BA810_team8

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Colab Link

1 Kenya Loan Default Prediction

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BA810 Supervised Machine Learning (Fall 2025)

Boston University, Questrom School of Business

2 1. Executive Summary

This project focuses on building a machine-learning model to predict whether a borrower will default on a credit-card loan. Using the Zindi credit-risk dataset, we explored the data, engineered features, and trained multiple classification models to understand which approaches performed best. Our evaluation combined standard accuracy metrics with a cost-sensitive framework to reflect the real financial consequences of misclassifying borrowers. Because the cost matrix was based on estimated values, the results highlight both the potential of cost-aware modeling and the need for real-world cost data in future iterations.

The model performs reasonably well in distinguishing high-risk and low-risk borrowers, offering useful guidance for lenders seeking to reduce losses while maintaining fair access to credit. At the same time, the analysis reveals challenges related to data quality, feature interactions, and model generalization, all of which influence overall performance. These findings emphasize the importance of careful data handling, ongoing model tuning, and responsible evaluation when applying machine learning to financial decision-making.

Overall, this project demonstrates how predictive modeling can support lenders, borrowers, and government stakeholders in creating a more stable, fair, and informed credit system. The results serve as a strong foundation for further improvements, including the use of real operational cost data, more advanced feature engineering, and broader evaluation strategies.

3 2. Data Source

##**2.1 Kenya Loan Dataset**

- **License Information**: The dataset used in this study was obtained from the African Credit Scoring Challenge hosted on Zindi. Access to the dataset requires agreement to the platform's official Terms of Use and Competition Rules, which govern data usage, redistribution, and publication. The dataset is not publicly licensed (e.g., not under CC, MIT, or other open-source licenses). Users must comply with all restrictions defined by the competition organizers, and redistribution of the data is strictly prohibited unless explicitly permitted by the original terms.
- **Access Instruction**: To access the dataset, users must accept terms of use on Zindi African Credit Scoring Challenge.

##**2.2 Kenya Monthly Economic Indicators**

- **License Information**: This dataset originates from the Central Bank of Kenya's Monthly Economic Indicators publication. The data is published by CBK and made publicly available on its website. There is no explicit open-data license (e.g., CC BY, MIT) clearly stated on the webpage. Therefore, usage of this data must comply with any usage restrictions or terms set by CBK. Redistribution, reuse, or publication should respect CBK's rights and any stated disclaimers on the website.
- **Access Instruction**: The dataset is publicly accessible and can be downloaded from Central Bank of Kenya

##**2.3 Data Dictionary** Data Size: 66854 rows x 26 columns

Column Name	Data Type	Description
ID	int64	A unique identifier for each entry in the dataset.
customer_id	int64	Unique identifier for each customer in the dataset.

Column Name	Data Type	Description
country_id	object	Identifier or code representing the country where the customer resides or where the loan was issued.
tbl_loan_id	int64	Unique identifier for each loan associated with the customer.
lender_id	int64	Unique identifier for the lender or institution that issued the loan.
loan_type	object	The category or type of loan.
Total_Amount	float64	The total loan amount initially disbursed to the customer.
Total_Amount_to_Repay	float64	The total amount the customer is expected to repay, including principal, interest, and fees.
disbursement_date	datetime64[ns]	The date when the loan amount was disbursed to the customer.
due_date	object	The date by which the loan repayment is due.
duration	int64	The length of the loan term, typically expressed in days.

Column Name	Data Type	Description
New_vs_Repeat	object	Indicates whether the loan is the customer's first loan ("New") or if the customer has taken loans before ("Repeat").
Amount_Funded_By_Lender	float64	The portion of the loan funded directly by the lender.
Lender_portion_Funded	float64	Percentage of the total loan amount funded by the lender.
Lender_portion_to_be_repaid	float64	The portion of the outstanding loan that needs to be repaid to the lender.
target	int64	This variables takes the value 0 or 1. 1 means the customer defaulted on the loan, whereas 0 means, the customer paid the loan.
year	int32	Year of the loan record.
month	int32	Month of the loan record.
overall_inflation	float64	Monthly inflation indicator.
CBR_interest_rates	float64	Central Bank Reference interest rate.
avg_exchange_rates_to_USD	float64	Average monthly exchange rate (KES to USD).
total_assets_of_banking_KSh_B	float64	Total banking sector assets (in billions KSh).

Column Name	Data Type	Description
external_debt_ratio	float64	External debt ratio for the period.
total_domestic_debt	float64	Total domestic debt level.
market_capitalization_KSh_B	float64	Market capitalization (in billions KSh).
bond_volume_KSh_M	float64	Bond market volume (in millions KSh).

4 3. Problem Definition

The primary objective of the project is to develop a model to predict loan defaults, providing insights that would allow stakeholders to make informed decisions about loan approval, management, and regulation. This predictive model would identify high-risk borrowers, enabling financial institutions to better assess risk, set appropriate loan terms, and avoid financial losses.

5 4. Data Cleaning

[ ]:
```
# Load Data
import pandas as pd
loan = pd.read_csv('https://raw.githubusercontent.com/whkung0903/
 ↪kenya-loan-credit-prediction/main/loan_raw.csv')
economics = pd.read_csv('https://raw.githubusercontent.com/whkung0903/
 ↪kenya-loan-credit-prediction/main/Kenya%20Monthly%20Economic%20Indicators.
 ↪csv')

# merge datasets
loan['disbursement_date'] = pd.to_datetime(loan['disbursement_date'],␣
 ↪errors='coerce')
loan['year'] = loan['disbursement_date'].dt.year
loan['month'] = loan['disbursement_date'].dt.month

full = pd.merge(loan, economics, on=['year', 'month'], how='left')
full.head()
```

[ ]:
```
                      ID  customer_id country_id  tbl_loan_id  lender_id  \
0  ID_266671248032267278       266671      Kenya       248032     267278
1  ID_248919228515267278       248919      Kenya       228515     267278
2  ID_308486370501251804       308486      Kenya       370501     251804
3  ID_266004285009267278       266004      Kenya       285009     267278
4  ID_253803305312267278       253803      Kenya       305312     267278
```

```
  loan_type  Total_Amount  Total_Amount_to_Repay disbursement_date  \
0    Type_1        8448.0                 8448.0        2022-08-30
1    Type_1       25895.0                25979.0        2022-07-30
2    Type_7        6900.0                 7142.0        2024-09-06
3    Type_1        8958.0                 9233.0        2022-10-20
4    Type_1        4564.0                 4728.0        2022-11-28

     due_date  …  year month  overall_inflation  CBR_interest_rates  \
0  2022-09-06  …  2022     8               8.53                7.50
1  2022-08-06  …  2022     7               8.32                7.50
2  2024-09-13  …  2024     9               3.56               12.75
3  2022-10-27  …  2022    10               9.59                8.25
4  2022-12-05  …  2022    11               9.48                8.75

   avg_exchange_rates_to_USD  total_assets_of_banking_KSh_B  \
0                     119.45                         6383.8
1                     118.32                         6345.9
2                     129.20                         7568.4
3                     121.03                         6388.6
4                     121.90                         6460.8

   external_debt_ratio  total_domestic_debt  market_capitalization_KSh_B  \
0                49.96               4335.3                      2142.12
1                49.94               4310.7                      2198.26
2                48.10               5601.7                      1676.24
3                49.85               4386.1                      2006.85
4                50.15               4435.9                      1970.63

   bond_volume_KSh_M
0           68356.38
1           61862.67
2          132523.85
3           56684.64
4           53617.16

[5 rows x 26 columns]
```

Load Data with Github Repository

```
[ ]: import pandas as pd

     base = "https://raw.githubusercontent.com/whkung0903/
      ↪kenya-loan-credit-prediction/main/"

     loan_url = base + "loan_raw.csv"
     kenya_url = base + "Kenya%20Monthly%20Economic%20Indicators.csv"
```

```python
full_url = base + "full.csv"

loan = pd.read_csv(loan_url)
economic = pd.read_csv(kenya_url)
full = pd.read_csv(full_url)

print("Loan raw shape:", loan.shape)
print("Kenya indicators shape:", economic.shape)
print("Full merged shape:", full.shape)

loan.head(), economic.head(), full.head()
```

```
Loan raw shape: (68654, 16)
Kenya indicators shape: (36, 10)
Full merged shape: (68615, 26)
```

[ ]:
```
(                      ID  customer_id country_id  tbl_loan_id  lender_id  \
 0  ID_266671248032267278       266671      Kenya       248032     267278
 1  ID_248919228515267278       248919      Kenya       228515     267278
 2  ID_308486370501251804       308486      Kenya       370501     251804
 3  ID_266004285009267278       266004      Kenya       285009     267278
 4  ID_253803305312267278       253803      Kenya       305312     267278

   loan_type  Total_Amount  Total_Amount_to_Repay disbursement_date  \
 0    Type_1        8448.0                 8448.0        2022-08-30
 1    Type_1       25895.0                25979.0        2022-07-30
 2    Type_7        6900.0                 7142.0        2024-09-06
 3    Type_1        8958.0                 9233.0        2022-10-20
 4    Type_1        4564.0                 4728.0        2022-11-28

      due_date  duration New_versus_Repeat  Amount_Funded_By_Lender  \
 0  2022-09-06         7       Repeat Loan                   120.85
 1  2022-08-06         7       Repeat Loan                  7768.50
 2  2024-09-13         7       Repeat Loan                  1380.00
 3  2022-10-27         7       Repeat Loan                  2687.40
 4  2022-12-05         7       Repeat Loan                  1369.20

    Lender_portion_Funded  Lender_portion_to_be_repaid  target
 0               0.014305                        121.0       0
 1               0.300000                       7794.0       0
 2               0.200000                       1428.0       0
 3               0.300000                       2770.0       0
 4               0.300000                       1418.0       0  ,
    year  month  overall_inflation  CBR_interest_rates  \
 0  2022      1               5.39                 7.0
 1  2022      2               5.08                 7.0
 2  2022      3               5.56                 7.0
```

```
3  2022      4              6.47                 7.0
4  2022      5              7.08                 7.5

   avg_exchange_rates_to_USD  total_assets_of_banking_KSh_B  \
0                     113.38                         5978.0
1                     113.66                         6064.9
2                     114.32                         6103.0
3                     115.40                         6207.6
4                     116.28                         6189.5

   external_debt_ratio  total_domestic_debt  market_capitalization_KSh_B  \
0                50.28               4110.1                      2543.44
1                49.86               4181.4                      2495.89
2                50.11               4191.8                      2425.53
3                50.10               4226.8                      2340.77
4                50.15               4268.7                      2006.14

   bond_volume_KSh_M
0           48426.29
1           54884.57
2           87640.42
3           71363.67
4           58877.81  ,
                     ID  customer_id country_id  tbl_loan_id  lender_id  \
0  ID_266671248032267278       266671      Kenya       248032     267278
1  ID_248919228515267278       248919      Kenya       228515     267278
2  ID_308486370501251804       308486      Kenya       370501     251804
3  ID_266004285009267278       266004      Kenya       285009     267278
4  ID_253803305312267278       253803      Kenya       305312     267278

  loan_type  Total_Amount  Total_Amount_to_Repay disbursement_date  \
0    Type_1        8448.0                 8448.0        2022-08-30
1    Type_1       25895.0                25979.0        2022-07-30
2    Type_7        6900.0                 7142.0        2024-09-06
3    Type_1        8958.0                 9233.0        2022-10-20
4    Type_1        4564.0                 4728.0        2022-11-28

     due_date  …  year month  overall_inflation  CBR_interest_rates  \
0  2022-09-06  …  2022     8               8.53                7.50
1  2022-08-06  …  2022     7               8.32                7.50
2  2024-09-13  …  2024     9               3.56               12.75
3  2022-10-27  …  2022    10               9.59                8.25
4  2022-12-05  …  2022    11               9.48                8.75

   avg_exchange_rates_to_USD  total_assets_of_banking_KSh_B  \
0                     119.45                         6383.8
1                     118.32                         6345.9
```

```
2                   129.20                         7568.4
3                   121.03                         6388.6
4                   121.90                         6460.8

   external_debt_ratio  total_domestic_debt  market_capitalization_KSh_B  \
0                49.96               4335.3                      2142.12
1                49.94               4310.7                      2198.26
2                48.10               5601.7                      1676.24
3                49.85               4386.1                      2006.85
4                50.15               4435.9                      1970.63

   bond_volume_KSh_M
0           68356.38
1           61862.67
2          132523.85
3           56684.64
4           53617.16

[5 rows x 26 columns])
```

[ ]:

```
# drop rows with no economic indicators
econ_cols = [
    'overall_inflation',
    'CBR_interest_rates',
    'avg_exchange_rates_to_USD',
    'total_assets_of_banking_KSh_B',
    'external_debt_ratio',
    'total_domestic_debt',
    'market_capitalization_KSh_B',
    'bond_volume_KSh_M'
]

full = full.dropna(subset=econ_cols)
```

5.1 4.1 Explore Data

[ ]:

```
full.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 68615 entries, 0 to 68614
Data columns (total 26 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   ID                            68615 non-null  object
 1   customer_id                   68615 non-null  int64
 2   country_id                    68615 non-null  object
 3   tbl_loan_id                   68615 non-null  int64
```

```
 4   lender_id                    68615 non-null  int64
 5   loan_type                    68615 non-null  object
 6   Total_Amount                 68615 non-null  float64
 7   Total_Amount_to_Repay        68615 non-null  float64
 8   disbursement_date            68615 non-null  object
 9   due_date                     68615 non-null  object
 10  duration                     68615 non-null  int64
 11  New_versus_Repeat            68615 non-null  object
 12  Amount_Funded_By_Lender      68615 non-null  float64
 13  Lender_portion_Funded        68615 non-null  float64
 14  Lender_portion_to_be_repaid  68615 non-null  float64
 15  target                       68615 non-null  int64
 16  year                         68615 non-null  int64
 17  month                        68615 non-null  int64
 18  overall_inflation            68615 non-null  float64
 19  CBR_interest_rates           68615 non-null  float64
 20  avg_exchange_rates_to_USD    68615 non-null  float64
 21  total_assets_of_banking_KSh_B 68615 non-null  float64
 22  external_debt_ratio          68615 non-null  float64
 23  total_domestic_debt          68615 non-null  float64
 24  market_capitalization_KSh_B  68615 non-null  float64
 25  bond_volume_KSh_M            68615 non-null  float64
dtypes: float64(13), int64(7), object(6)
memory usage: 13.6+ MB
```

[ ]:
```
full.head(3)
```

[ ]:
```
                      ID  customer_id country_id  tbl_loan_id  lender_id  \
0  ID_266671248032267278       266671      Kenya       248032     267278
1  ID_248919228515267278       248919      Kenya       228515     267278
2  ID_308486370501251804       308486      Kenya       370501     251804

  loan_type  Total_Amount  Total_Amount_to_Repay disbursement_date  \
0    Type_1        8448.0                 8448.0        2022-08-30
1    Type_1       25895.0                25979.0        2022-07-30
2    Type_7        6900.0                 7142.0        2024-09-06

     due_date  …  year month  overall_inflation  CBR_interest_rates  \
0  2022-09-06  …  2022     8               8.53                7.50
1  2022-08-06  …  2022     7               8.32                7.50
2  2024-09-13  …  2024     9               3.56               12.75

   avg_exchange_rates_to_USD  total_assets_of_banking_KSh_B  \
0                     119.45                         6383.8
1                     118.32                         6345.9
2                     129.20                         7568.4
```

```
   external_debt_ratio  total_domestic_debt  market_capitalization_KSh_B  \
0                49.96               4335.3                      2142.12
1                49.94               4310.7                      2198.26
2                48.10               5601.7                      1676.24

   bond_volume_KSh_M
0           68356.38
1           61862.67
2          132523.85

[3 rows x 26 columns]
```

[ ]:
```
full.describe()
```

[ ]:
```
         customer_id    tbl_loan_id      lender_id  Total_Amount  \
count   68615.000000   68615.000000   68615.000000  6.861500e+04
mean   254424.381520  263144.853720  266432.047293  1.483925e+04
std     26528.301486   39322.347271    3559.145669  1.416901e+05
min       145.000000  109684.000000  245684.000000  2.000000e+00
25%    248952.000000  233978.000000  267278.000000  2.295000e+03
50%    255361.000000  260333.000000  267278.000000  5.249000e+03
75%    262275.000000  286974.500000  267278.000000  1.145500e+04
max    312737.000000  375320.000000  267278.000000  2.300000e+07

       Total_Amount_to_Repay      duration  Amount_Funded_By_Lender  \
count           6.861500e+04  68615.000000             6.861500e+04
mean            1.564231e+04      8.535131             2.541732e+03
std             1.651252e+05     13.339540             1.192473e+04
min             0.000000e+00      1.000000             0.000000e+00
25%             2.327500e+03      7.000000             2.337000e+02
50%             5.320000e+03      7.000000             9.147000e+02
75%             1.165150e+04      7.000000             2.268000e+03
max             2.541500e+07   1096.000000             1.600000e+06

       Lender_portion_Funded  Lender_portion_to_be_repaid        target  \
count           68615.000000                 6.861500e+04  68615.000000
mean                0.218272                 2.648281e+03      0.018028
std                 0.128629                 1.338238e+04      0.133054
min                 0.000000                 0.000000e+00      0.000000
25%                 0.118344                 2.390000e+02      0.000000
50%                 0.300000                 9.330000e+02      0.000000
75%                 0.300000                 2.314000e+03      0.000000
max                 1.168119                 1.821338e+06      1.000000

               year         month  overall_inflation  CBR_interest_rates  \
count  68615.000000  68615.000000       68615.000000        68615.000000
mean    2022.104642      8.781054           8.709491            8.243985
```

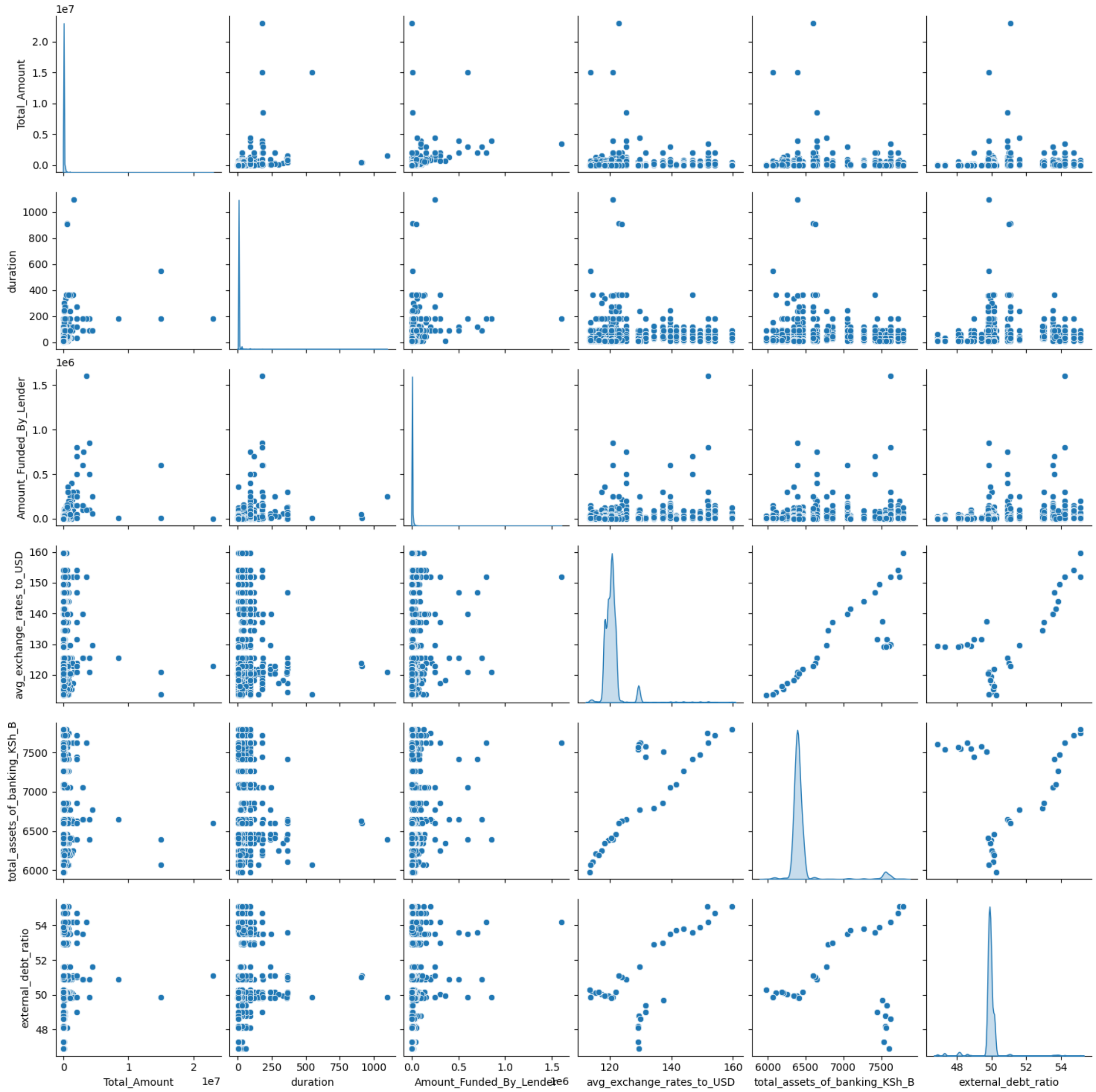
```
std       0.424576      1.630283           1.251418            1.071939
min    2022.000000      1.000000           2.720000            7.000000
25%    2022.000000      8.000000           8.530000            7.500000
50%    2022.000000      9.000000           9.180000            8.250000
75%    2022.000000     10.000000           9.480000            8.250000
max    2024.000000     12.000000           9.590000           13.000000

       avg_exchange_rates_to_USD  total_assets_of_banking_KSh_B  \
count               68615.000000                   68615.000000
mean                  120.889595                    6457.967853
std                     3.968152                     266.951681
min                   113.380000                    5978.000000
25%                   119.450000                    6383.800000
50%                   120.420000                    6388.600000
75%                   121.030000                    6415.100000
max                   159.690000                    7793.600000

       external_debt_ratio  total_domestic_debt  market_capitalization_KSh_B  \
count         68615.000000         68615.000000                 68615.000000
mean             49.915777          4422.293153                  2045.373820
std               0.662378           259.941781                   135.691081
min              46.900000          4110.100000                  1383.610000
25%              49.820000          4335.300000                  2000.820000
50%              49.940000          4366.300000                  2006.850000
75%              49.960000          4386.100000                  2142.120000
max              55.100000          5808.800000                  2543.440000

       bond_volume_KSh_M
count       68615.000000
mean        64580.492090
std         15073.312361
min         36194.350000
25%         56684.640000
50%         61862.670000
75%         66741.950000
max        271247.460000
```

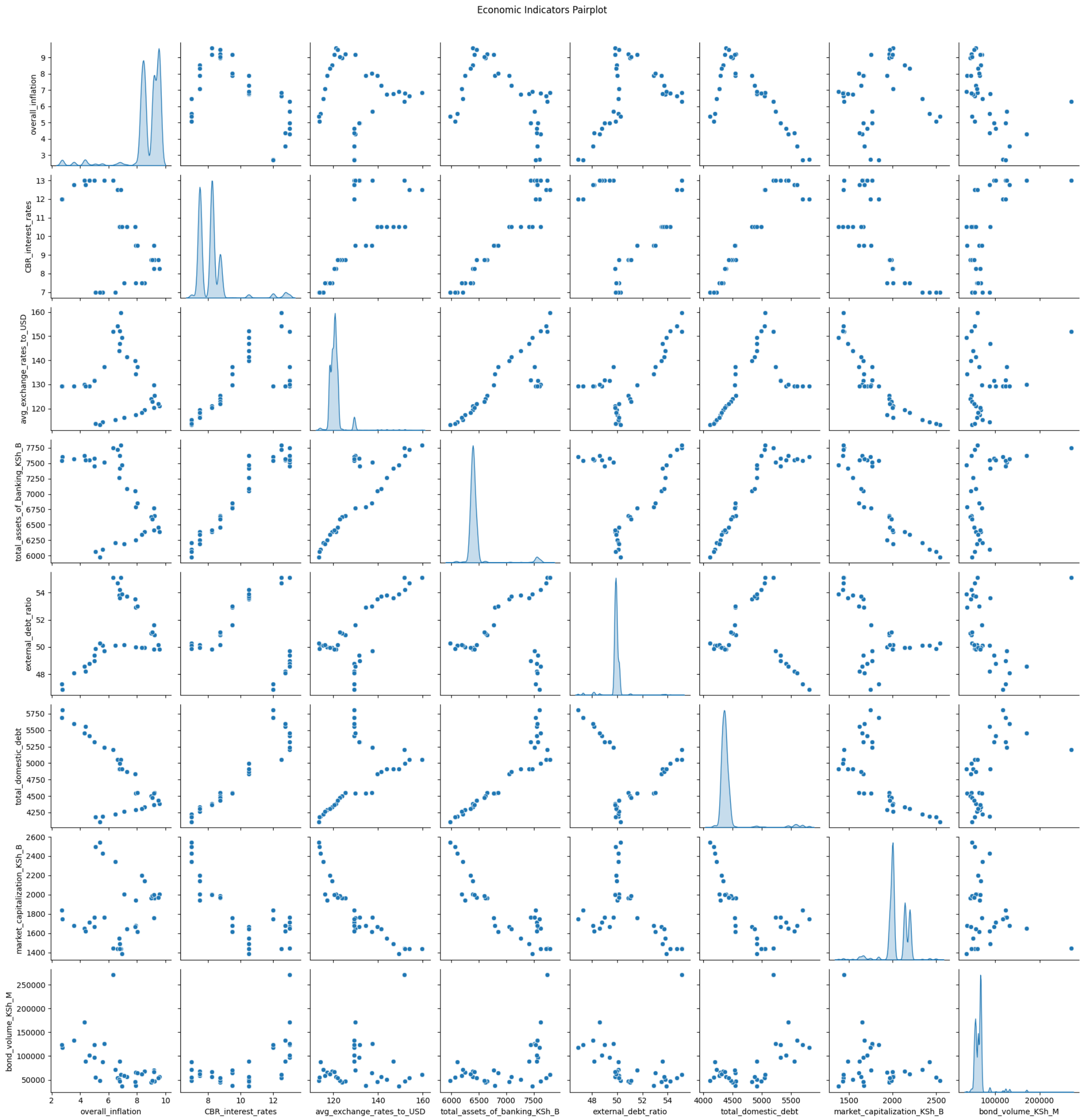
5.2 4.2 Pairplots

[ ]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

loan_cols = [
    'Total_Amount',
    'duration',
    'Amount_Funded_By_Lender',
    'avg_exchange_rates_to_USD',
```

```
    'total_assets_of_banking_KSh_B',
    'external_debt_ratio'
]

g1 = sns.pairplot(full[loan_cols], diag_kind='kde')
g1.fig.suptitle("Loan-related Variables Pairplot", y=1.02)
plt.show()

economic_cols = [
    'overall_inflation',
    'CBR_interest_rates',
    'avg_exchange_rates_to_USD',
    'total_assets_of_banking_KSh_B',
    'external_debt_ratio',
    'total_domestic_debt',
    'market_capitalization_KSh_B',
    'bond_volume_KSh_M'
]

g2 = sns.pairplot(full[economic_cols], diag_kind='kde')
g2.fig.suptitle("Economic Indicators Pairplot", y=1.02)
plt.show()
```

Loan-related Variables Pairplot

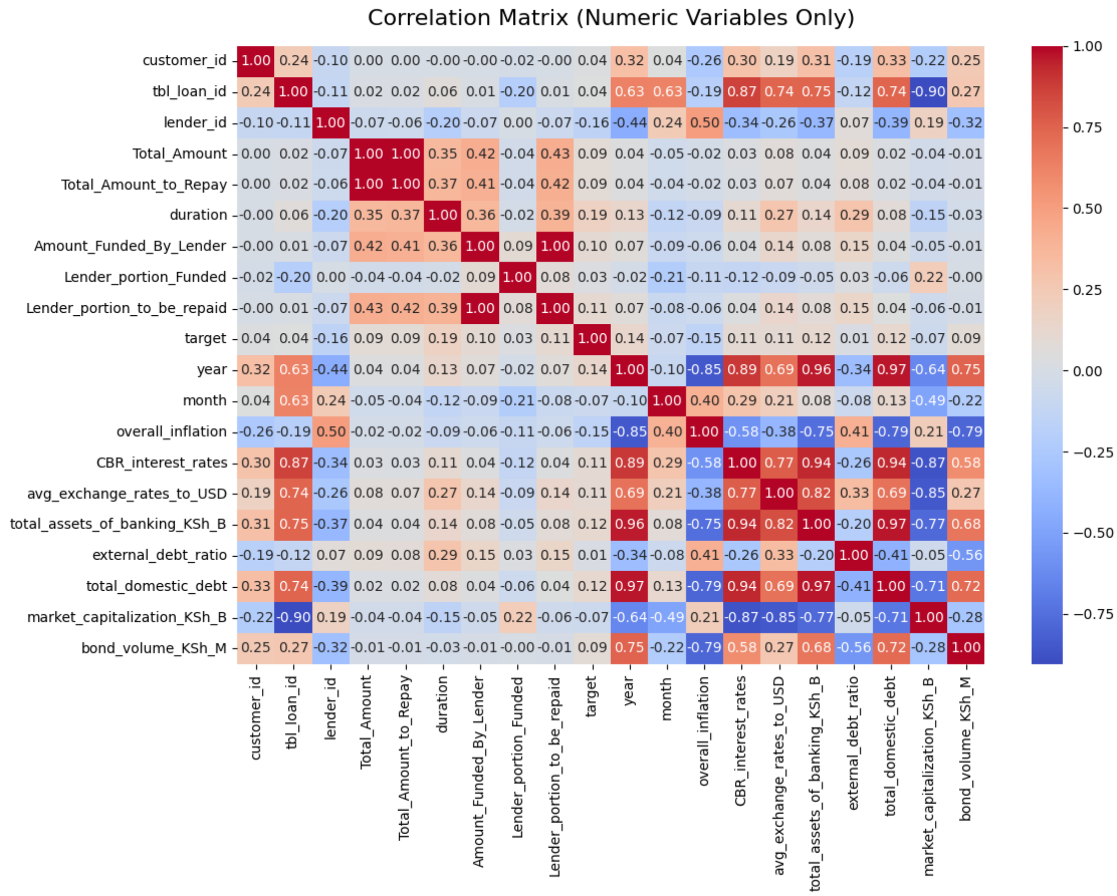




5.3 4.3 Correlation Matrix

[ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

numeric = full.select_dtypes(include=['float64', 'int64', 'int32'])

corr = numeric.corr()

plt.figure(figsize=(12, 8))
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Matrix (Numeric Variables Only)", fontsize=16, pad=15)
```

```
plt.show()
```

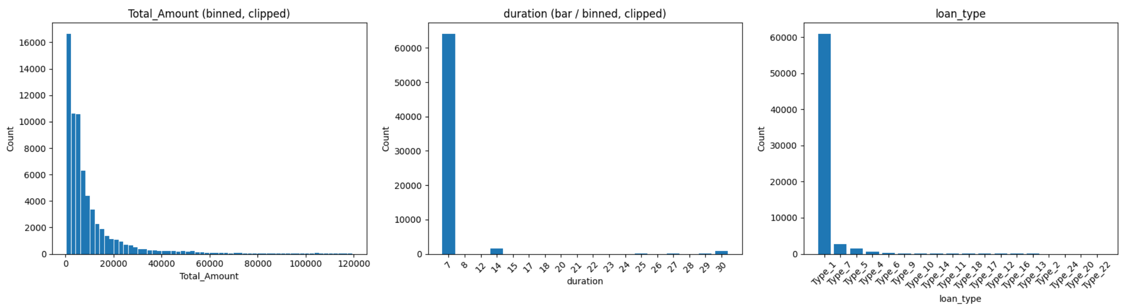


5.4 4.4 Distribution

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

full = pd.read_csv('https://raw.githubusercontent.com/whkung0903/
 ↪kenya-loan-credit-prediction/main/full.csv')

cols = ["Total_Amount", "duration", "loan_type", "target"]
df = full[cols].copy()

# filter extreme values
def clip_by_quantile(data: pd.DataFrame, col: str, low_q=0.01, high_q=0.99):
    x = pd.to_numeric(data[col], errors="coerce")
    lo, hi = x.quantile(low_q), x.quantile(high_q)
    return data[(x >= lo) & (x <= hi)]
```

```python
df_f = df.copy()
for c in ["Total_Amount", "duration"]:
    df_f = clip_by_quantile(df_f, c, low_q=0.01, high_q=0.99)

# plot
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

## Total_Amount
x = pd.to_numeric(df_f["Total_Amount"], errors="coerce").dropna()
if len(x) > 0:
    q75, q25 = np.percentile(x, [75, 25])
    iqr = q75 - q25
    bin_width = 2 * iqr * (len(x) ** (-1/3)) if iqr > 0 else None
    bins = int(np.ceil((x.max() - x.min()) / bin_width)) if bin_width and␣
 ↪bin_width > 0 else 30
    bins = max(10, min(bins, 60))

    counts, edges = np.histogram(x, bins=bins)
    mids = (edges[:-1] + edges[1:]) / 2
    axes[0].bar(mids, counts, width=(edges[1] - edges[0]) * 0.9)
axes[0].set_title("Total_Amount (binned, clipped)")
axes[0].set_xlabel("Total_Amount")
axes[0].set_ylabel("Count")

## duration
d = pd.to_numeric(df_f["duration"], errors="coerce").dropna()
if d.nunique() <= 30 and d.nunique() > 0:
    vc = d.value_counts().sort_index()
    axes[1].bar(vc.index.astype(str), vc.values)
    axes[1].tick_params(axis="x", rotation=45)
else:
    bins = 30
    counts, edges = np.histogram(d, bins=bins)
    mids = (edges[:-1] + edges[1:]) / 2
    axes[1].bar(mids, counts, width=(edges[1] - edges[0]) * 0.9)
axes[1].set_title("duration (bar / binned, clipped)")
axes[1].set_xlabel("duration")
axes[1].set_ylabel("Count")

## loan_type
loan_counts = df_f["loan_type"].astype("string").fillna("NaN").value_counts()
axes[2].bar(loan_counts.index.astype(str), loan_counts.values)
axes[2].set_title("loan_type")
axes[2].set_xlabel("loan_type")
axes[2].set_ylabel("Count")
axes[2].tick_params(axis="x", rotation=45)
```

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

## target (only text)
print("\nTarget counts:")
print(df_f["target"].value_counts(dropna=False).sort_index())
```




```
Target counts:
target
0    65610
1     1031
Name: count, dtype: int64
```

5.5 4.5 Indication

1. Most of economic factors increase / decrease over time. > Use time-based splits (train on earlier periods, test on later periods)
2. Most of economic factors correlate to others. > Prefer regularization (L2 / Elastic Net) for logistic regression
3. The dataset is highly imbalanced. Only 1% of loans are defaulted. > Use Balanced Accuracy, class_weight='balanced'. Tune the decision threshold
4. Almost all loans' durations are 7-day. > Consider dropping duration.

6 5. Preprocessing and Feature Engineering

6.1 5.1 Train-Test Split

[ ]:
```
import pandas as pd
full = pd.read_csv('https://raw.githubusercontent.com/whkung0903/
↪kenya-loan-credit-prediction/main/full.csv')

from sklearn.model_selection import train_test_split
```

```
# datetime
full["disbursement_date"] = pd.to_datetime(full["disbursement_date"],␣
↪errors="coerce")
full = full.dropna(subset=["disbursement_date"]).
↪sort_values("disbursement_date").reset_index(drop=True)

# split over time
X = full.drop("target", axis=1)
y = full["target"]

split_idx = int(len(full) * 0.8)
X_train, X_test = X.iloc[:split_idx], X.iloc[split_idx:]
y_train, y_test = y.iloc[:split_idx], y.iloc[split_idx:]

# check
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[ ]: ((54892, 25), (13723, 25), (54892,), (13723,))

6.2 5.2 Preprocessing

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

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.cluster import KMeans
from sklearn.feature_selection import SelectKBest, f_classif

# Load data from GitHub
loan = pd.read_csv("https://raw.githubusercontent.com/whkung0903/
↪kenya-loan-credit-prediction/main/loan_raw.csv")
economic = pd.read_csv("https://raw.githubusercontent.com/whkung0903/
↪kenya-loan-credit-prediction/main/Kenya%20Monthly%20Economic%20Indicators.
↪csv")
full = pd.read_csv("https://raw.githubusercontent.com/whkung0903/
↪kenya-loan-credit-prediction/main/full.csv",␣
↪parse_dates=["disbursement_date", "due_date"])

# Macroeconomic columns as they appear in full
macro_cols = [
    "overall_inflation",
    "CBR_interest_rates",
    "avg_exchange_rates_to_USD",
```

```
    "total_assets_of_banking_KSh_B",
    "external_debt_ratio",
    "total_domestic_debt",
    "market_capitalization_KSh_B",
    "bond_volume_KSh_M"
]

# sort by time
full = full.dropna(subset=["target", "disbursement_date"]).
 ↪sort_values("disbursement_date").reset_index(drop=True)


# Forward-fill missing macro values
full[macro_cols] = full[macro_cols].ffill()

# Date-based features
full["Year"] = full["disbursement_date"].dt.year
full["Month"] = full["disbursement_date"].dt.month
full["DayOfWeek"] = full["disbursement_date"].dt.dayofweek
full["Loan_Age"] = (full["due_date"] - full["disbursement_date"]).dt.days

full["log_Total_Amount"] = np.log1p(full["Total_Amount"])
full["log_Amount_Funded"] = np.log1p(full["Amount_Funded_By_Lender"])
full["log_Total_Repay"] = np.log1p(full["Total_Amount_to_Repay"])

# split
y = full["target"]
categorical_cols = ["loan_type", "New_versus_Repeat", "country_id"]

numeric_cols = [ # drop duration
    "Total_Amount",
    "Total_Amount_to_Repay",
    "Amount_Funded_By_Lender",
    "Lender_portion_Funded",
    "Lender_portion_to_be_repaid",
    "Year",
    "Month",
    "DayOfWeek",
    "Loan_Age",
    "log_Total_Amount",
    "log_Amount_Funded",
    "log_Total_Repay"
] + macro_cols

X_base = full[categorical_cols + numeric_cols].copy()

X_train, X_test, y_train, y_test = train_test_split(
```

```
    X_base, y, test_size=0.2, shuffle=False
)

# fit clustering
cluster_cols = ["Total_Amount", "Amount_Funded_By_Lender"] + macro_cols
scaler_cluster = StandardScaler()
Xc_train = scaler_cluster.fit_transform(X_train[cluster_cols])
Xc_test  = scaler_cluster.transform(X_test[cluster_cols])

kmeans = KMeans(n_clusters=4, random_state=42, n_init="auto")
X_train["cluster_group"] = kmeans.fit_predict(Xc_train).astype(str)
X_test["cluster_group"]  = kmeans.predict(Xc_test).astype(str)

# update columns
categorical_cols = categorical_cols + ["cluster_group"]

# Preprocessing: one-hot encode categorical variables, scale numeric variables
preprocessor = ColumnTransformer(
    transformers=[
        ("cat", OneHotEncoder(handle_unknown="ignore"), categorical_cols),
        ("num", StandardScaler(), numeric_cols),
    ]
)
```

6.3 5.3 Feature Engineering

[ ]:
```
X_train_processed = preprocessor.fit_transform(X_train)

# Feature selector (to be used in pipelines)
selector = SelectKBest(score_func=f_classif, k=20)
selector.fit(X_train_processed, y_train)
```

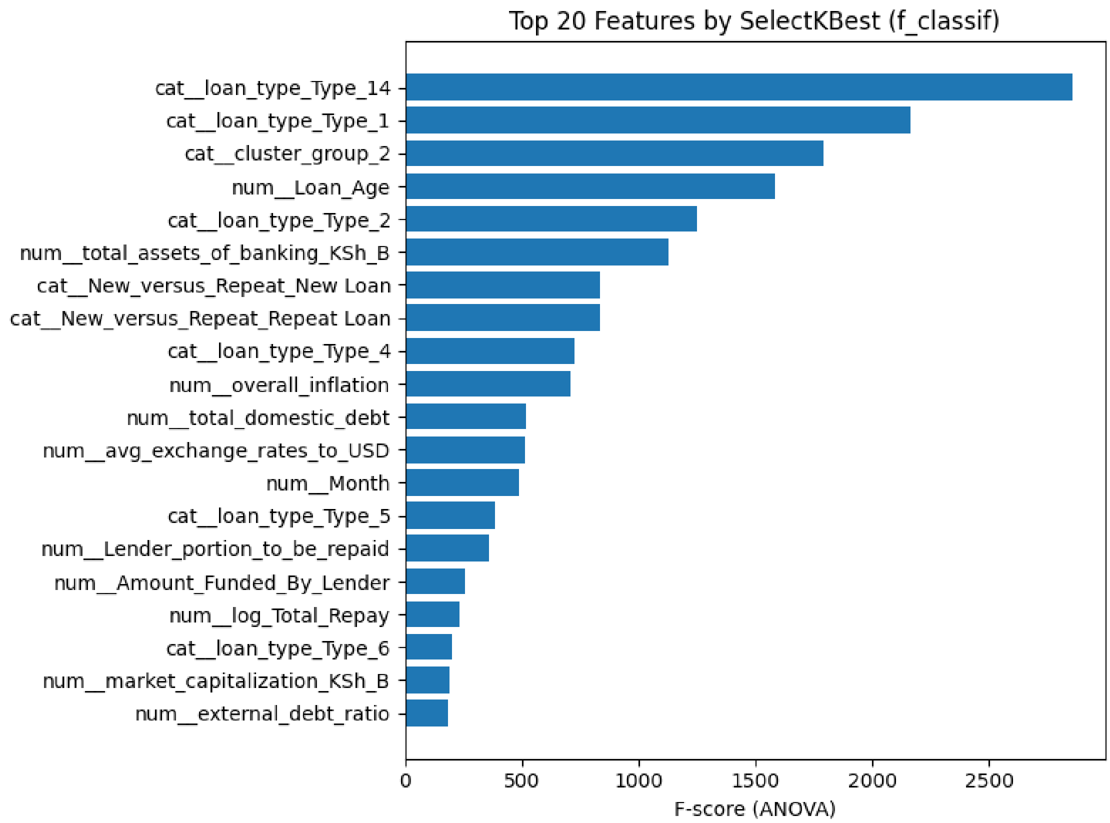
```
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:111: UserWarning:
Features [17 27] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx,
UserWarning)
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:112: RuntimeWarning:
invalid value encountered in divide
  f = msb / msw
```

[ ]:
```
SelectKBest(k=20)
```

[ ]:
```
feature_names = preprocessor.get_feature_names_out()
len(feature_names), X_train_processed.shape[1]
```

[ ]: (42, 42)

[ ]:
```python
import matplotlib.pyplot as plt

fs_df = pd.DataFrame({
    "feature": feature_names,
    "score": selector.scores_,
    "pvalue": selector.pvalues_,
})

# sort by score
fs_df_sorted = fs_df.sort_values("score", ascending=False)

# bar chart
top_k = 20
top_features = fs_df_sorted.head(top_k)

plt.figure(figsize=(8, 6))
plt.barh(top_features["feature"], top_features["score"])
plt.gca().invert_yaxis()
plt.xlabel("F-score (ANOVA)")
plt.title(f"Top {top_k} Features by SelectKBest (f_classif)")
plt.tight_layout()
plt.show()
```



Interpretation

Why those features impact more?

1. Loan Type > Products with different target audience, interest rates, rule, etc. have various risks. For example, Type_4 looks like short-term, high risk and smaller amount, while Type_1 seems like prominent product.
2. cluster_group > One of the groups could be small amount + high interest rates + high inflation, and another could be large amount + stable exchange rate + low inflation. If some clusters show higher ratio of default, it gains higher f_classif.
3. Time related features (Month, Loan_Age) > Default rate could be related to prosperity, policies, central bank interest rate, and inflation.
4. Amount related features > When amount increases, the paying pressure and risk rises accordingly.
5. Macroeconomic Indicators > Default risk may rise because borrowers' pressure to repay increase due to inflation. Bank system indicators reflect overall funding environment and uncertainty.

6.4 5.4 Pipeline

[ ]:
```
from sklearn import set_config
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression

set_config(display="diagram")

clf = LogisticRegression(max_iter=1000)

loan_pipeline = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("selector", selector),
    ("classifier", clf),
])

loan_pipeline
```

[ ]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('cat',
OneHotEncoder(handle_unknown='ignore'),
                                                  ['loan_type',
                                                   'New_versus_Repeat',
                                                   'country_id',
                                                   'cluster_group']),
                                                 ('num', StandardScaler(),
                                                  ['Total_Amount',
                                                   'Total_Amount_to_Repay',
                                                   'Amount_Funded_By_Lender',
                                                   'Lender_portion_Funded',
'Lender_portion_to_be_repaid',
                                                   'Year', 'Month', 'DayOfWeek',
                                                   'Loan_Age',
                                                   'log_Total_Amount',
                                                   'log_Amount_Funded',
                                                   'log_Total_Repay',
                                                   'overall_inflation',
                                                   'CBR_interest_rates',
                                                   'avg_exchange_rates_to_USD',
'total_assets_of_banking_KSh_B',
                                                   'external_debt_ratio',
                                                   'total_domestic_debt',
'market_capitalization_KSh_B',
                                                   'bond_volume_KSh_M'])])),
                ('selector', SelectKBest(k=20)),
                ('classifier', LogisticRegression(max_iter=1000))])
```

7 6. Model Training and Evaluation

```
[ ]: import pandas as pd
     import numpy as np
     from sklearn.metrics import accuracy_score, balanced_accuracy_score, f1_score,␣
      ↪precision_score, recall_score, confusion_matrix, ConfusionMatrixDisplay
     from sklearn.metrics import accuracy_score, roc_auc_score, classification_report

     def print_scores(y_test, y_pred): #This code is from lecture 12. where we have␣
      ↪highly inbalanced datasets
       plt.rc("font", size=10)
       fig, ax = plt.subplots(figsize=(2.5, 2.5))
       cmd = ConfusionMatrixDisplay.from_predictions(y_test, y_pred, cmap=plt.cm.
      ↪Blues, colorbar=False, ax=ax)
       plt.tight_layout()
       plt.show()
       accuracy = accuracy_score(y_test, y_pred)
       balanced_accuracy = balanced_accuracy_score(y_test, y_pred)
       print(f'Accuracy={accuracy:.4f}, Balanced Accuracy={balanced_accuracy:.4f}')
       precision = precision_score(y_test, y_pred, pos_label= 1)
       recall = recall_score(y_test, y_pred, pos_label= 1)
       f1 = f1_score(y_test, y_pred, pos_label= 1)
       print(f'Precision={precision:.4f}, Recall={recall:.4f}, F1-score={f1:.4f}')

     results = []

     def collect_results(model_name, y_test, y_pred, y_prob=None):
         row = {
             "model": model_name,
             "accuracy": accuracy_score(y_test, y_pred),
             "balanced_accuracy": balanced_accuracy_score(y_test, y_pred),
             "precision": precision_score(y_test, y_pred, pos_label=1),
             "recall": recall_score(y_test, y_pred, pos_label=1),
             "f1": f1_score(y_test, y_pred, pos_label=1),
             "auc": roc_auc_score(y_test, y_prob) if y_prob is not None else np.nan
         }
         results.append(row)
```

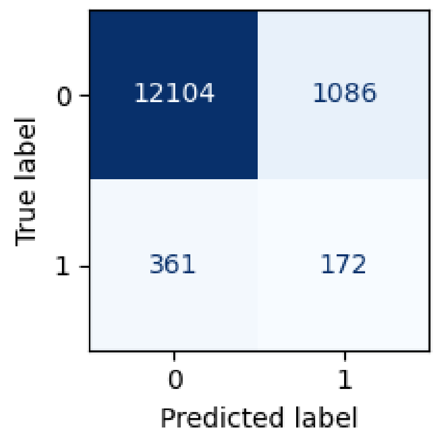
7.1 6.1 Logistic Regression

```
[ ]: from sklearn.pipeline import Pipeline
     from sklearn.linear_model import LogisticRegression
     from sklearn.metrics import accuracy_score, roc_auc_score, classification_report

     log_reg_pipeline = Pipeline(steps=[
         ("preprocess", preprocessor),
```

```python
    ("select", selector),
    ("clf", LogisticRegression(max_iter=1000, solver="liblinear"))
])

log_reg_pipeline.fit(X_train, y_train)
y_pred = log_reg_pipeline.predict(X_test)
y_prob = log_reg_pipeline.predict_proba(X_test)[:, 1]

print("Test Accuracy:", accuracy_score(y_test, y_pred))
print("Test AUC:", roc_auc_score(y_test, y_prob))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

print_scores(y_test,y_pred)

collect_results("Logistic Regression", y_test, y_pred, y_prob)
```

```
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:111: UserWarning:
Features [17 27] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx,
UserWarning)
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:112: RuntimeWarning:
invalid value encountered in divide
  f = msb / msw
```

```
Test Accuracy: 0.8945565838373534
Test AUC: 0.5253898498919671

Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.92      0.94     13190
           1       0.14      0.32      0.19       533

    accuracy                           0.89     13723
   macro avg       0.55      0.62      0.57     13723
weighted avg       0.94      0.89      0.91     13723
```



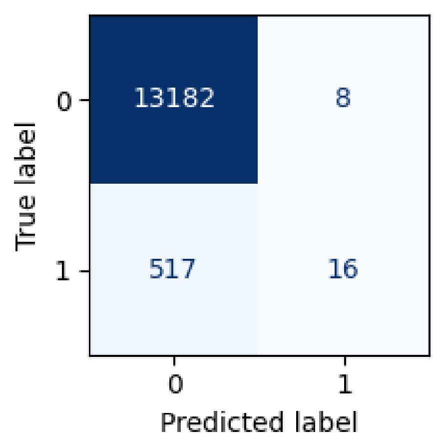

```
Accuracy=0.8946, Balanced Accuracy=0.6202
Precision=0.1367, Recall=0.3227, F1-score=0.1921
```

7.2 6.2 KNeighborsClassifier

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier

knn_pipe = Pipeline(steps=[
    ("preprocess", preprocessor),
    ("select", selector),
    ("clf", KNeighborsClassifier(n_neighbors=15,n_jobs= -1))
])

knn_pipe.fit(X_train, y_train)
y_pred = knn_pipe.predict(X_test)
y_prob = knn_pipe.predict_proba(X_test)[:, 1]

print("Test Accuracy:", accuracy_score(y_test, y_pred))
print("Test AUC:", roc_auc_score(y_test, y_prob))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

print_scores(y_test,y_pred) #Even though overall accuracy is high, prediction␣
 ↪is still bad since it predicts "No" for most of the time.
collect_results("KNeighborsClassifier", y_test, y_pred, y_prob)
```

```
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:111: UserWarning:
Features [17 27] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx,
UserWarning)
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:112: RuntimeWarning:
```

```
invalid value encountered in divide
  f = msb / msw

Test Accuracy: 0.961743059097865
Test AUC: 0.6225341985442949

Classification Report:
               precision    recall  f1-score   support

           0       0.96      1.00      0.98     13190
           1       0.67      0.03      0.06       533

    accuracy                           0.96     13723
   macro avg       0.81      0.51      0.52     13723
weighted avg       0.95      0.96      0.94     13723
```



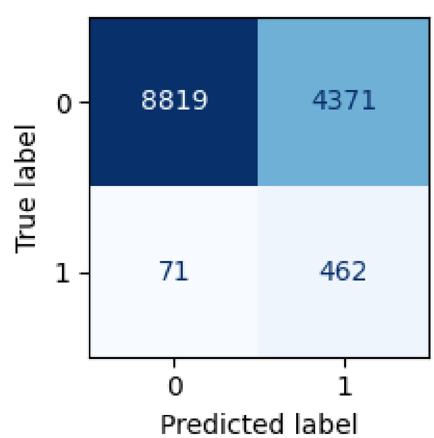

```
Accuracy=0.9617, Balanced Accuracy=0.5147
Precision=0.6667, Recall=0.0300, F1-score=0.0575
```

7.3 6.3 GaussianNB

[ ]:
```
from sklearn.naive_bayes import GaussianNB
gaussian_pipe = Pipeline(steps=[
    ("preprocess", preprocessor),
    ("select", selector),
    ("clf", GaussianNB())
])

gaussian_pipe.fit(X_train,y_train)
y_pred = gaussian_pipe.predict(X_test)
y_prob = gaussian_pipe.predict_proba(X_test)[:, 1]
```

```python
print("Test Accuracy:", accuracy_score(y_test, y_pred))
print("Test AUC:", roc_auc_score(y_test, y_prob))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

print_scores(y_test,y_pred)
collect_results("GaussianNB", y_test, y_pred, y_prob)
```

```
Test Accuracy: 0.6763098447861254
Test AUC: 0.768817698324531

Classification Report:
               precision    recall  f1-score   support

           0       0.99      0.67      0.80     13190
           1       0.10      0.87      0.17       533

    accuracy                           0.68     13723
   macro avg       0.54      0.77      0.49     13723
weighted avg       0.96      0.68      0.77     13723


/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:111: UserWarning:
Features [17 27] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx,
UserWarning)
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:112: RuntimeWarning:
invalid value encountered in divide
  f = msb / msw
```

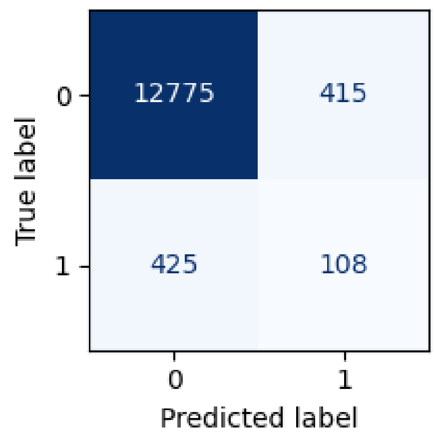


```
Accuracy=0.6763, Balanced Accuracy=0.7677
Precision=0.0956, Recall=0.8668, F1-score=0.1722
```

7.4 6.4 DecisionTreeClassifier

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

dt_pipe = Pipeline(steps=[
    ("preprocess", preprocessor),
    ("clf", DecisionTreeClassifier(
        random_state=42,
        max_depth=None,
        min_samples_split=2,
        min_samples_leaf=1
    ))
])

dt_pipe.fit(X_train, y_train)

y_pred = dt_pipe.predict(X_test)
y_prob = dt_pipe.predict_proba(X_test)[:, 1]

print("Test Accuracy:", accuracy_score(y_test, y_pred))
print("Test AUC:", roc_auc_score(y_test, y_prob))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

print_scores(y_test, y_pred)
collect_results("Decision Tree Classifier", y_test, y_pred, y_prob)
```

```
Test Accuracy: 0.9387888945565839
Test AUC: 0.5855817059657737

Classification Report:
               precision    recall  f1-score   support

           0       0.97      0.97      0.97     13190
           1       0.21      0.20      0.20       533

    accuracy                           0.94     13723
   macro avg       0.59      0.59      0.59     13723
weighted avg       0.94      0.94      0.94     13723
```

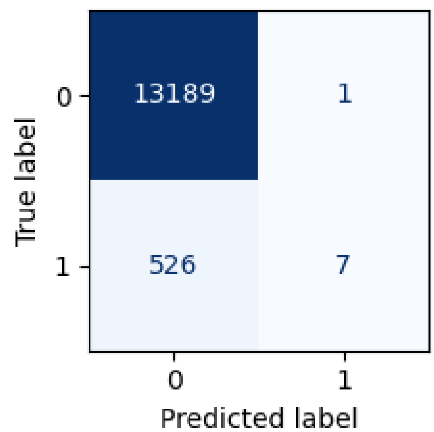



```
Accuracy=0.9388, Balanced Accuracy=0.5856
Precision=0.2065, Recall=0.2026, F1-score=0.2045
```

7.5 6.5 RandomForestClassifier

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

rf_pipe = Pipeline(steps=[
    ("preprocess", preprocessor),
    ("clf", RandomForestClassifier(
        n_estimators=200,
        max_depth=None,
        min_samples_split=2,
        min_samples_leaf=1,
        class_weight="balanced",
        random_state=42,
        n_jobs=-1
    ))
])

rf_pipe.fit(X_train, y_train)

y_pred = rf_pipe.predict(X_test)
y_prob = rf_pipe.predict_proba(X_test)[:, 1]

print("Random Forest - Test Accuracy:", accuracy_score(y_test, y_pred))
print("Random Forest - Test AUC:", roc_auc_score(y_test, y_prob))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

print_scores(y_test, y_pred)
collect_results("Random Forest Classifier", y_test, y_pred, y_prob)
```

```
Random Forest - Test Accuracy: 0.9615973183706187
Random Forest - Test AUC: 0.8688003447947235

Classification Report:
              precision    recall  f1-score   support

           0       0.96      1.00      0.98     13190
           1       0.88      0.01      0.03       533

    accuracy                           0.96     13723
   macro avg       0.92      0.51      0.50     13723
weighted avg       0.96      0.96      0.94     13723
```



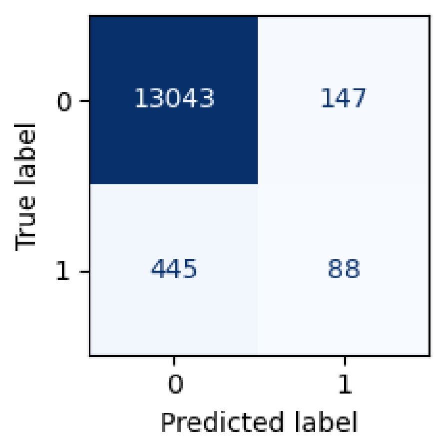

```
Accuracy=0.9616, Balanced Accuracy=0.5065
Precision=0.8750, Recall=0.0131, F1-score=0.0259
```

7.6 6.6 BaggingClassifier

[ ]:
```python
from sklearn.ensemble import BaggingClassifier

bagging_pipe = Pipeline(steps=[
    ("preprocess", preprocessor),
    ("clf", BaggingClassifier(
        estimator=DecisionTreeClassifier(random_state=42),
        n_estimators=100,
        max_samples=0.8,
        max_features=1.0,
        bootstrap=True,
        random_state=42,
        n_jobs=-1
    ))
```

```
])

bagging_pipe.fit(X_train, y_train)

y_pred = bagging_pipe.predict(X_test)
y_prob = bagging_pipe.predict_proba(X_test)[:, 1]

print("Bagging - Test Accuracy:", accuracy_score(y_test, y_pred))
print("Bagging - Test AUC:", roc_auc_score(y_test, y_prob))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

print_scores(y_test, y_pred)
collect_results("Bagging Classifier", y_test, y_pred, y_prob)
```

```
Bagging - Test Accuracy: 0.9568607447351162
Bagging - Test AUC: 0.878195858765026

Classification Report:
               precision    recall  f1-score   support

           0       0.97      0.99      0.98     13190
           1       0.37      0.17      0.23       533

    accuracy                           0.96     13723
   macro avg       0.67      0.58      0.60     13723
weighted avg       0.94      0.96      0.95     13723
```



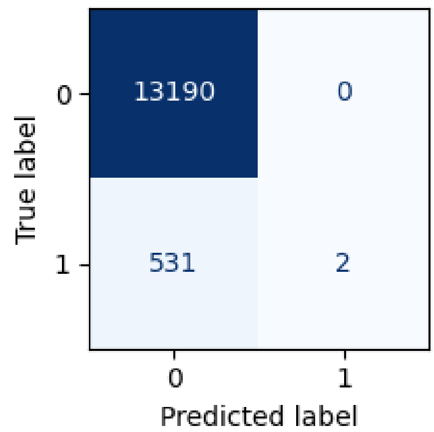

```
Accuracy=0.9569, Balanced Accuracy=0.5770
Precision=0.3745, Recall=0.1651, F1-score=0.2292
```

7.7 6.7 Linear SVM

[ ]:
```python
from sklearn.svm import LinearSVC
from sklearn.calibration import CalibratedClassifierCV

svm_linear = Pipeline(steps=[
    ("preprocess", preprocessor),
    ("select", selector),
    ("clf", CalibratedClassifierCV(
        estimator=LinearSVC(class_weight="balanced", random_state=42),
        cv=3
    ))
])

svm_linear.fit(X_train, y_train)

y_pred = svm_linear.predict(X_test)
y_prob = svm_linear.predict_proba(X_test)[:, 1]

print("Linear SVM - Test Accuracy:", accuracy_score(y_test, y_pred))
print("Linear SVM - Test AUC:", roc_auc_score(y_test, y_prob))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

print_scores(y_test, y_pred)
collect_results("Linear SVM", y_test, y_pred, y_prob)
```

```
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:111: UserWarning:
Features [17 27] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx,
UserWarning)
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:112: RuntimeWarning:
invalid value encountered in divide
  f = msb / msw
```

```
Linear SVM - Test Accuracy: 0.9613058369161263
Linear SVM - Test AUC: 0.7897477621769862

Classification Report:
               precision    recall  f1-score   support

           0       0.96      1.00      0.98     13190
           1       1.00      0.00      0.01       533

    accuracy                           0.96     13723
   macro avg       0.98      0.50      0.49     13723
weighted avg       0.96      0.96      0.94     13723
```



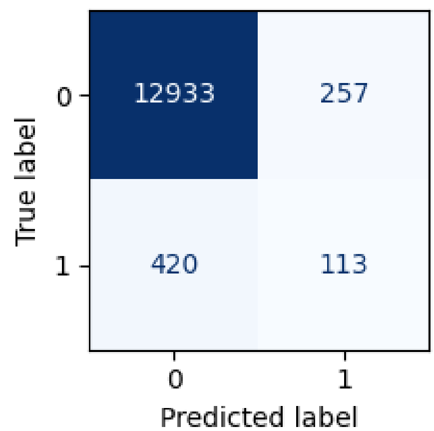

```
Accuracy=0.9613, Balanced Accuracy=0.5019
Precision=1.0000, Recall=0.0038, F1-score=0.0075
```

7.8 6.8 GradientBoosting

```
[ ]: from sklearn.ensemble import GradientBoostingClassifier

gb_pipe = Pipeline(steps=[
    ("preprocess", preprocessor),
    ("clf", GradientBoostingClassifier(
        n_estimators=200,
        learning_rate=0.05,
        max_depth=3,
        min_samples_split=2,
        min_samples_leaf=1,
        subsample=1.0,
        random_state=42
    ))
])

gb_pipe.fit(X_train, y_train)

y_pred = gb_pipe.predict(X_test)
y_prob = gb_pipe.predict_proba(X_test)[:, 1]

print("Gradient Boosting - Test Accuracy:", accuracy_score(y_test, y_pred))
print("Gradient Boosting - Test AUC:", roc_auc_score(y_test, y_prob))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

print_scores(y_test, y_pred)
```

```
collect_results("GradientBoosting", y_test, y_pred, y_prob)
```

```
Gradient Boosting - Test Accuracy: 0.9506667638271515
Gradient Boosting - Test AUC: 0.8814320787110594

Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.98      0.97     13190
           1       0.31      0.21      0.25       533

    accuracy                           0.95     13723
   macro avg       0.64      0.60      0.61     13723
weighted avg       0.94      0.95      0.95     13723
```




```
Accuracy=0.9507, Balanced Accuracy=0.5963
Precision=0.3054, Recall=0.2120, F1-score=0.2503
```

7.9 6.9 Model Comparison

[ ]:
```
results_df = pd.DataFrame(results)

# sort by balanced_accuracy
results_df = results_df.sort_values(by="balanced_accuracy", ascending=False)

results_df
results_df.style.format({
    "accuracy": "{:.4f}",
    "balanced_accuracy": "{:.4f}",
    "precision": "{:.4f}",
```

```
    "recall": "{:.4f}",
    "f1": "{:.4f}",
    "auc": "{:.4f}",
})
```

[ ]: <pandas.io.formats.style.Styler at 0x7f9dc63f8bf0>

Selected Models for Stacking: > GaussianNB, Logistic Regression, GradientBoosting

Reason 1: Higher balanced_accuracy * The 3 models show the highest balanced_accuracy, indicating higher recall for both categories.

Reason 2: Higher recall * The 3 models show the highest recall as well, indicating they deal with True Positive well. KNN, RF, and SVM show extremely low recall, so we don't take them into consideration.

Reason 3: With close recall, GradientBoosting has higher AUC than Decision Tree

Reason 4: With close AUC, GradientBoosting has higher recall than Bagging

How they work together * NB boosts recall * GB boosts discriminative power * LR adds stability/calibration.

8 7. Hyperparameter Tuning and Stacking

We chose **Random Search** because Grid Search was too slow and computationally expensive for our large dataset. Random Search let us explore the parameter space much more efficiently while still finding strong configurations within a reasonable runtime.

8.1 7.1 GaussianNB

[ ]:
```
from sklearn.model_selection import RandomizedSearchCV, TimeSeriesSplit
from scipy.stats import uniform
from sklearn.naive_bayes import GaussianNB
from sklearn.pipeline import Pipeline

tscv = TimeSeriesSplit(n_splits=3)

param_distribs_gnb = [
    {
        "clf__var_smoothing": uniform(1e-12, 1e-8)
    }
]

gnb_random_search = RandomizedSearchCV(
    estimator=gaussian_pipe,
    param_distributions=param_distribs_gnb,
    n_iter=10,
    cv=tscv,
    scoring="balanced_accuracy",
```

```
    random_state=42,
    n_jobs=-1,
    verbose=1,
    refit=True,
)

gnb_random_search.fit(X_train, y_train)

best_gnb = gnb_random_search.best_estimator_
gnb_random_search.best_params_, gnb_random_search.best_score_

cv_df = pd.DataFrame(gnb_random_search.cv_results_)
cols = [c for c in cv_df.columns if c.startswith("param_")] + [
    "mean_test_score",
    "std_test_score",
    "rank_test_score",
]
cv_df = cv_df[cols].sort_values("mean_test_score", ascending=False)
cv_df.head(10)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

```
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:111: UserWarning:
Features [17 27] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx,
UserWarning)
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:112: RuntimeWarning:
invalid value encountered in divide
  f = msb / msw
```

[ ]:

	param_clf__var_smoothing	mean_test_score	std_test_score	rank_test_score
0	3.746401e-09	0.567031	0.032064	1
1	9.508143e-09	0.567031	0.032064	1
2	7.320939e-09	0.567031	0.032064	1
3	5.987585e-09	0.567031	0.032064	1
4	1.561186e-09	0.567031	0.032064	1
5	1.560945e-09	0.567031	0.032064	1
6	5.818361e-10	0.567031	0.032064	1
7	8.662761e-09	0.567031	0.032064	1
8	6.012150e-09	0.567031	0.032064	1
9	7.081726e-09	0.567031	0.032064	1

8.2 7.2 Logistic Regression

[ ]:
```
from sklearn.model_selection import RandomizedSearchCV, TimeSeriesSplit
from scipy.stats import loguniform

tscv = TimeSeriesSplit(n_splits=3)

param_distribs_logreg = [
    {
        "clf__C": loguniform(0.0001, 10000),
        "clf__penalty": ["l1", "l2"],
        "clf__class_weight": [None, "balanced"]
    }
]

logreg_random_search = RandomizedSearchCV(
    estimator=log_reg_pipeline,
    param_distributions=param_distribs_logreg,
    n_iter=10,
    cv=tscv,
    scoring="balanced_accuracy",
    random_state=42,
    n_jobs=-1,
    verbose=1,
    refit=True,
)

logreg_random_search.fit(X_train, y_train)

best_logreg = logreg_random_search.best_estimator_
logreg_random_search.best_params_, logreg_random_search.best_score_

cv_df = pd.DataFrame(logreg_random_search.cv_results_)
cols = [c for c in cv_df.columns if c.startswith("param_")] + [
    "mean_test_score",
    "std_test_score",
    "rank_test_score",
]
cv_df = cv_df[cols].sort_values("mean_test_score", ascending=False)
cv_df.head(10)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

```
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:111: UserWarning:
Features [17 27] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx,
UserWarning)
```

```
/usr/local/lib/python3.12/dist-
packages/sklearn/feature_selection/_univariate_selection.py:112: RuntimeWarning:
invalid value encountered in divide
  f = msb / msw
```

[ ]:

```
    param_clf__C param_clf__class_weight param_clf__penalty  mean_test_score  \
6    456.605487                balanced                 l2         0.704092
8      0.027161                balanced                 l1         0.690570
4      6.440508                balanced                 l1         0.680720
1     71.771419                    None                 l1         0.588265
9      0.285470                    None                 l1         0.568060
5      0.000146                balanced                 l2         0.547303
3      0.000292                balanced                 l1         0.541622
0      0.099156                    None                 l1         0.535087
7      0.002848                    None                 l1         0.503869
2      0.001771                    None                 l1         0.501265

   std_test_score  rank_test_score
6        0.156006                1
8        0.107065                2
4        0.140892                3
1        0.059327                4
9        0.059129                5
5        0.025091                6
3        0.024446                7
0        0.038995                8
7        0.005472                9
2        0.001789               10
```

8.3 7.3 GradientBoosting

[ ]:

```python
from sklearn.model_selection import RandomizedSearchCV, TimeSeriesSplit
from scipy.stats import randint, uniform
from sklearn.pipeline import Pipeline
from sklearn.ensemble import GradientBoostingClassifier

tscv = TimeSeriesSplit(n_splits=3)

param_distribs_gb = [
    {
        "clf__n_estimators": randint(100, 600),
        "clf__learning_rate": uniform(0.01, 0.19),
        "clf__max_depth": randint(2, 6),
        "clf__subsample": uniform(0.6, 0.4),
        "clf__min_samples_split": randint(2, 50),
        "clf__min_samples_leaf": randint(1, 30),
        "clf__max_features": [None, "sqrt", "log2"],
```

```
    }
]

gb_random_search = RandomizedSearchCV(
    estimator=gb_pipe,
    param_distributions=param_distribs_gb,
    n_iter=10,
    cv=tscv,
    scoring="balanced_accuracy",
    random_state=42,
    n_jobs=-1,
    verbose=1,
    refit=True,
)

gb_random_search.fit(X_train, y_train)

best_gb = gb_random_search.best_estimator_
gb_random_search.best_params_, gb_random_search.best_score_

cv_df = pd.DataFrame(gb_random_search.cv_results_)
cols = [c for c in cv_df.columns if c.startswith("param_")] + [
    "mean_test_score",
    "std_test_score",
    "rank_test_score",
]
cv_df = cv_df[cols].sort_values("mean_test_score", ascending=False)
cv_df.head(10)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

[ ]:

```
   param_clf__learning_rate  param_clf__max_depth param_clf__max_features  \
2                  0.144534                     3                    None
7                  0.190288                     5                    sqrt
8                  0.140004                     4                    log2
1                  0.094708                     4                    log2
9                  0.084302                     3                    sqrt
4                  0.092070                     2                    log2
6                  0.098685                     2                    log2
3                  0.010148                     5                    None
0                  0.081163                     2                    log2
5                  0.054227                     3                    log2

   param_clf__min_samples_leaf  param_clf__min_samples_split  \
2                            2                            25
7                           18                            10
8                           12                             9
```

```
1                            11                          25
9                             6                          43
4                            27                          43
6                             7                          22
3                             1                          13
0                            11                           9
5                            19                          45

   param_clf__n_estimators  param_clf__subsample  mean_test_score  \
2                      591              0.975421         0.825020
7                      445              0.639069         0.736912
8                      530              0.669346         0.714516
1                      472              0.840446         0.711078
9                      359              0.673942         0.585879
4                      575              0.989502         0.561849
6                      428              0.626021         0.550948
3                      413              0.809903         0.537330
0                      288              0.838740         0.536565
5                      154              0.993292         0.524979

   std_test_score  rank_test_score
2        0.025315                1
7        0.017995                2
8        0.056540                3
1        0.036456                4
9        0.047717                5
4        0.045812                6
6        0.035536                7
3        0.022615                8
0        0.024789                9
5        0.026950               10
```

8.4 7.4 Stack models after Tuning

Why not Voting?

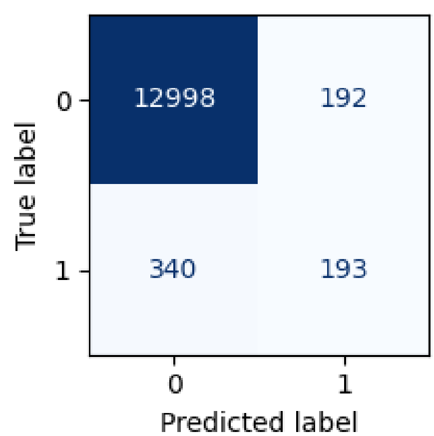
Voting doesn't learn model weights: It simply averages predictions, while stacking learns which models are more reliable through a meta-learner. Weak models can hurt the ensemble: Models like KNN and GaussianNB performed poorly, and voting treats all models equally, reducing overall performance. Limited performance gain: Voting rarely outperforms the strongest individual models, especially when top models already perform well.

[ ]:
```
from sklearn.ensemble import StackingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score, classification_report
from sklearn.model_selection import StratifiedKFold

inner_cv = StratifiedKFold(n_splits=3, shuffle=True, random_state=42)
```

```python
estimators = [
    ("gnb", best_gnb),
    ("logreg", best_logreg),
    ("gb", best_gb),
]

# meta-model = LogisticRegression
meta_model = LogisticRegression(max_iter=3000, class_weight="balanced",␣
 ↪solver="liblinear")

stack_clf = StackingClassifier(
    estimators=estimators,
    final_estimator=meta_model,
    stack_method="predict_proba",
    cv=inner_cv,
    n_jobs=-1,
    passthrough=False
)
```

[ ]:

```python
stack_clf.fit(X_train, y_train)

y_pred = stack_clf.predict(X_test)
y_prob = stack_clf.predict_proba(X_test)[:, 1]

print_scores(y_test, y_pred)
collect_results("Stacking (GNB + LogReg + GB)", y_test, y_pred, y_prob)

print("Test AUC:", roc_auc_score(y_test, y_prob))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```



```
Accuracy=0.9612, Balanced Accuracy=0.6738
Precision=0.5013, Recall=0.3621, F1-score=0.4205
Test AUC: 0.5611293022885322

Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.99      0.98     13190
           1       0.50      0.36      0.42       533

    accuracy                           0.96     13723
   macro avg       0.74      0.67      0.70     13723
weighted avg       0.96      0.96      0.96     13723
```

9 8. Threshold Tuning

Assumed cost matrix: | Cost matrix | **Predicted -** | **Predicted +** | |————-|—————|—————| | **Actual -** | 0 | 1 | | **Actual +** | 5 | 0 |

[ ]:
```python
# cost function
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import make_scorer, confusion_matrix

FN_COST = 5
FP_COST = 1

def default_cost(y_true, y_pred):
    cm = confusion_matrix(y_true, y_pred, labels=[0, 1])
    fn = cm[1, 0]
    fp = cm[0, 1]
    return fn * FN_COST + fp * FP_COST

# scorer
scorer = make_scorer(default_cost, greater_is_better=False)
```

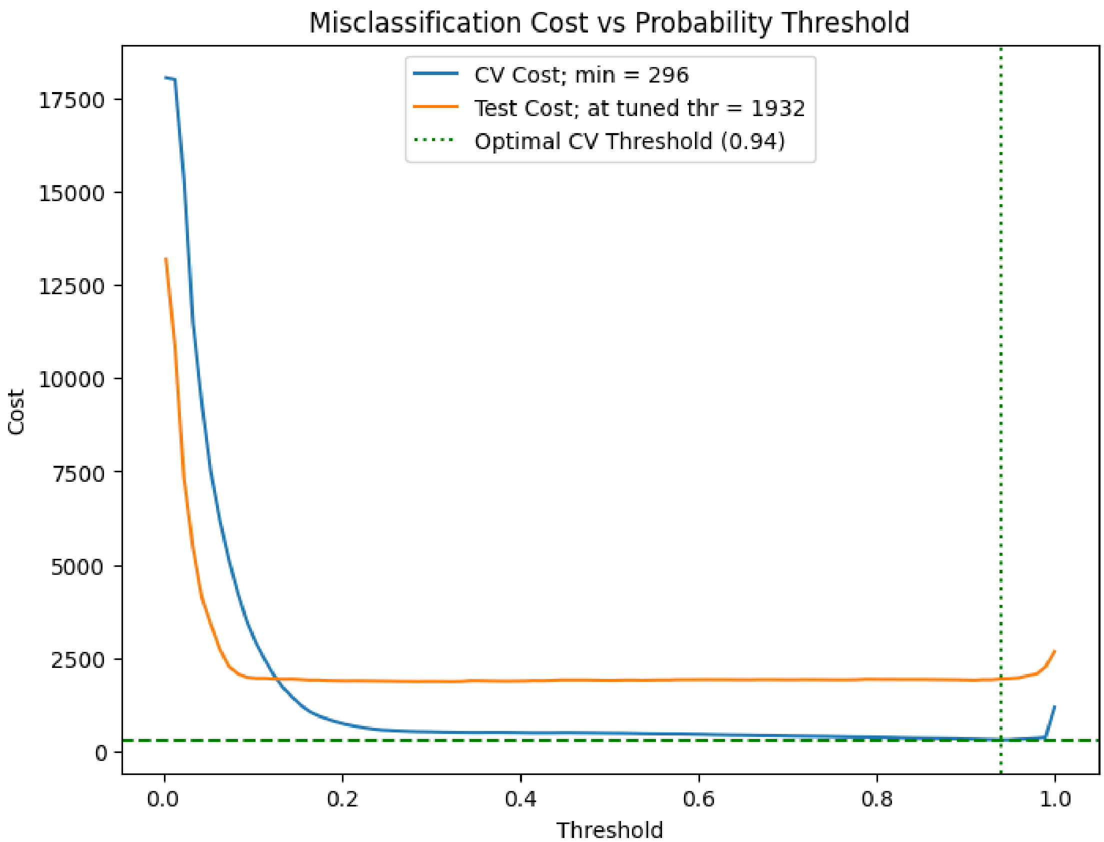
[ ]:
```python
# TunedThresholdClassifierCV
from sklearn.model_selection import TimeSeriesSplit, TunedThresholdClassifierCV

inner_cv = StratifiedKFold(n_splits=3, shuffle=True, random_state=42)

tuned_threshold_model = TunedThresholdClassifierCV(
    estimator=stack_clf,
    scoring=scorer,
    cv=inner_cv,
    store_cv_results=True
```

```
)

tuned_threshold_model.fit(X_train, y_train)

cost_after_tuning = default_cost(y_test, tuned_threshold_model.predict(X_test))
print(f"Cost AFTER threshold tuning (test): {cost_after_tuning}")
print(f"Optimal threshold: {tuned_threshold_model.best_threshold_:.4f}")
```

```
Cost AFTER threshold tuning (test): 1932
Optimal threshold: 0.9396
```

[ ]:
```
# visualization
from sklearn.model_selection import FixedThresholdClassifier
from sklearn.frozen import FrozenEstimator
from sklearn.model_selection import StratifiedKFold

# tuned_threshold_model.cv_results_
thresholds = tuned_threshold_model.cv_results_["thresholds"]
cv_costs = -tuned_threshold_model.cv_results_["scores"]  # transform to positive

ix = np.argmin(cv_costs)
opt_thresh_cv = thresholds[ix]
min_cost_cv = cv_costs[ix]

# Freeze one fitted estimator
frozen_stack = FrozenEstimator(stack_clf.fit(X_train, y_train))

test_costs = [
    default_cost(y_test, FixedThresholdClassifier(estimator=frozen_stack,␣
 ↪threshold=t).predict(X_test))
    for t in thresholds
]

opt_cost_test_at_cv_thresh = test_costs[ix]

plt.figure(figsize=(8, 6))
plt.plot(thresholds, cv_costs, label=f'CV Cost; min = {min_cost_cv:.0f}')
plt.plot(thresholds, test_costs, label=f'Test Cost; at tuned thr =␣
 ↪{opt_cost_test_at_cv_thresh:.0f}')

plt.axvline(opt_thresh_cv, 0, 1, ls=':', color='green', label=f'Optimal CV␣
 ↪Threshold ({opt_thresh_cv:.2f})')
plt.axhline(min_cost_cv, xmin=0, xmax=1, ls='--', color='green')

plt.xlabel('Threshold')
plt.ylabel('Cost')
plt.title('Misclassification Cost vs Probability Threshold')
```

```
plt.legend()
plt.show()
```



10 9. Final Evaluation

[ ]:
```
final_predictions = tuned_threshold_model.predict(X_test)

final_cost = default_cost(y_test, final_predictions)
print(f"Cost of tuned-threshold model (test): {final_cost}")

from sklearn.metrics import balanced_accuracy_score
print("Balanced Accuracy:", balanced_accuracy_score(y_test, final_predictions))
print("Best threshold:", tuned_threshold_model.best_threshold_)
```

```
Cost of tuned-threshold model (test): 1932
Balanced Accuracy: 0.6535423959534983
Best threshold: 0.9395856963391475
```

[ ]:
```
# save
import joblib

final_model = tuned_threshold_model
joblib.dump(final_model, "kenya_loan_prediction.pkl")
```

[ ]: ['kenya_loan_prediction.pkl']

[ ]:
```
# bootstrap
import numpy as np
import pandas as pd
from sklearn.metrics import balanced_accuracy_score, recall_score,␣
 ↪precision_score, f1_score

final_model = tuned_threshold_model

B = 1000
rng = np.random.default_rng(42)
n = len(y_test)

rows = []
for b in range(B):
    idx = rng.integers(0, n, size=n)
    Xb = X_test.iloc[idx] if hasattr(X_test, "iloc") else X_test[idx]
    yb = y_test.iloc[idx] if hasattr(y_test, "iloc") else y_test[idx]

    y_pred_b = final_model.predict(Xb)

    rows.append({
        "cost": default_cost(yb, y_pred_b),
        "balanced_accuracy": balanced_accuracy_score(yb, y_pred_b),
        "recall": recall_score(yb, y_pred_b, pos_label=1),
        "precision": precision_score(yb, y_pred_b, pos_label=1),
        "f1": f1_score(yb, y_pred_b, pos_label=1),
    })

boot_df = pd.DataFrame(rows)

def ci(x, lo=2.5, hi=97.5):
    return np.percentile(x, [lo, hi])

summary = pd.DataFrame({
    "metric": ["cost", "balanced_accuracy", "recall", "precision", "f1"],
    "mean": [boot_df[m].mean() for m in␣
 ↪["cost","balanced_accuracy","recall","precision","f1"]],
    "ci_low": [ci(boot_df[m])[0] for m in␣
 ↪["cost","balanced_accuracy","recall","precision","f1"]],
```

```
    "ci_high": [ci(boot_df[m])[1] for m in␣
↪["cost","balanced_accuracy","recall","precision","f1"]],
})

summary
```

[ ]:

	metric	mean	ci_low	ci_high
0	cost	1930.723000	1743.975000	2123.000000
1	balanced_accuracy	0.653997	0.634564	0.673606
2	recall	0.316104	0.277482	0.355274
3	precision	0.611774	0.557554	0.665400
4	f1	0.416537	0.375900	0.456176

11 10. Challenges and Next Steps

###**10.1 Estimated Cost Matrix**

Our cost matrix was constructed using reasonable estimates rather than verified operational or financial data. While this allowed us to approximate asymmetric penalties and explore cost-sensitive learning, the model's optimization is ultimately constrained by the accuracy of these assumptions. Incorporating real cost information would likely shift decision boundaries and improve practical relevance.

###**10.2 Data Quality Issues**

The dataset exhibited noticeable variance and potential outliers that influenced model stability. Although preprocessing steps mitigated some noise, residual anomalies may have skewed decision thresholds or reduced the model's ability to generalize. More thourough data cleaning and adding relevant features from multiple data sources would improve model reliability.

###**10.3 Model Complexity and Generalization Trade-offs**

While more flexible models can fit the training data more closely, they also increase the risk of overfitting. Our chosen models balanced complexity and interpretability, but constraints in hyperparameter tuning and cross-validation resources may have left performance gains unexplored. Trying additional model types and more time for tuning would achieve better generalization to new data.

###**10.4 Evaluation Limitations**

The evaluation framework relied on static train-test splits and a limited set of metrics. As a result, the model's performance on the test dataset may not fully reflect how the model would behave in real-world conditions. Future evaluations using additional tests or more varied metrics could provide a more cohesive picture of the model performance.

###**10.5 Hyperparameter Tuning Search Limitations**

Our ability to perform extensive hyperparameter tuning was limited because grid search could not run efficiently on the full dataset. The large data size and high time complexity of search methods made it impractical to explore broader parameter ranges. As a result, the final model may not reflect the best possible configuration. Additional tuning with optimized search strategies or better computational resources could improve the model.

12 11. Conclusion

This project developed a machine-learning model to predict credit-card loan defaults using the Zindi dataset. After preprocessing and model selection, the final model achieved a **balanced accuracy of 0.65**, reflecting *moderate* ability to separate defaulters from non-defaulters despite dataset noise and feature limitations. Performance on the positive (default) class shows the expected trade-off for imbalanced credit-risk problems: recall was 0.32, indicating the model misses some true defaulters, while precision reached 0.61, meaning that when the model predicts a default, it is often correct. The resulting F1 score of 0.42 highlights the difficulty of consistently identifying high-risk borrowers in this dataset.

Using a cost-sensitive evaluation, the model achieved an average expected cost of 1930.72, with confidence bounds indicating stable performance across folds. While the cost matrix was based on estimated rather than real operational values, it still helped align the model with the financial implications of misclassification and provided a practical decision-making perspective.

Overall, this project shows both the potential and the complexity of applying machine learning to credit-risk problems. Future improvements such as more advanced feature engineering, real-world cost data, and more extensive hyperparameter tuning could further enhance predictive accuracy and reduce expected financial loss.

Throughout the project, we learned several skills and insights that are valuable in real-world machine-learning practice. We gained hands-on experience with cleaning noisy tabular data, handling outliers, and designing features that improve model understanding. We also deepened our understanding of how model evaluation must go beyond accuracy in high-stakes settings by comparing different metrics, exploring class imbalance, and applying cost-sensitive decision making. Finally, the project reinforced the importance of interpretability, fairness, and stakeholder alignment whenever ML models influence financial decisions.

13 12. References

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#13. Generative AI Disclosure

We used generative AI tools to support our project in the following ways:

- **Clarifying Concepts and Debugging:** We used generative AI tools to help explain machine-learning concepts and interpret error messages. The guidance supported our learning but did not replace our own analytical work
- **Improving Code Readability and Efficiency:** AI tools were occasionally used to suggest cleaner or more efficient versions of code we had already written. All suggested code was reviewed and modified by our team to ensure alignment with project requirements
- **Refining Written Documentation:** We used AI assistance to help polish grammar for the written sections of the notebook. All final text reflects our team's understanding and was edited to ensure accuracy and consistency with our results

All AI-assisted content was carefully reviewed, modified, and finalized by our team to ensure originality, accuracy, and full compliance with academic integrity guidelines.