days_past_due                203590 non-null  float64
 28  aging_bucket                 288446 non-null  object
 29  collection_rate              288446 non-null  float64
 30  revenue_earned               269785 non-null  float64
 31  outstanding_revenue          288446 non-null  float64
 32  revenue_per_loan             269785 non-null  float64
dtypes: datetime64[ns](3), float64(17), int64(8), object(5)
memory usage: 72.6+ MB
```

[8]:
```
# List out and enumerate the columns present in the dataframe
print (df.columns,sep='\n')

print(f'The DataFrame has a total of {len(df.columns)} columns.')
```

```
Index(['loan_id', 'agent_id', 'loan_amount', 'loan_balance', 'amount_paid',
       'outstanding_principle', 'outstanding_daily_interest',
```

```
'outstanding_setup_fees', 'outstanding_penalty_fees', 'interest_earned',
'principle_repayment', 'setup_fees_repayment',
'daily_interest_repayment', 'penalty_fees_repayment', 'status_id',
'defaulted', 'eligible_amount', 'created_at', 'due_date',
'last_repayment_date', 'days_interest_calculated', 'age', 'is_npl',
'created_month', 'due_month', 'last_repayment_month',
'days_since_last_repayment', 'days_past_due', 'aging_bucket',
'collection_rate', 'revenue_earned', 'outstanding_revenue',
'revenue_per_loan'],
dtype='object')
The DataFrame has a total of 33 columns.
```

[9]:

```python
# Calculate the count of NaN values per column as a ratio of the overall
nan_counts = df.isna().sum() / len(df)

# Filter to include only columns with NaN values
nan_columns_df = nan_counts[nan_counts > 0].reset_index()
nan_columns_df.columns = ['Column', 'NaN_Count_Ratio']

# Print out the results
print(nan_columns_df)
```

```
                     Column  NaN_Count_Ratio
0       principle_repayment         0.064695
1      setup_fees_repayment         0.064695
2  daily_interest_repayment         0.064695
3    penalty_fees_repayment         0.064695
4                  due_date         0.294183
5                 due_month         0.294183
6              days_past_due         0.294183
7            revenue_earned         0.064695
8          revenue_per_loan         0.064695
```

- Since deleting null values would result in a data loss of 6% at best and 30% at worst, it is imperative that alternative cleaning methods are applied to minimize data loss. The first strategy is to fill in all null values within monetary columns with zeros as it can be assumed that no revenue/fees were collected in these cases.
- Lastly, the 'age' column can be used to make inferences regarding the columns with missing date values.

[10]:

```python
# Fill all monetary related columns with 0.
# NB: The assumption made is that no revenue/repayments were collected in these␣
↪cases
money_columns = ['principle_repayment', 'setup_fees_repayment',
                 'daily_interest_repayment', 'penalty_fees_repayment',
                 'revenue_earned','revenue_per_loan']
# Fill NaN values with 0 for the specified columns
df[money_columns] = df[money_columns].fillna(0)
```

[11]:
```
# Even though the 'due_date' column has null values but the 'age column doesnt;
# hence, we can use the age of the loan in days to find the missing values in␣
 ↪the 'due_date' column
df['calculated_due_date'] = df['created_at'] + pd.to_timedelta(df['age'],␣
 ↪unit='d')
```

[12]:
```
# Combine pre-existing due dates with calculated due dates
df['due_date'] = pd.to_datetime(df['due_date'])  # Ensure existing dates are in␣
 ↪datetime format
df['due_date'] = df['due_date'].fillna(df['calculated_due_date'])
```

[13]:
```
similar_count = (df['due_date'] == df['calculated_due_date']).sum()
print(f"Number of similar values: {similar_count}")
```

```
Number of similar values: 119571
```

[14]:
```
# Add a column to indicate if the values are similar
df['is_similar'] = df['due_date'] == df['calculated_due_date']

print(df['is_similar'].value_counts())
```

```
is_similar
False    168875
True     119571
Name: count, dtype: int64
```

[15]:
```
# Calculate 'due_month' using new 'calculated_due_month' column
df['due_month'] = df['calculated_due_date'].dt.to_period('M')
```

[16]:
```
df.isna().sum()
```

[16]:
```
loan_id                          0
agent_id                         0
loan_amount                      0
loan_balance                     0
amount_paid                      0
outstanding_principle            0
outstanding_daily_interest       0
outstanding_setup_fees           0
outstanding_penalty_fees         0
interest_earned                  0
principle_repayment              0
setup_fees_repayment             0
daily_interest_repayment         0
penalty_fees_repayment           0
status_id                        0
defaulted                        0
```

```
eligible_amount                0
created_at                     0
due_date                       0
last_repayment_date            0
days_interest_calculated       0
age                            0
is_npl                         0
created_month                  0
due_month                      0
last_repayment_month           0
days_since_last_repayment      0
days_past_due              84856
aging_bucket                   0
collection_rate                0
revenue_earned                 0
outstanding_revenue            0
revenue_per_loan               0
calculated_due_date            0
is_similar                     0
dtype: int64
```

[17]:

```python
# The timestamp (6/8/2024  12:00:00 AM) is fixed as that is the period of␣
↪analysis required for the project,
# consequently, we calculate 'days_past_due' using this value

# Define the fixed timestamp for calculation
fixed_timestamp = pd.Timestamp('2024-06-08 00:00:00')

# Compute the number of days past the due date if the loan is overdue
df['days_past_due'] = (fixed_timestamp - df['due_date']).dt.days

# Apply a lambda function to ensure no negative values
df['days_past_due'] = df['days_past_due'].apply(lambda x: max(x, 0))
```

[18]:

```python
# Ensure the column no longer has null values
df['days_past_due'].isna().sum()
```

[18]: np.int64(0)

[19]:

```python
# Confirm that the dataset has no ore null values
df.isna().sum()
```

[19]:

```
loan_id                    0
agent_id                   0
loan_amount                0
loan_balance               0
amount_paid                0
```

```
outstanding_principle         0
outstanding_daily_interest    0
outstanding_setup_fees        0
outstanding_penalty_fees      0
interest_earned               0
principle_repayment           0
setup_fees_repayment          0
daily_interest_repayment      0
penalty_fees_repayment        0
status_id                     0
defaulted                     0
eligible_amount               0
created_at                    0
due_date                      0
last_repayment_date           0
days_interest_calculated      0
age                           0
is_npl                        0
created_month                 0
due_month                     0
last_repayment_month          0
days_since_last_repayment     0
days_past_due                 0
aging_bucket                  0
collection_rate               0
revenue_earned                0
outstanding_revenue           0
revenue_per_loan              0
calculated_due_date           0
is_similar                    0
dtype: int64
```

- Now that all null values have been eliminated from the data, we are now ready to do some modeling.

NB: 'defaulted', 'status_id', and 'is_npl' columns have similar outputs hence can be used interchangably

[20]:
```
df.columns
```

[20]:
```
Index(['loan_id', 'agent_id', 'loan_amount', 'loan_balance', 'amount_paid',
       'outstanding_principle', 'outstanding_daily_interest',
       'outstanding_setup_fees', 'outstanding_penalty_fees', 'interest_earned',
       'principle_repayment', 'setup_fees_repayment',
       'daily_interest_repayment', 'penalty_fees_repayment', 'status_id',
       'defaulted', 'eligible_amount', 'created_at', 'due_date',
       'last_repayment_date', 'days_interest_calculated', 'age', 'is_npl',
       'created_month', 'due_month', 'last_repayment_month',
```

```
 'days_since_last_repayment', 'days_past_due', 'aging_bucket',
 'collection_rate', 'revenue_earned', 'outstanding_revenue',
 'revenue_per_loan', 'calculated_due_date', 'is_similar'],
dtype='object')
```

1.4 DATA MODELING

1.4.1 Feature Engineering

Case 1: Determining Feature importance using Random Forest

- At this juncture we begin selecting features that will be most relevant to the modeling that is to be performed. We drop all date and categorical columns from the dataset and focus on numerical columns mainly.

[21]:
```python
# Select only the numeric features that could be relevant to correlation
numerical_features = [
    'loan_amount', 'loan_balance', 'amount_paid', 'outstanding_principle',
    'outstanding_daily_interest', 'outstanding_setup_fees',␣
 ↪'outstanding_penalty_fees',
    'interest_earned', 'principle_repayment', 'setup_fees_repayment',
    'daily_interest_repayment', 'penalty_fees_repayment', 'eligible_amount',
    'days_interest_calculated', 'age', 'days_since_last_repayment',␣
 ↪'days_past_due',
    'collection_rate', 'revenue_earned', 'outstanding_revenue',␣
 ↪'revenue_per_loan'
]

# Add the 'defaulted' column (or 'is_npl' depending on which you use) to the␣
 ↪features to calculate correlation
features = numerical_features + ['is_npl']

# Select only the relevant columns from the dataframe
df_selected = df[features].copy()
```

[22]:
```python
#Obtain metadata of the selected dataframe
df_selected.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 288446 entries, 0 to 288445
Data columns (total 22 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   loan_amount                 288446 non-null  int64
 1   loan_balance                288446 non-null  float64
 2   amount_paid                 288446 non-null  float64
 3   outstanding_principle       288446 non-null  float64
 4   outstanding_daily_interest  288446 non-null  float64
```

```
 5   outstanding_setup_fees      288446 non-null  float64
 6   outstanding_penalty_fees    288446 non-null  float64
 7   interest_earned             288446 non-null  float64
 8   principle_repayment         288446 non-null  float64
 9   setup_fees_repayment        288446 non-null  float64
 10  daily_interest_repayment    288446 non-null  float64
 11  penalty_fees_repayment      288446 non-null  float64
 12  eligible_amount             288446 non-null  float64
 13  days_interest_calculated    288446 non-null  int64
 14  age                         288446 non-null  int64
 15  days_since_last_repayment   288446 non-null  int64
 16  days_past_due               288446 non-null  int64
 17  collection_rate             288446 non-null  float64
 18  revenue_earned              288446 non-null  float64
 19  outstanding_revenue         288446 non-null  float64
 20  revenue_per_loan            288446 non-null  float64
 21  is_npl                      288446 non-null  int64
dtypes: float64(16), int64(6)
memory usage: 48.4 MB
```

[23]:

```
# Statistical summary of the selected dataframe
df_selected.describe()
```

[23]:

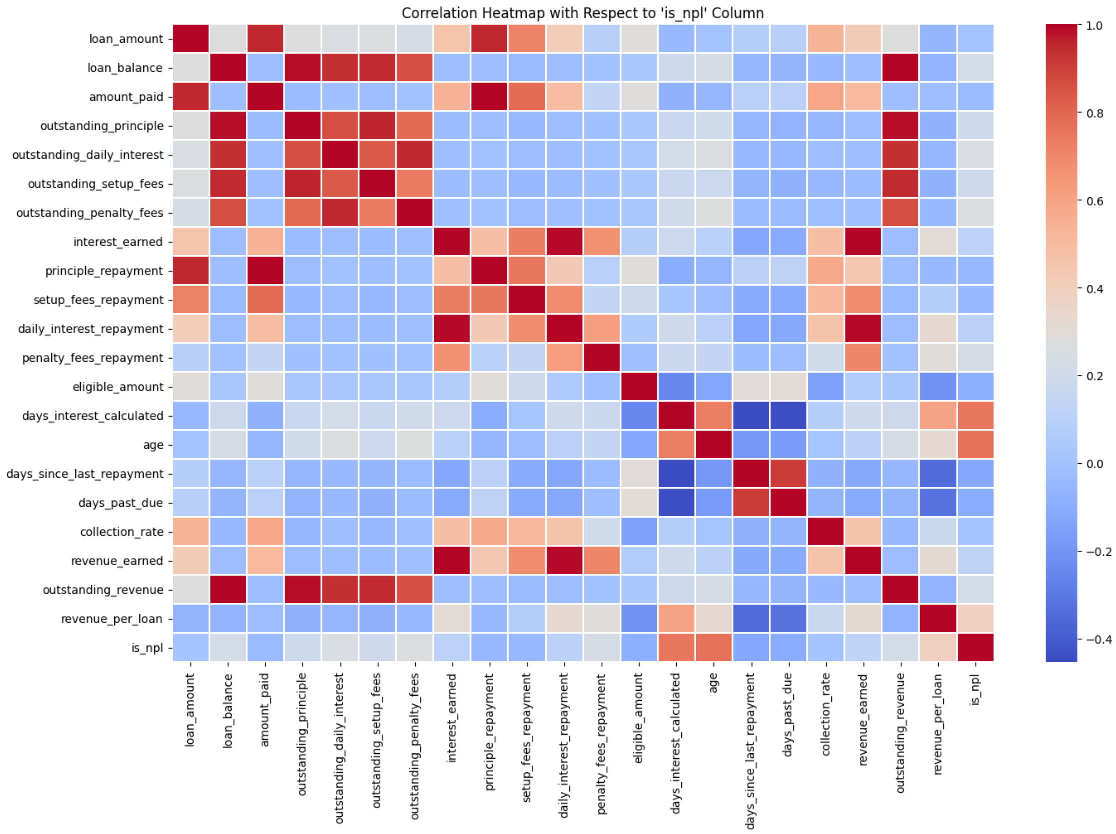
```
        loan_amount   loan_balance   amount_paid  outstanding_principle  \
count  2.884460e+05  2.884460e+05  2.884460e+05           2.884460e+05
mean   2.394264e+04  2.408474e+03  2.338799e+04           1.820662e+03
std    5.840495e+04  2.442308e+04  5.850679e+04           1.751825e+04
min    1.000000e+00  0.000000e+00  0.000000e+00          -1.030000e+05
25%    3.500000e+03  0.000000e+00  2.768000e+03           0.000000e+00
50%    9.946000e+03  0.000000e+00  8.839470e+03           0.000000e+00
75%    2.250000e+04  0.000000e+00  2.211000e+04           0.000000e+00
max    2.065000e+06  2.646558e+06  2.567576e+06           1.741500e+06

       outstanding_daily_interest  outstanding_setup_fees  \
count               288446.000000           288446.000000
mean                   415.676313               47.308286
std                   5349.097861              436.738347
min                  -2334.000000             -925.000000
25%                      0.000000                0.000000
50%                      0.000000                0.000000
75%                      0.000000                0.000000
max                 620924.000000            43538.000000

       outstanding_penalty_fees  interest_earned  principle_repayment  \
count             288446.000000    288446.000000         2.884460e+05
mean                 123.252379      1266.009303         2.212198e+04
std                 1972.549331      4490.971691         5.619063e+04
```

```
min                   0.000000       0.000000        0.000000e+00
25%                   0.000000      52.500000        2.510000e+03
50%                   0.000000     288.000000        8.169000e+03
75%                   0.000000    1079.000000        2.050000e+04
max              240596.000000  865866.000000        2.065000e+06

       setup_fees_repayment  …  eligible_amount  days_interest_calculated  \
count         288446.000000  …     2.884460e+05             288446.000000
mean             347.499927  …     1.718977e+05                  6.801814
std              879.681848  …     1.981511e+05                  7.589373
min                0.000000  …     5.000000e+04                  0.000000
25%               31.130000  …     5.000000e+04                  0.000000
50%              125.000000  …     5.000000e+04                  7.000000
75%              358.000000  …     2.390975e+05                  7.000000
max            51625.000000  …     2.726780e+06                171.000000

                 age  days_since_last_repayment  days_past_due  \
count  288446.000000              288446.000000  288446.000000
mean        9.795598                 263.305558     108.795657
std        22.309433                 143.683535     124.306566
min         0.000000                   0.000000       0.000000
25%         1.000000                 157.000000       0.000000
50%         7.000000                 238.000000      66.000000
75%         8.000000                 364.000000     192.000000
max       356.000000                 688.000000     516.000000

       collection_rate  revenue_earned  outstanding_revenue  revenue_per_loan  \
count    288446.000000    2.884460e+05         2.884460e+05     288446.000000
mean         18.466052    2.184519e+03         2.406899e+03          0.116541
std          27.992265    8.362877e+03         2.442476e+04          0.159276
min           0.000000    0.000000e+00        -1.035150e+05          0.000000
25%           2.481383    6.000000e+01         0.000000e+00          0.005000
50%           8.489266    4.110000e+02         0.000000e+00          0.065596
75%          22.550000    1.750000e+03         0.000000e+00          0.172846
max        2140.659418    1.689189e+06         2.646558e+06          1.540000

              is_npl
count  288446.000000
mean        0.052426
std         0.222884
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000

[8 rows x 22 columns]
```

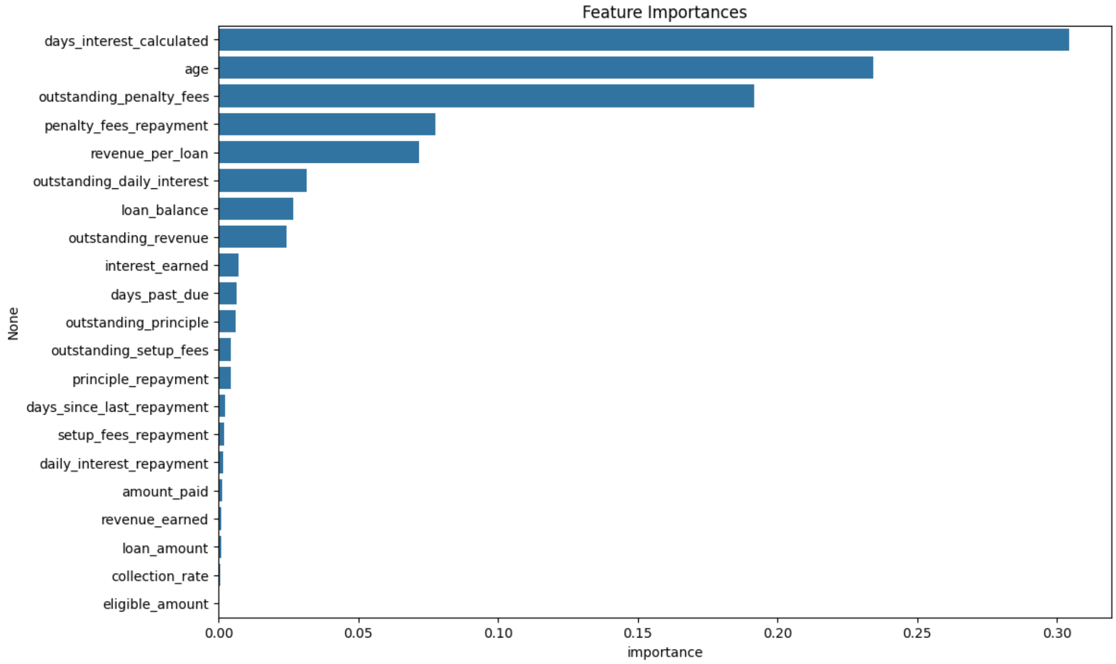
[24]:
```
# Calculate correlation matrix
correlation_matrix = df_selected.corr()

# Filter the correlation matrix to only show correlations with the 'defaulted'␣
↪column (or 'is_npl')
correlation_with_defaulted = correlation_matrix[['is_npl']].
↪sort_values(by='is_npl', ascending=False)

# Print the correlation of all features with 'defaulted'
print(correlation_with_defaulted)
```

```
                              is_npl
is_npl                      1.000000
age                         0.765282
days_interest_calculated    0.752808
revenue_per_loan            0.391772
outstanding_penalty_fees    0.265645
outstanding_daily_interest  0.251620
penalty_fees_repayment      0.229860
outstanding_revenue         0.217277
loan_balance                0.217276
outstanding_setup_fees      0.198514
outstanding_principle       0.191247
revenue_earned              0.124582
interest_earned             0.111966
daily_interest_repayment    0.106349
loan_amount                 0.010341
collection_rate             0.007988
amount_paid                -0.038347
setup_fees_repayment       -0.041138
principle_repayment        -0.048876
eligible_amount            -0.085644
days_past_due              -0.102401
days_since_last_repayment  -0.119254
```

[25]:
```
# Generate the heatmap
plt.figure(figsize=(16, 10))
sns.heatmap(correlation_matrix, annot=False, cmap='coolwarm', linewidths=0.1)
# Title and labels
plt.title("Correlation Heatmap with Respect to 'is_npl' Column")
# Save the heatmap as an image
plt.savefig('correlation_heatmap.png')
plt.show()
```



[26]:
```
# Define X & y for the Random Forest Classifier
X = df[numerical_features]
y = df['is_npl']
# Create and fit a Random Forest Classifier
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X, y)
# Obtain feature importances
feature_importances = pd.DataFrame(rf.feature_importances_,
                                   index=X.columns,
                                   columns=['importance']).
 ↪sort_values('importance', ascending=False)

# Plot feature importances
plt.figure(figsize=(12, 8))
sns.barplot(x=feature_importances.importance, y=feature_importances.index)
plt.title('Feature Importances')
# Save plot as image
plt.savefig('RF_feature_importance.png')
plt.show()
```

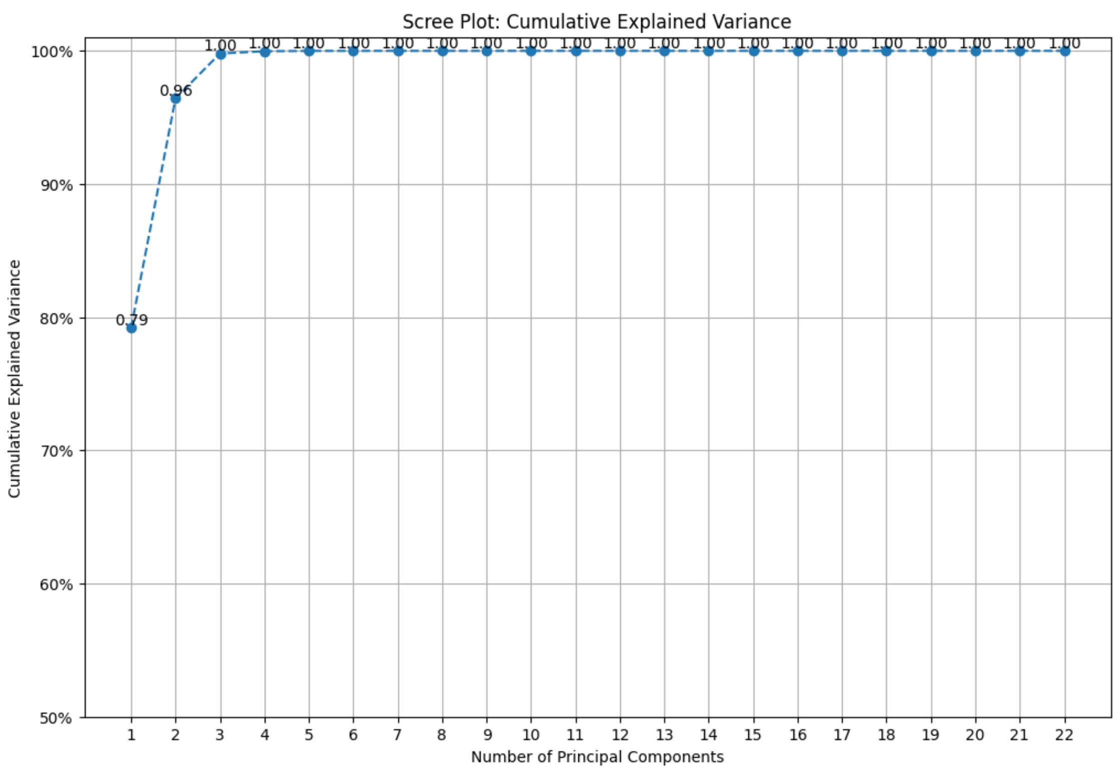


Case 2: Determining Feature Importance using PCA

[27]:
```
# Create and fit a PCA object
pca = PCA(n_components=len(df_selected.columns))
pca.fit(df_selected)

# Calculate cumulative explained variance
cumulative_explained_variance = pca.explained_variance_ratio_.cumsum()
```

[28]:
```
# Create the scree plot
plt.figure(figsize=(12, 8))
plt.plot(
    range(1, len(df_selected.columns) + 1),
    cumulative_explained_variance,
    marker='o',
    linestyle='--'
)

# Add labels and annotations
plt.xticks(range(1, len(df_selected.columns) + 1))
plt.yticks([i / 100 for i in range(50, 101, 10)], labels=[f"{i}%" for i in␣
 ↪range(50, 101, 10)])
for i, ev in enumerate(cumulative_explained_variance):
    if ev >= 0.5:  # Only label points in range
        plt.text(i + 1, ev, f"{ev:.2f}", ha='center', va='bottom')
```

```
# Add title and labels
plt.title('Scree Plot: Cumulative Explained Variance')
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.grid()
# Save the scree plot as an image
plt.savefig('scree_plot.png')
plt.show();
```



[29]:
```
print(pca.explained_variance_ratio_)
```

```
[7.91886401e-01 1.72395533e-01 3.36991049e-02 1.72512557e-03
 2.71065770e-04 1.01164193e-05 6.40286809e-06 4.38873223e-06
 8.84627404e-07 5.52366002e-07 3.77159257e-07 2.96114250e-08
 8.86647761e-09 7.82843252e-09 3.64152165e-10 2.65604644e-13
 2.56739972e-13 6.40477948e-17 1.83883118e-19 0.00000000e+00
 0.00000000e+00 0.00000000e+00]
```

[30]:
```
print(type(pca.explained_variance_ratio_))
```

```
<class 'numpy.ndarray'>
```

[31]:
```
cumulative_variance = np.cumsum(pca.explained_variance_ratio_)
num_components = np.argmax(cumulative_variance >= 0.99) + 1  # +1 to convert␣
 ↪index to count

print(f"The principal components required to explain 99% of the variance in␣
 ↪this dataset are {num_components}.")
```

```
The principal components required to explain 99% of the variance in this dataset
are 3.
```

- With further refinement through PCA we identify that a minimum of 3 principal components are required to describe upto 99.% of the variance in the data . Furthermore , by use of RandomForest we are able to obtain a sorted list of the most important features.

1.4.2 Cluster Assignment

The following features were found to have the greatest impact on loan performance according to Random Forest feature importance as well as PCA analyses. The features chosen for clustering i.e cluster_features are chosen as a result of their higher relative correlation with respect to the 'is_npl' column with a threshold of approximately $\pm$ 0.2. The features chosen are as follows;

- 'age'
- 'days_interest_calculated'
- 'revenue_per_loan'
- 'outstanding_penalty_fees'
- 'outstanding_daily_interest'
- 'penalty_fees_repayment'
- 'outstanding_revenue'
- 'loan_balance'
- 'outstanding_setup_fees'
- 'outstanding_principle'
- 'is_npl'

From the above information, the following can be deduced;

- 'age', 'days_interest_calculated' have the highest influence on default rate('is_npl) with correlations exceeding +0.75
- 'revenue_per-loan', 'outstanding_penalty_fees', 'outstanding_daily_interest' have moderate influence on default rate with corrlations between +0.25 but less than +0.75.
- 'penalty_fees_repayment', 'outstanding_revenue', 'loan_balance' have weak influence on the taget variable with correlations between +0.2 and +0.25
- 'Despite 'outstanding_setup_fees', 'outstanding_principle' having the least influence on the default rate with correlations slightly less than +0.2, they were included in the model for robustness.

[32]:
```
# Select the most relevant features based on feature importance analysis
cluster_features = ['age', 'days_interest_calculated', 'revenue_per_loan',
       'outstanding_penalty_fees', 'outstanding_daily_interest',
       'penalty_fees_repayment', 'outstanding_revenue',
       'loan_balance', 'outstanding_setup_fees', 'outstanding_principle',
```

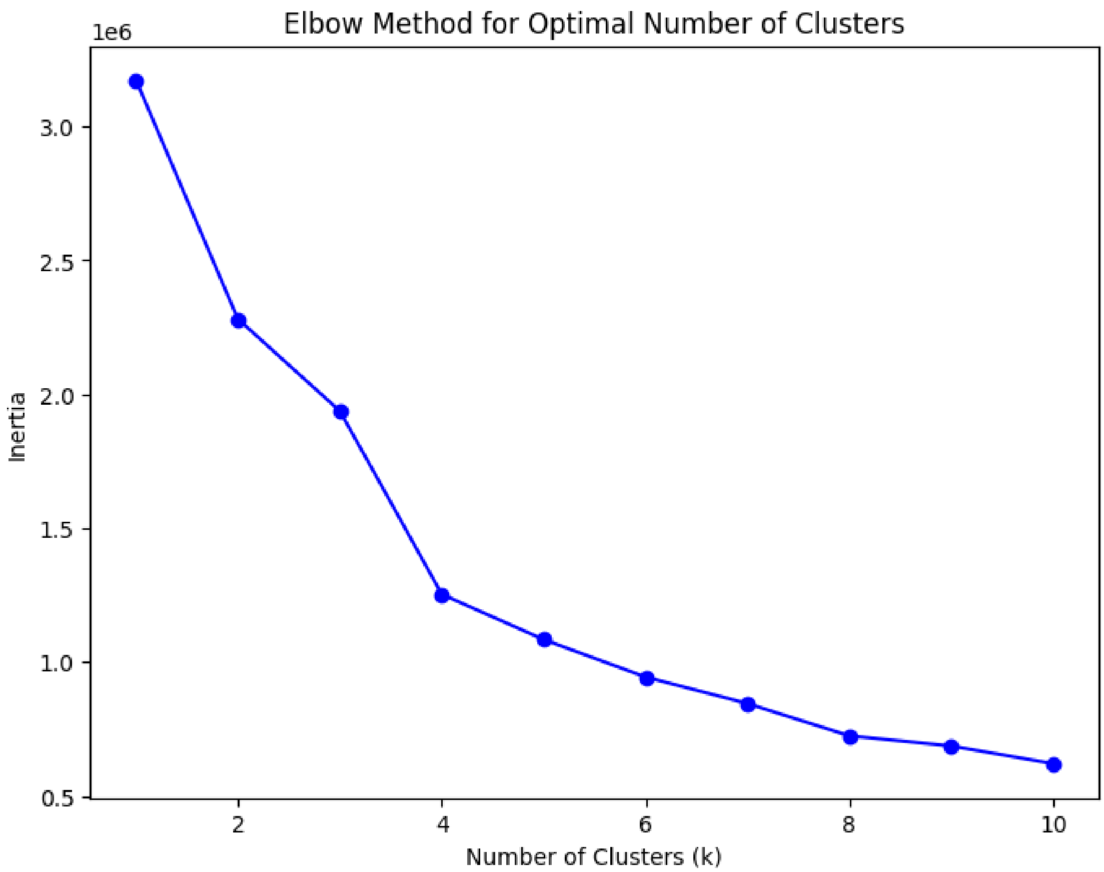
```python
        'is_npl']

# Select these features from the dataset
df_cluster = df[cluster_features].copy()

# Check for missing values (you already handled null values earlier)
print(df_cluster.isnull().sum())
```

```
age                          0
days_interest_calculated     0
revenue_per_loan             0
outstanding_penalty_fees     0
outstanding_daily_interest   0
penalty_fees_repayment       0
outstanding_revenue          0
loan_balance                 0
outstanding_setup_fees       0
outstanding_principle        0
is_npl                       0
dtype: int64
```

[33]:
```python
# Define the preprocessing pipeline
preprocessor = Pipeline(steps=[
    ('scaler', StandardScaler())  # Standardizes the features
])

# Apply preprocessing to the selected features
df_scaled = preprocessor.fit_transform(df[cluster_features])  # Note: df_scaled␣
 ↪is now ready for clustering
```

[34]:
```python
# Create a pipeline with preprocessing and KMeans
inertia = []
K_range = range(1, 11)  # Test for 1 to 10 clusters

for k in K_range:
    clustering_pipeline = Pipeline(steps=[
        ('preprocessor', preprocessor),  # Preprocessing step
        ('kmeans', KMeans(n_clusters=k, random_state=42))
    ])
    clustering_pipeline.fit(df[cluster_features])
    inertia.append(clustering_pipeline['kmeans'].inertia_)  # Store inertia

# Plot the Elbow curve
plt.figure(figsize=(8, 6))
plt.plot(K_range, inertia, 'bo-')
plt.title('Elbow Method for Optimal Number of Clusters')
plt.xlabel('Number of Clusters (k)')
```

```
plt.ylabel('Inertia')
# Save the Elbow curve as an image
plt.savefig('clusters_elbow_curve.png')

plt.show();
```



[35]:
```
# Define the pipeline with the chosen number of clusters (i.e., k=4)

optimal_clusters = 4     #As observed in the above visualization (at the point␣
 ↪of greatest change in inertia in the curve)

clustering_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('kmeans', KMeans(n_clusters=optimal_clusters, random_state=42))
])

# Fit the pipeline and predict cluster labels
df['Cluster'] = clustering_pipeline.fit_predict(df[cluster_features])
```

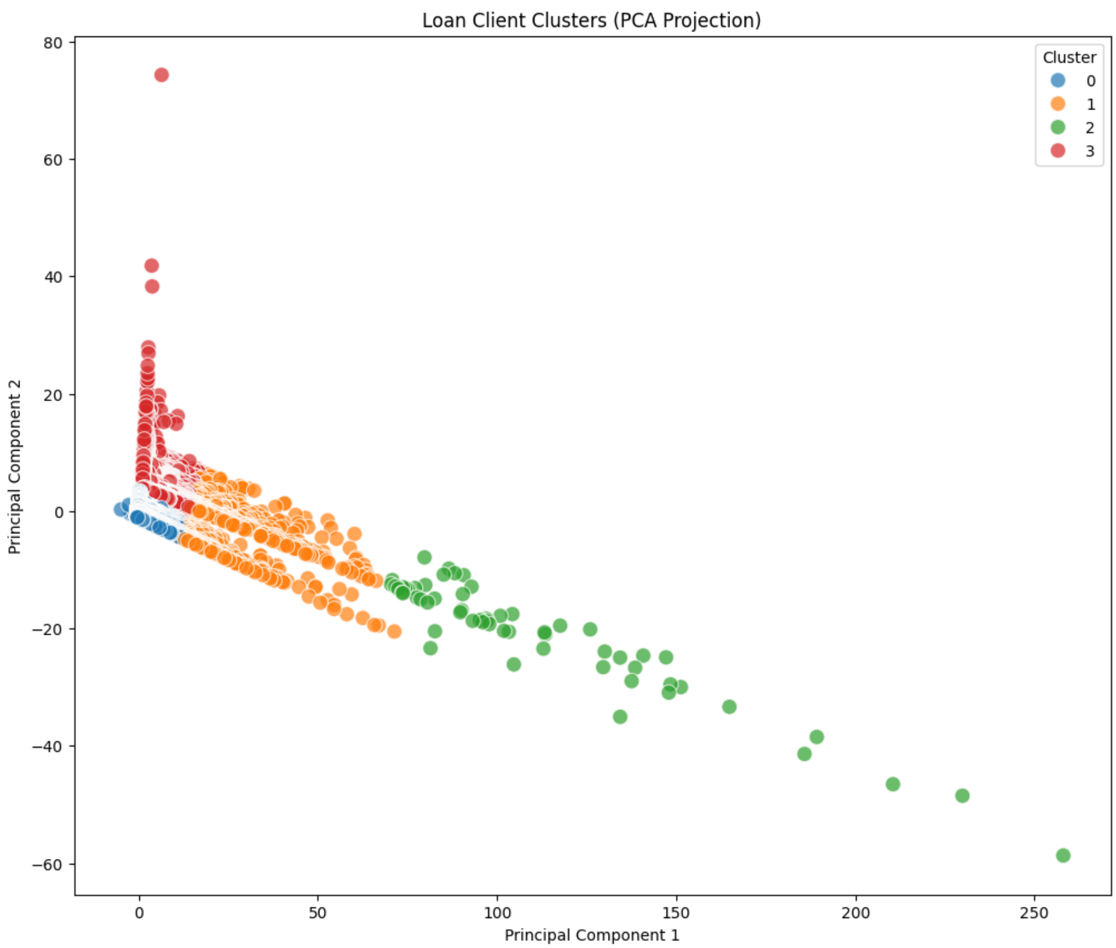
```python
# Display the first few rows of the dataset with cluster labels
print(df[['loan_id', 'Cluster']].head())
```

```
                            loan_id  Cluster
0  37c8a45dbbcf8e09189064ea4457adb0        0
1  975d6d720f528cf94f523d6ba1d5c111        0
2  6cb7205ddab12cc7c8cb1d7df1c6ce86        0
3  c9138fc7078f254aeea92f1d17807bd2        0
4  35b052df405c78add3a3c152ecbaeeff        0
```

[36]:
```python
# Add Cluster cloumn to original modeling dataframe and export for future use
#future_modeling_df = df.merge(df[['loan_id', 'Cluster']], on='loan_id',␣
↪how='left')
# Export the dataframe to a CSV file
#future_modeling_df.to_csv('C:/Users/Hp/Documents/WORK/TURBO GROUP/
↪future_modeling_data.csv', index=False)
```

1.4.3 Visualization of Clusters

[37]:
```python
from sklearn.decomposition import PCA

# Add PCA for dimensionality reduction
pca_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),  # Preprocessing step
    ('pca', PCA(n_components=3))     # PCA for 2D visualization
])

# Transform the data to 2D
df_pca = pca_pipeline.fit_transform(df[cluster_features])

# Visualize the clusters
plt.figure(figsize=(12, 10))
sns.scatterplot(x=df_pca[:, 0], y=df_pca[:, 1], hue=df['Cluster'],␣
↪palette='tab10', s=100, alpha=0.7)
plt.title('Loan Client Clusters (PCA Projection)')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')

# Save plot as image for Powerpoint presentation
plt.savefig('clusters_pca_projection.png')

plt.show();
```



1.4.4 Cluster Summary (Numerical)

[38]:
```python
# Summarize the average characteristics of each cluster and store it as a␣
↪DataFrame
cluster_summary = df.groupby('Cluster')[cluster_features].mean().reset_index()

# Display the resulting DataFrame
cluster_summary_table = pd.DataFrame(data = cluster_summary)
cluster_summary_table
```

[38]:
```
   Cluster         age  days_interest_calculated  revenue_per_loan  \
0        0    5.768090                  5.446174          0.101959
1        1   68.088685                 22.646789          0.000150
2        2  123.112903                 31.032258          0.000000
3        3   81.565099                 31.185871          0.393191

   outstanding_penalty_fees  outstanding_daily_interest  \
```

```
0                0.000000                  74.654478
1            15572.367752               49145.900428
2            97444.726452              265616.540968
3             1315.303483                3464.717259

   penalty_fees_repayment  outstanding_revenue  loan_balance  \
0                0.000000         8.836605e+02  8.853328e+02
1                0.000000         2.728224e+05  2.728223e+05
2                0.000000         1.139863e+06  1.139862e+06
3              841.312595         1.387675e+04  1.387661e+04

   outstanding_setup_fees  outstanding_principle    is_npl
0               20.677085             788.328933  0.000000
1             5144.893823          202959.222110  0.623853
2            17154.312097          759646.957097  0.935484
3              243.105480            8853.627161  0.997482
```

[39]:
```
# Optionally, save to a CSV file if needed
#cluster_summary_table.to_csv("cluster_summary_table.csv", index=False)
```

1.5 KEY INSIGHTS

1.5.1 Feature Importance

The following features from the original dataset were found to have the greatest influence on a client's ability to fulfill their loan repayment obligations: - 'age' - 'days_interest_calculated' - 'revenue_per_loan' - 'outstanding_penalty_fees' - 'outstanding_daily_interest' - 'penalty_fees_repayment' - 'outstanding_revenue' - 'loan_balance' - 'outstanding_setup_fees' - 'outstanding_principle' - 'is_npl'

1.5.2 Explanation of Results of K_Means Clustering

1.) **Cluster 0 (Low-Risk Borrowers)**
- Relatively low age indicating that borrowers tend to pay back loans within a short period. - Minimal outstanding penalty fees and daily interest indicating timely loan repayments. - High revenue per loan averaging approximately 10% for this group. - Low loan balance averaging less than 1000 units. - This suggests responsible borrowers who repay on time, generating steady income.

2.) **Cluster 1 (High-Risk Defaulters)**
- Relatively high age (averaging roughly 9 weeks) stipulating clients borrowing loans over longer periods of time. - High levels of outstanding fees including outstanding; setup fees, principle, revenue daily interest and penalty fees. - Tendency not to pay penalty fees indicates lack of commitment to loan repayment responsibilities. - Very low revenue per loan ratio, shows poor return on investment from this group of clients.
- Extremely high outstanding loan balances, suggesting prolonged non-repayment.
- This cluster represents long-term defaulters.

3.) **Cluster 2 (Moderate-Risk Borrowers with Partial Repayments)**

- High loan age (averaging roughly 10 weeks), even higher than that in Cluster 1. - Some penalty fees have been repaid, unlike Cluster 1, indicating a desire to pay back the money borrowed by the clients in this group. - Reasonable outstanding loan balance; which averages at about 12,700 units as compared to cluster 1, whose outstanding loan balance averages out at abround 269,605 units. Despite having lower outstanding loan balances, they still pose risk to the loanbook.
- This cluster consists of borrowers making partial repayments but struggling.

4.) **Cluster 3 (Extreme Defaulters with Large Loans)**
- Very high outstanding balances, setup fees, and penalties even when compared to cluster 1(High Risk Defaulters)
- Zero revenue per loan, indicating severe non-payment and no benefit ot the business from this group of clients.
- Highest outstanding principle, suggesting large loan sizes.
- This represents the riskiest segment, possibly requiring legal action or write-offs.

Inferences:

- Clusters 0 and 2 contain manageable borrowers, with Cluster 0 being the most profitable. Cluster 2 is categorized by clients who though risky, show initiative in fulfilling their loan obligations. Measures should be established to incentivize this group (cluster 2) to make more regular and timely payments.
- Clusters 1 and 3 pose high financial risk, with Cluster 3 being the most problematic. Loan agents should focus on mitigating risk in Clusters 1 and 3, possibly through stricter lending criteria or tailored repayment plans.

1.6 RECOMMENDATIONS

1. Generate stricter criteria for borrowing large sums of money over extended periods(as noted in clusters 1 & 3) as this has shown to be problematic once the recovery stage is reached. These common features amonst risky borrowers should be targeted and mitigated to prevent exposure of the business to averse risk.
2. Generate short as well as long term strategies to recover loan book portfolio at risk. Short term strategies can include establishing incentives for early/ timely loan and fees repayments.

1.6.1 NEXT STEP(S)

Develop an early warning loan default detection machine-learning model

- Using time-series as well as sequential modelling to create a system that is able to detect and flag loans likely to go into default in the near future.

1.7 CONCLUSION

The clustering analysis successfully delineated four distinct borrower segments, each exhibiting unique repayment behaviors and risk profiles. Low-risk borrowers demonstrated prompt repayment and stable revenue contributions, while high-risk segments—particularly the extreme defaulters—were characterized by prolonged non-repayment and substantial outstanding balances. The feature importance analysis further highlighted critical predictors of credit risk, underscoring the significance of loan age, days interest calculated, and revenue per loan. These findings not only validate the effectiveness of unsupervised clustering in credit risk assessment but also lay the groundwork for advanced predictive modeling, such as early warning systems for loan defaults. Overall, the project provides actionable insights to optimize loan management practices and mitigate potential financial risks.

1.7.1 Author:

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