sample

December 2, 2025

0.1 Part 1: Dataset Simulation

[1]:
```
# Library imports

import pandas as pd
import numpy as np
from datetime import datetime
import random
from google import genai
from google.genai import types
from collections import Counter
import os
import math
import time
import json

import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, LabelEncoder

from dotenv import load_dotenv
load_dotenv()

output_filename = 'data/sim_customers_seed_42.csv'
```

[6]:
```
# Helper: robustly convert various SDK response types to plain string for JSON␣
↪parsing

def _extract_text(obj):
    """Recursively extract text from SDK response objects.
    Handles str/bytes, lists, objects with .text/.content/.output, pydantic␣
↪models, response.candidates, and fallbacks to str().
    """
    if obj is None:
        return ""
    if isinstance(obj, str):
```

```
        return obj
    if isinstance(obj, (bytes, bytearray)):
        try:
            return obj.decode('utf-8')
        except Exception:
            return str(obj)
    # If object has 'parts' (GenAI SDK), extract part contents
    try:
        if hasattr(obj, 'parts') and obj.parts:
            # join all part contents
            return "\n".join(_extract_text(p) for p in obj.parts)
    except Exception:
        pass
    # If it's a list or tuple, join items
    if isinstance(obj, (list, tuple)):
        return "\n".join(_extract_text(x) for x in obj)
    # Common nested attributes
    for attr in ("text", "content", "output", "value", "data"):
        try:
            val = getattr(obj, attr, None)
        except Exception:
            val = None
        if val:
            return _extract_text(val)
    # If object is a dict-like
    try:
        if isinstance(obj, dict):
            return json.dumps(obj)
    except Exception:
        pass
    # Try pydantic/BaseModel .json() or .dict()
    try:
        if hasattr(obj, 'json') and callable(obj.json):
            return obj.json()
    except Exception:
        pass
    try:
        if hasattr(obj, 'dict') and callable(obj.dict):
            return json.dumps(obj.dict())
    except Exception:
        pass
    # Fallback to string
    return str(obj)
```

[26]:
```
# Methods used in the simulation

# Set random seed for reproducibility
```

```
np.random.seed(42)
random.seed(42)

TRANSACTION_CATEGORIES = ["groceries", "utilities", "entertainment", "dining", 
 ↪"transport", "healthcare", "shopping", "education", "rent", "salary", 
 ↪"transfer"]

def generate_feedback_gemini_batch(summaries, n_requests=10, model="gemini-2.
 ↪5-flash", max_retries=3, retry_delay=5, batch_delay_seconds=4):
    """Send summaries to Gemini in n_requests batches and return feedback map.

    This function WILL raise if the GenAI SDK is missing, the GOOGLE_API_KEY 
 ↪env var
    is not set, or if Gemini fails to produce valid JSON for any batch after 
 ↪retries.

    summaries: list of dicts, each must include 'customer_id' and other summary 
 ↪fields.
    n_requests: desired number of Gemini calls (e.g., 10 to respect quotas).
    batch_delay_seconds: seconds to sleep between successful batch calls to 
 ↪avoid bursts.
    Returns: {customer_id: feedback_text}
    """
    # Strict preconditions for Gemini-only mode
    if 'genai' not in globals() or genai is None or 'types' not in globals() or 
 ↪types is None:
        raise RuntimeError("Google GenAI SDK not available. Install the 
 ↪official SDK before enabling Gemini.")

    GOOGLE_API_KEY = os.getenv("GOOGLE_API_KEY")
    if not GOOGLE_API_KEY:
        raise ValueError("GOOGLE_API_KEY not found in environment variables; 
 ↪required for Gemini mode.")

    client = genai.Client(api_key=GOOGLE_API_KEY)

    feedback_map = {}
    total = len(summaries)
    if total == 0:
        return feedback_map

    batch_size = max(1, math.ceil(total / n_requests))

    for i in range(0, total, batch_size):
        batch = summaries[i:i+batch_size]
        # Build strict JSON-response prompt
```

```
        items_text = []
        for s in batch:
            items_text.append(f"ID: {s['customer_id']} | credits:␣
↪{s['total_credits']:.2f} | debits: {s['total_debits']:.2f} | end_balance:␣
↪{s['ending_balance']:.2f} | top: {s['top_category']}")
        prompt_body = "\n".join(items_text)
        prompt = (
            "You are given multiple short customer monthly summaries (one per␣
↪line in the format 'ID: <id> | ...').\n"
            "For each summary, produce a JSON array of objects with fields␣
↪{\"customer_id\": <id>, \"feedback\": <short advice sentence>} and NOTHING␣
↪ELSE.\n"
            "Keep each feedback within 10 words and make them varied and␣
↪realistic. Example: \"I plan to increase my savings next month.\"\n"
            "Respond with valid JSON only (no extra commentary).\n\n"
            f"Summaries:\n{prompt_body}"
        )

        attempt = 0
        resp_text = None
        last_exception = None
        while attempt < max_retries:
            try:
                response = client.models.generate_content(
                    model=model,
                    contents=[prompt],
                    config=types.GenerateContentConfig(
                        system_instruction="You are generating short customer␣
↪feedback notes for a synthetic banking dataset.",
                        thinking_config=types.ThinkingConfig(thinking_budget=-1)
                    )
                )
                # Extract returned text conservatively
                resp_text = _extract_text(response)
                if resp_text:
                    break
                else:
                    raise RuntimeError('Empty response from Gemini')
            except Exception as e:
                last_exception = e
                attempt += 1
                wait = retry_delay * (2 ** (attempt - 1))
                # If the exception contains retry info, prefer that␣
↪(best-effort)
                try:
```

~~~python
                    # attempt to read retryDelay from exception message or object
                    # Not all exceptions expose this; this is best-effort
                    print(f"Gemini batch request failed (attempt {attempt}/{max_retries}): {e}. Retrying in {wait}s...")
                except Exception:
                    pass
                time.sleep(wait)

        if resp_text is None:
            # unrecoverable for this batch
            raise RuntimeError(f"Gemini failed for batch starting at index {i} after {max_retries} attempts.") from last_exception

        # Parse JSON exactly; be strict in Gemini-only mode
        # Clean markdown code blocks
        if resp_text.startswith('```json') and resp_text.endswith('```'):
            resp_text = resp_text[7:-3].strip()
        elif resp_text.startswith('```') and resp_text.endswith('```'):
            resp_text = resp_text[3:-3].strip()
        parsed = None
        try:
            parsed = json.loads(resp_text)
        except Exception:
            # attempt to extract JSON substring
            start = resp_text.find('[')
            end = resp_text.rfind(']')
            if start != -1 and end != -1 and end > start:
                parsed = json.loads(resp_text[start:end+1])

        if not isinstance(parsed, list):
            raise ValueError(f"Gemini response for batch starting at index {i} did not parse to a JSON list.\nResponse:\n{resp_text}")

        for obj in parsed:
            cid = obj.get('customer_id') or obj.get('ID') or obj.get('id')
            fb = obj.get('feedback') or obj.get('note') or obj.get('text')
            if not cid or not fb:
                raise ValueError(f"Invalid object in Gemini JSON output: {obj}")
            feedback_map[str(cid)] = str(fb)

        # Sleep a short while between batches to avoid quota bursts
        time.sleep(batch_delay_seconds)

    return feedback_map
~~~

```python
# Replace daily series to *require* Gemini use and map feedbacks strictly
def generate_customer_dataset(num_customers=500, seed=42, gemini_requests=10, batch_delay_seconds=4):
    np.random.seed(seed)
    random.seed(seed)

    rows = []
    month_end_date = datetime(2025, 1, 31).date()

    customer_summaries = []

    for cid in range(1, num_customers + 1):
        customer_id = f"CUST{str(cid).zfill(5)}"
        age = int(np.clip(np.random.normal(40, 12), 18, 80))
        monthly_income = float(np.round(np.clip(np.random.normal(4000, 2000), 500, None), 2))
        occupation = random.choice(["Engineer", "Teacher", "Healthcare", "Retail", "Finance", "Student", "Self-employed", "Unemployed", "Manager", "Technician"])
        starting_balance = float(np.round(monthly_income * np.random.uniform(0.2, 4.0) + np.random.uniform(-500, 500), 2))
        credit_score = int(np.clip(np.random.normal(680, 50), 300, 850))
        invest_pct = float(np.round(np.random.normal(0.8, 1.2), 2))

        # Simulate monthly transactions
        balance = starting_balance
        monthly_credits_total = 0.0
        monthly_debits_total = 0.0
        categories_counter = Counter()

        # Salary credit
        salary = monthly_income
        monthly_credits_total += salary
        balance += salary
        categories_counter.update(["salary"])

        # Random transfers
        n_transfers = np.random.poisson(2)
        for _ in range(n_transfers):
            transfer = float(np.random.exponential(scale=monthly_income / 10.0))
            monthly_credits_total += transfer
            balance += transfer
            categories_counter.update(["transfer"])

        # Investment gains
        monthly_invest_gain = (balance * max(0.0, invest_pct) / 100.0)
        monthly_credits_total += monthly_invest_gain
```

```
        balance += monthly_invest_gain

        # Debits
        n_txns = np.random.poisson(30)  # approx daily
        for _ in range(n_txns):
            cat = random.choice(TRANSACTION_CATEGORIES[:-3])
            amt = float(np.random.exponential(scale=monthly_income / 120.0)) +␣
↪np.random.uniform(5, 50)
            monthly_debits_total += amt
            balance -= amt
            categories_counter.update([cat])

        # Big spends
        n_big = np.random.poisson(3)
        for _ in range(n_big):
            big_cat = random.choice(["shopping", "healthcare", "education",␣
↪"rent"])
            big_amt = float(np.random.exponential(scale=monthly_income / 4.0))
            monthly_debits_total += big_amt
            balance -= big_amt
            categories_counter.update([big_cat])

        ending_balance = float(np.round(balance, 2))

        # Credit score change
        credit_score_change = np.random.choice([-10, -5, 5, 10])
        final_credit_score = int(np.clip(credit_score + credit_score_change,␣
↪300, 850))

        top_category = categories_counter.most_common(1)[0][0] if␣
↪categories_counter else None

        row = {
            "customer_id": customer_id,
            "date": month_end_date.isoformat(),
            "age": age,
            "occupation": occupation,
            "monthly_income": monthly_income,
            "monthly_credit": float(round(monthly_credits_total, 2)),
            "monthly_debit": float(round(monthly_debits_total, 2)),
            "starting_balance": starting_balance,
            "ending_balance": ending_balance,
            "monthly_invest_gain": float(round(monthly_invest_gain, 2)),
            "monthly_invest_return_pct": invest_pct,
            "initial_credit_score": credit_score,
            "final_credit_score": final_credit_score,
            "transaction_category_major": top_category,
```

```
            "customer_feedback": None
        }
        rows.append(row)

        summary = {
            "customer_id": customer_id,
            "total_credits": monthly_credits_total,
            "total_debits": monthly_debits_total,
            "ending_balance": ending_balance,
            "top_category": top_category
        }
        customer_summaries.append(summary)

    # Generate feedbacks using Gemini batches (Gemini-only mode)
    feedback_map = generate_feedback_gemini_batch(customer_summaries,␣
↪n_requests=gemini_requests, batch_delay_seconds=batch_delay_seconds)


    # Ensure every customer got a Gemini feedback
    missing = [s['customer_id'] for s in customer_summaries if s['customer_id']␣
↪not in feedback_map]
    if missing:
        raise RuntimeError(f"Gemini did not return feedback for the following␣
↪customers: {missing[:10]}{'...' if len(missing)>10 else ''}")

    # Attach feedbacks
    for r in rows:
        cid = r['customer_id']
        fb = feedback_map[cid]
        r['customer_feedback'] = fb

    df = pd.DataFrame(rows)

    # Inject missingness and noise
    inc_idx = df.sample(frac=0.02, random_state=seed).index
    df.loc[inc_idx, "monthly_income"] = np.nan

    txn_idx = df.sample(frac=0.03, random_state=seed+1).index
    df.loc[txn_idx, ["monthly_credit", "monthly_debit"]] = np.nan

    cs_idx = df.sample(frac=0.01, random_state=seed+2).index
    df.loc[cs_idx, "final_credit_score"] = df.loc[cs_idx, "final_credit_score"].
↪apply(lambda x: int(x + np.random.choice([-500, 400])))

    fb_idx = df[df["customer_feedback"].notnull()].sample(frac=0.05,␣
↪random_state=seed+3).index
    df.loc[fb_idx, "customer_feedback"] = None
```

```
    ol_idx = df.sample(n=12, random_state=seed+4).index
    df.loc[ol_idx, "monthly_debit"] = df.loc[ol_idx, "monthly_debit"] * np.
↪random.uniform(5, 25, size=len(ol_idx))

    col_order = [
        "customer_id", "date", "age", "occupation", "monthly_income",
        "monthly_credit", "monthly_debit", "starting_balance", "ending_balance",
        "monthly_invest_gain", "monthly_invest_return_pct",␣
↪"initial_credit_score",
        "final_credit_score", "transaction_category_major", "customer_feedback"
    ]
    df = df[col_order]

    return df


def save_simulation(df: pd.DataFrame, path: str):
    os.makedirs(os.path.dirname(path), exist_ok=True)
    df.to_csv(path, index=False)
```

[ ]:
```
# Configuration and run

NUM_CUSTOMERS = 500
SEED = 42

print("Generating synthetic banking customer dataset...")
df = generate_customer_dataset(num_customers=NUM_CUSTOMERS, seed=SEED)

print(f"\n  Dataset generated successfully! Rows: {len(df)} Customers:␣
↪{df['customer_id'].nunique()}")
print(f"Date: {df['date'].iloc[0]}")

# Show missing data summary
print("\nMissing data summary:")
print(df.isnull().sum())

# Show sample of feedbacks
print("\nSample feedbacks (first 10 customers):")
sample_feedbacks = df[['customer_id','customer_feedback']].head(10)
print(sample_feedbacks.to_string(index=False))

save_simulation(df, output_filename)
print(f"\n  Dataset saved to: {output_filename}")

print("\nBasic numeric stats:")
```

```
print(df[['monthly_credit','monthly_debit','ending_balance','monthly_invest_return_pct']].
    ↪describe())
```

0.2 Part 2.1: Exploratory Data Analysis (EDA)

[2]:
```
# EDA: load the saved CSV and perform quick exploratory analysis with visuals␣
    ↪and summaries
pd.set_option('display.max_columns', None)

# Load dataset saved earlier (falls back to generated `df` if file missing)
try:
    df_eda = pd.read_csv(output_filename)
    print(f"Loaded dataset from {output_filename} - rows: {len(df_eda)}")
except Exception as e:
    print(f"Could not load {output_filename} ({e}), using in-memory `df` from␣
    ↪simulation - rows: {len(df)}")
    df_eda = df.copy()
```

```
Loaded dataset from data/sim_customers_seed_42.csv - rows: 500
```

[15]:
```
# Quick peek
print('\n-- Head (first 8 rows) --')
print(df_eda.head(8).to_string(index=False))

# Data types & missingness
print('\n-- Info & dtypes --')
print(df_eda.dtypes)

print('\n-- Missing values per column --')
print(df_eda.isnull().sum())

# Numeric summary
numeric_cols = [c for c in df_eda.columns if df_eda[c].dtype in␣
    ↪['int64','float64']]
print('\n-- Numeric summary (describe) --')
print(df_eda[numeric_cols].describe())

# Show value counts for categorical fields
cat_cols = ['occupation', 'transaction_category_major']
for c in cat_cols:
    if c in df_eda.columns:
        print(f"\nTop categories for {c}:")
        print(df_eda[c].value_counts(dropna=False).head(10))

# Visualizations (seaborn-only)
sns.set_theme(style='whitegrid')
```

```
# 1) Missingness map
ax = sns.heatmap(df_eda.isnull(), cbar=False)
ax.set_title('Missing values map (True = missing)')
ax.set_xlabel('Rows (index)')
ax.set_ylabel('Columns')
fig = ax.get_figure()
fig.set_size_inches(10,4)
fig.tight_layout()
plt.show()

# 2) Distributions (income, credit, debit, ending balance) - separate figures
sns.histplot(df_eda['monthly_income'].dropna(), bins=40, kde=True).
 ↪set(title='Monthly income')
plt.show()

sns.histplot(df_eda['monthly_credit'].dropna(), bins=40, kde=True).
 ↪set(title='Monthly credit')
plt.show()

sns.histplot(np.log1p(df_eda['monthly_debit'].dropna()), bins=40, kde=True).
 ↪set(title='Log(1 + monthly_debit)')
plt.show()

sns.histplot(df_eda['ending_balance'].dropna(), bins=40, kde=True).
 ↪set(title='Ending balance')
plt.show()

# 3) Boxplots by occupation for monthly_debit (clip extreme outliers for␣
 ↪readability)
if 'occupation' in df_eda.columns:
    tmp = df_eda.copy()
    tmp['monthly_debit_clipped'] = tmp['monthly_debit'].
 ↪clip(upper=tmp['monthly_debit'].quantile(0.95))
    ax = sns.boxplot(x='occupation', y='monthly_debit_clipped', data=tmp)
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
    ax.set_title('Monthly debit by occupation (95th-percentile clipped)')
    fig = ax.get_figure()
    fig.tight_layout()
    plt.show()

# 4) Category counts
if 'transaction_category_major' in df_eda.columns:
    vc = df_eda['transaction_category_major'].value_counts(dropna=False)
    ax = sns.barplot(x=vc.values, y=vc.index)
    ax.set_title('Major transaction category (counts)')
    ax.set_xlabel('Count')
```

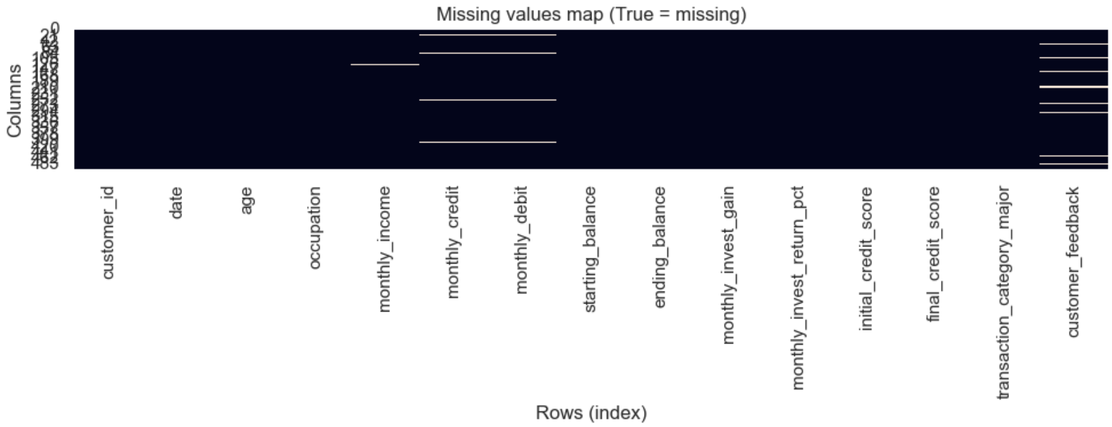
```
    ax.set_ylabel('Category')
    fig = ax.get_figure()
    fig.tight_layout()
    plt.show()

# 5) Correlation heatmap of numeric fields (auto-filtered for clean plot)
# Remove columns with zero variance or >50% missing values
num_for_corr = [
    c for c in numeric_cols
    if df_eda[c].nunique(dropna=True) > 1 and df_eda[c].notnull().sum() >␣
↪len(df_eda)*0.5
]
if num_for_corr:
    corr = df_eda[num_for_corr].corr()
    ax = sns.heatmap(corr, annot=True, fmt='.2f', cmap='coolwarm', center=0)
    ax.set_title('Correlation matrix (numeric features, cleaned)')
    fig = ax.get_figure()
    fig.set_size_inches(10,8)
    fig.tight_layout()
    plt.show()
else:
    print('No suitable numeric columns for correlation matrix after filtering.')

# 6) Small textual analysis: sample customer feedbacks
print('\n-- Sample (non-null) customer feedbacks (10) --')
if 'customer_feedback' in df_eda.columns:
    nonnull_fb = df_eda[df_eda['customer_feedback'].
↪notnull()][['customer_id','customer_feedback']]
    if len(nonnull_fb) == 0:
        print('No non-null feedbacks to show.')
    else:
        sample_fb = nonnull_fb.sample(n=min(10, len(nonnull_fb)),␣
↪random_state=42)
        print(sample_fb.to_string(index=False))
else:
    print('No customer_feedback column found.')

# Save a small EDA summary file for quick reference
eda_summary = {
    'rows': len(df_eda),
    'columns': list(df_eda.columns),
    'missing_per_column': df_eda.isnull().sum().to_dict(),
    'numeric_summary': df_eda[numeric_cols].describe().to_dict()
}

with open('data/eda_summary.json','w', encoding='utf-8') as f:
    json.dump(eda_summary, f, indent=2)
```

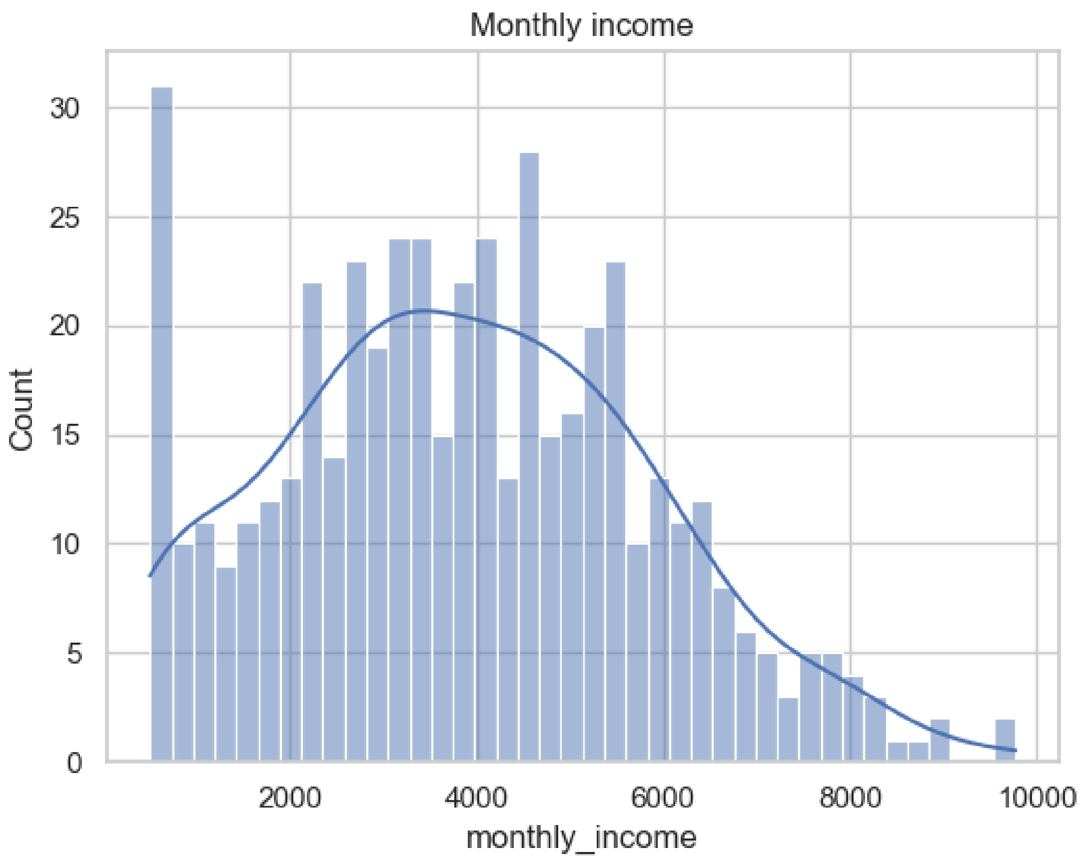
```python
print('\n  EDA complete - summary written to data/eda_summary.json')
```

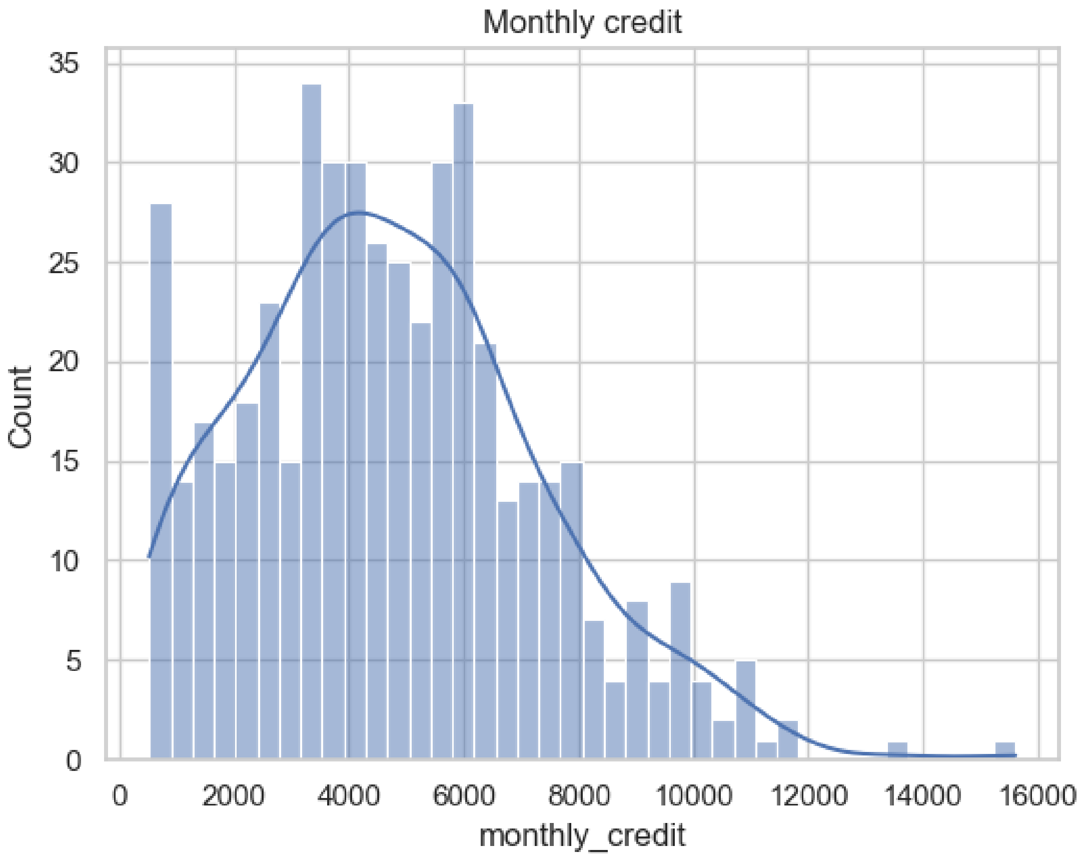
```
Loaded dataset from data/sim_customers_seed_42.csv - rows: 500

-- Head (first 8 rows) --
customer_id       date  age    occupation  monthly_income  monthly_credit
monthly_debit  starting_balance  ending_balance  monthly_invest_gain
monthly_invest_return_pct  initial_credit_score  final_credit_score
transaction_category_major
customer_feedback
  CUST00001 2025-01-31   45       Teacher         3723.47         3801.07
2467.52          11200.47         12534.02                77.60
0.52                    668                 673                   dining
Dining was enjoyable, but finances remain strong.
  CUST00002 2025-01-31   21       Teacher         5275.91         6245.50
6829.58          12190.17         11606.10               315.29
1.74                    633                 638               healthcare
Healthcare costs were high, good reserves helped.
  CUST00003 2025-01-31   45 Self-employed         3481.94         4089.60
5530.05           3511.02          2070.57                59.57
0.79                    696                 686                   dining
Dining out was excessive; need to cut back.
  CUST00004 2025-01-31   50 Self-employed         3940.55         5116.70
6419.16           7142.85          5840.39               265.08
2.21                    748                 753                utilities
Utilities were costly; exploring ways to save energy.
  CUST00005 2025-01-31   32        Retail         5704.87         6097.01
2152.20          10235.67         14180.49               295.09
1.84                    705                 700                   dining
Excellent savings this month, very happy with progress!
  CUST00006 2025-01-31   26      Engineer         6563.84         7271.12
5903.91           7811.20          9178.41               352.05
2.39                    627                 622                   dining
Managed dining costs well, financial health is good.
  CUST00007 2025-01-31   36    Healthcare         3990.87         6456.65
8676.66           7461.86          5241.84               236.70
1.73                    743                 738                 shopping
Shopping spree impacted balance; will be more mindful.
  CUST00008 2025-01-31   44       Finance         7823.06         8723.14
7201.27          24270.85         25792.72               494.00
1.52                    759                 769                education
Education investment continues; strong savings too.

-- Info & dtypes --
customer_id                    object
date                           object
age                             int64
```

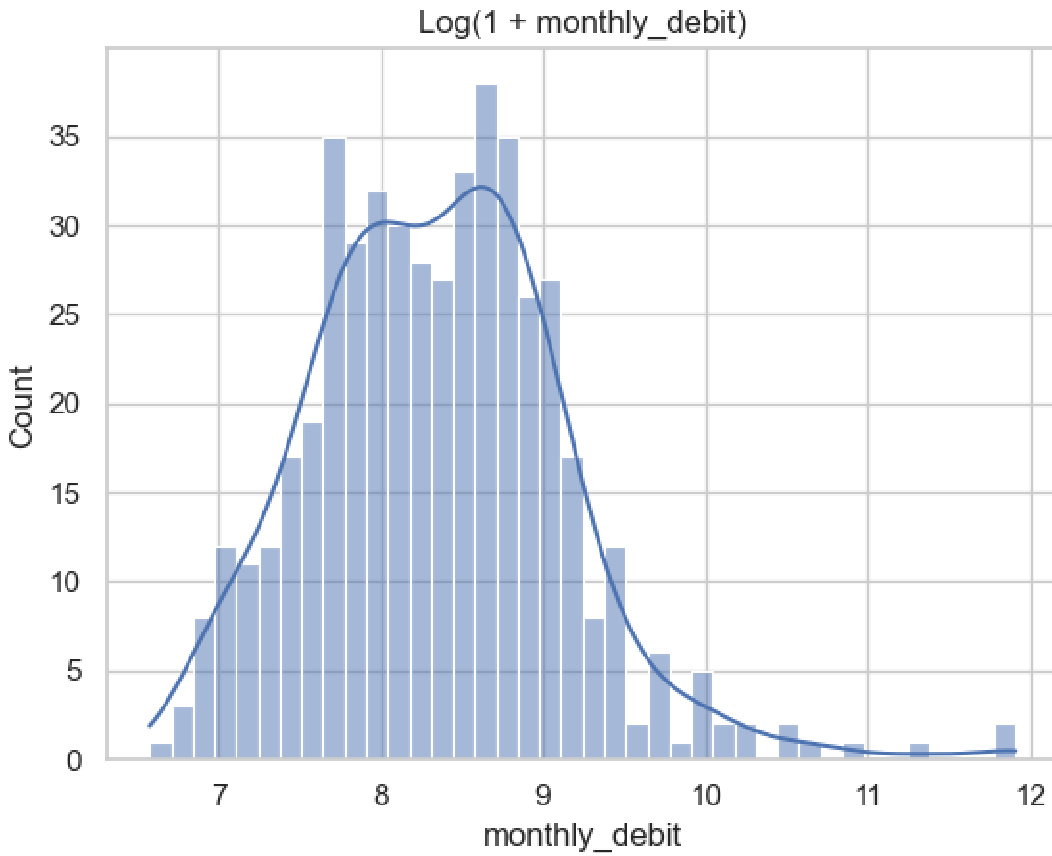
```
occupation                       object
monthly_income                  float64
monthly_credit                  float64
monthly_debit                   float64
starting_balance                float64
ending_balance                  float64
monthly_invest_gain             float64
monthly_invest_return_pct       float64
initial_credit_score              int64
final_credit_score                int64
transaction_category_major       object
customer_feedback                object
dtype: object

-- Missing values per column --
customer_id                   0
date                          0
age                           0
occupation                    0
monthly_income               10
monthly_credit               15
monthly_debit                15
starting_balance              0
ending_balance                0
monthly_invest_gain           0
monthly_invest_return_pct     0
initial_credit_score          0
final_credit_score            0
transaction_category_major    0
customer_feedback            25
dtype: int64

-- Numeric summary (describe) --
             age  monthly_income  monthly_credit  monthly_debit  \
count  500.00000      490.000000      485.000000     485.000000
mean    39.12200     3866.868020     4757.023814    6235.750087
std     11.06671     1977.735479     2564.605983   10977.072664
min     18.00000      500.000000      510.090000     717.820000
25%     32.00000     2401.985000     2917.520000    2456.830000
50%     39.00000     3813.220000     4598.850000    4189.850000
75%     47.00000     5304.980000     6245.500000    6629.330000
max     72.00000     9768.460000    15613.120000  148981.884457

       starting_balance  ending_balance  monthly_invest_gain  \
count         500.00000      500.000000           500.000000
mean         7899.50754     7640.055400           127.123260
std          6291.82864     7246.865008           162.981478
min           -66.84000    -6347.860000             0.000000
```

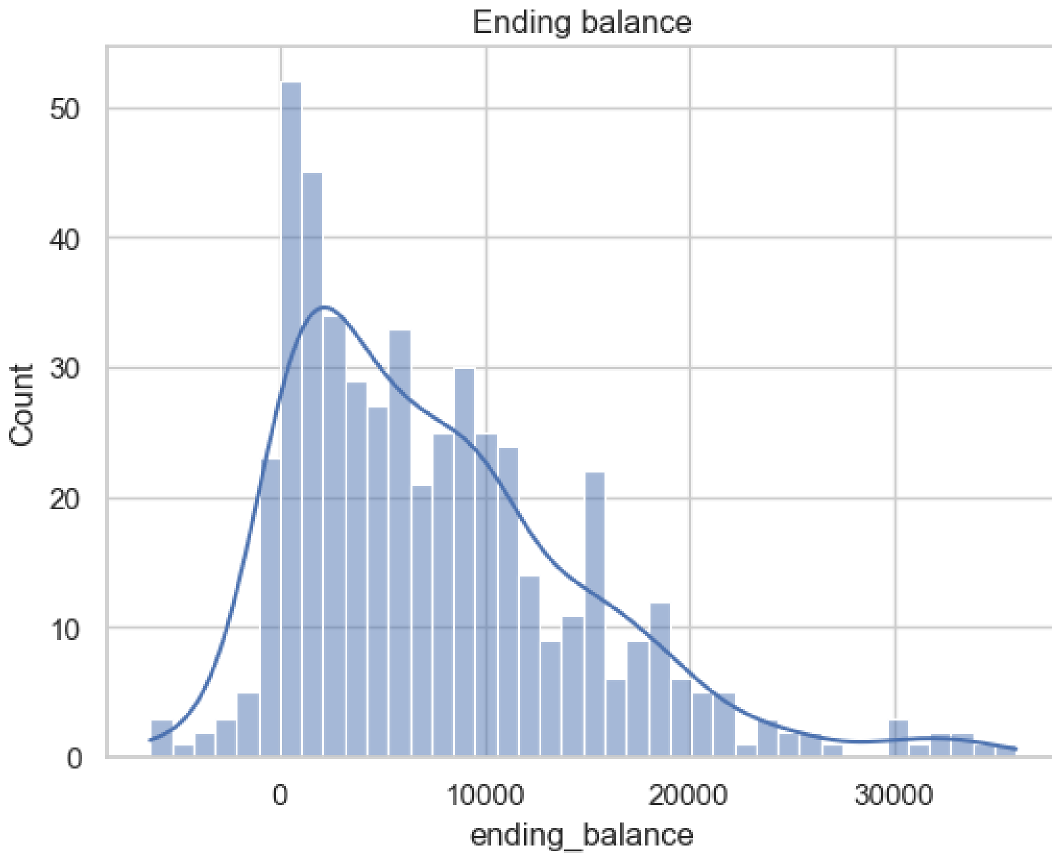
```
25%          2977.16000     1855.445000            0.000000
50%          6270.91500     6041.695000           69.545000
75%         11205.29250    11323.280000          186.392500
max         31466.28000    35952.210000         1495.780000

       monthly_invest_return_pct  initial_credit_score  final_credit_score
count                 500.000000            500.000000          500.000000
mean                    0.857640            679.618000          678.118000
std                     1.256535             48.601773           66.190743
min                    -3.960000            506.000000          177.000000
25%                    -0.002500            645.000000          644.000000
50%                     0.845000            679.500000          681.000000
75%                     1.690000            714.000000          714.000000
max                     4.680000            837.000000         1038.000000

Top categories for occupation:
occupation
Self-employed    62
Retail           61
Manager          58
Teacher          54
Finance          49
Engineer         46
Student          44
Healthcare       43
Unemployed       43
Technician       40
Name: count, dtype: int64

Top categories for transaction_category_major:
transaction_category_major
shopping         100
education         86
healthcare        83
entertainment     51
utilities         47
dining            46
groceries         43
transport         41
transfer           3
Name: count, dtype: int64
```


Missing values map (True = missing)
Columns
customer_id
date
age
occupation
monthly_income
monthly_credit
monthly_debit
starting_balance
ending_balance
monthly_invest_gain
monthly_invest_return_pct
initial_credit_score
final_credit_score
transaction_category_major
customer_feedback
Rows (index)

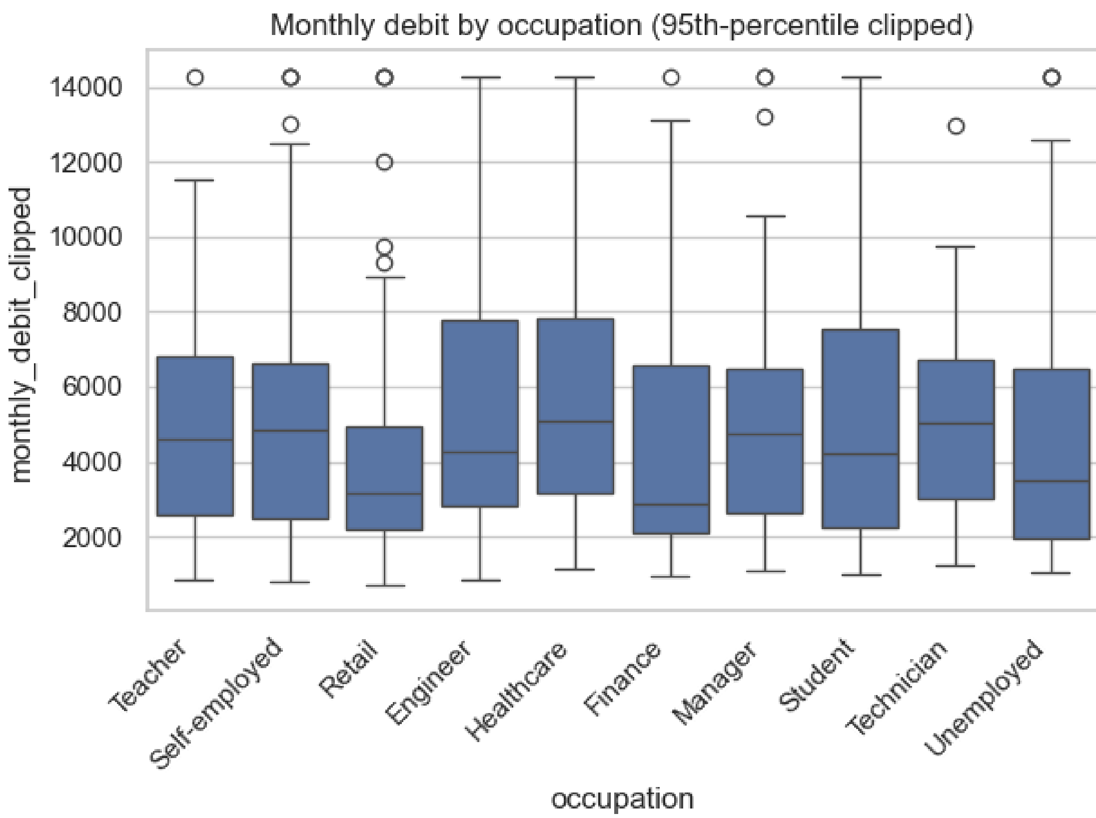

Monthly income
Count
monthly_income
0
5
10
15
20
25
30
2000
4000
6000
8000
10000

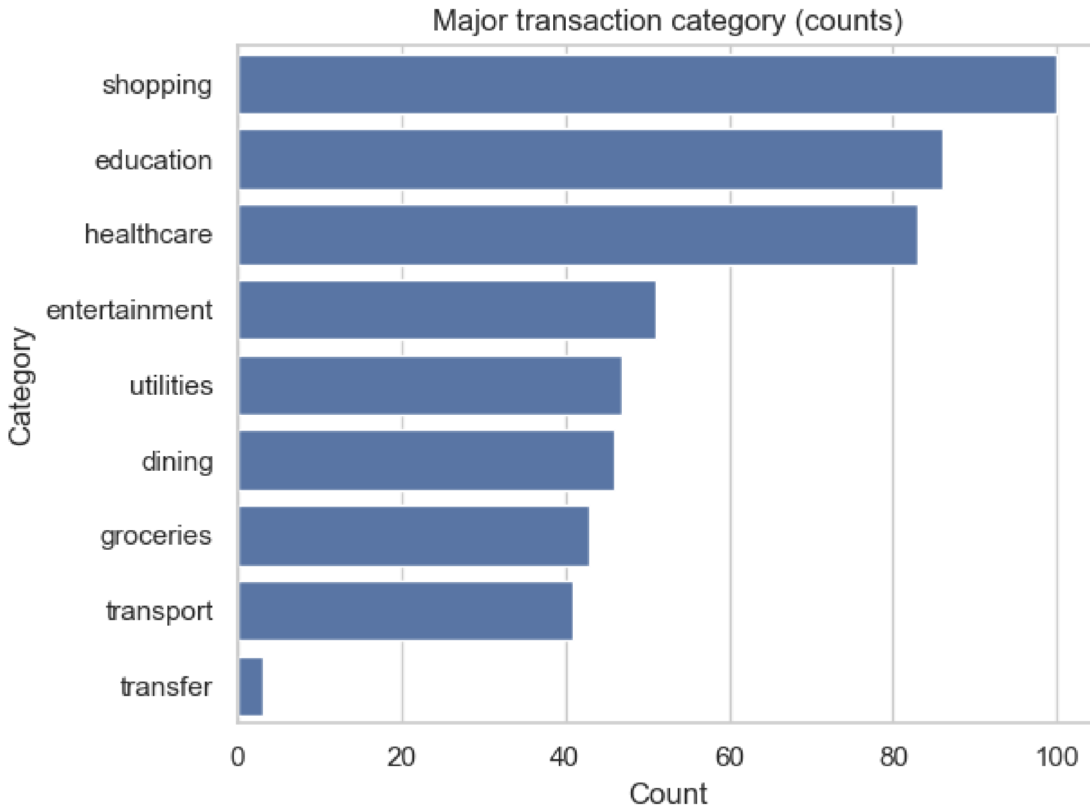

Monthly credit
Count
monthly_credit
35
30
25
20
15
10
5
0
0
2000
4000
6000
8000
10000
12000
14000
16000


Log(1 + monthly_debit)
Count
monthly_debit
0
5
10
15
20
25
30
35
7
8
9
10
11
12




```
C:\Users\Jonas\AppData\Local\Temp\ipykernel_10444\2943935619.py:66: UserWarning:
set_ticklabels() should only be used with a fixed number of ticks, i.e. after
set_ticks() or using a FixedLocator.
  ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
```


Monthly debit by occupation (95th-percentile clipped)
monthly_debit_clipped
14000
12000
10000
8000
6000
4000
2000
Teacher
Self-employed
Retail
Engineer
Healthcare
Finance
Manager
Student
Technician
Unemployed
occupation

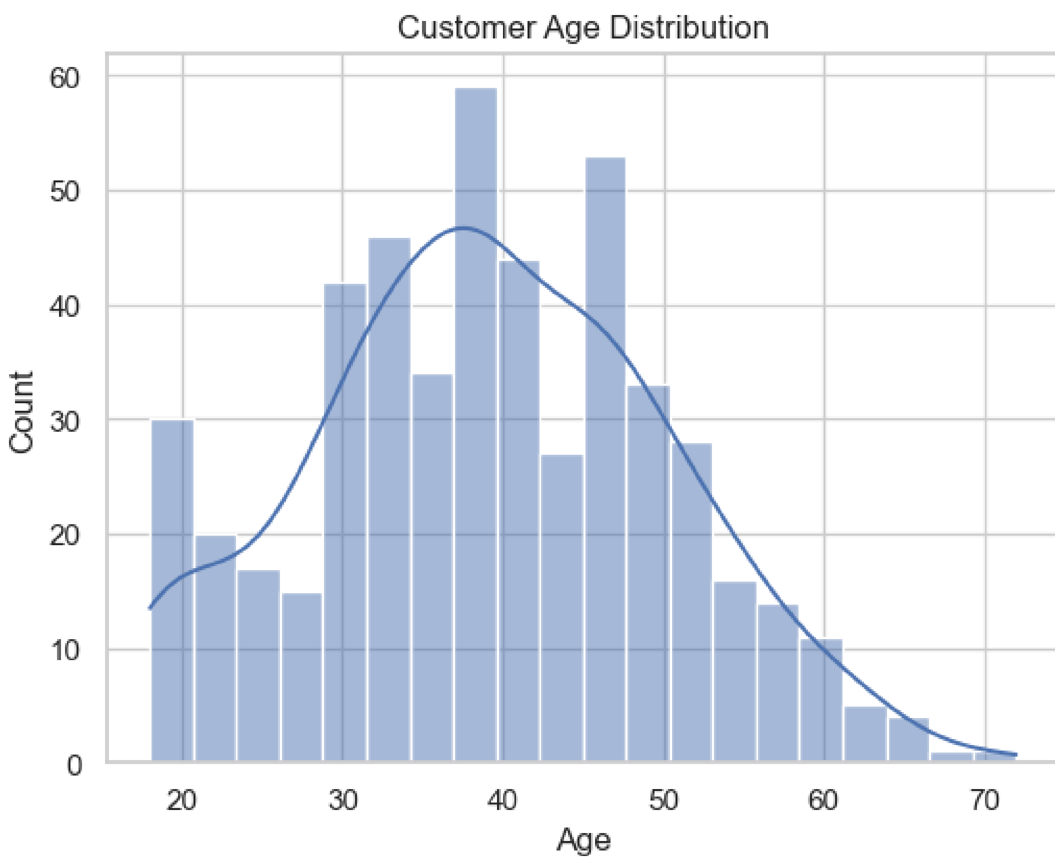

Major transaction category (counts)
shopping
education
healthcare
entertainment
utilities
dining
groceries
transport
transfer
Category
0
20
40
60
80
100
Count


```
-- Sample (non-null) customer feedbacks (10) --
customer_id                                               customer_feedback
  CUST00396            Debits slightly up. Keep an eye on healthcare spending.
  CUST00444   Great savings! Keep up excellent management of grocery expenses.
  CUST00010        Groceries were pricey; next month requires strict budgeting.
  CUST00078 Excellent cash flow. Consider ways to optimize your utility bills.
  CUST00375              High healthcare debits, but strong end balance. Good.
  CUST00034             Shopping was okay; steady progress on financial goals.
  CUST00083   Monitor dining expenses closely to prevent future balance drops.
  CUST00465   Excellent month! Consider adding more to your long-term savings.
  CUST00124        Good balance. Keep monitoring healthcare expenses carefully.
  CUST00095 Monitor shopping closely to maintain your current healthy balance.

 EDA complete - summary written to data/eda_summary.json
```

[11]:
```
# Additional charts
```

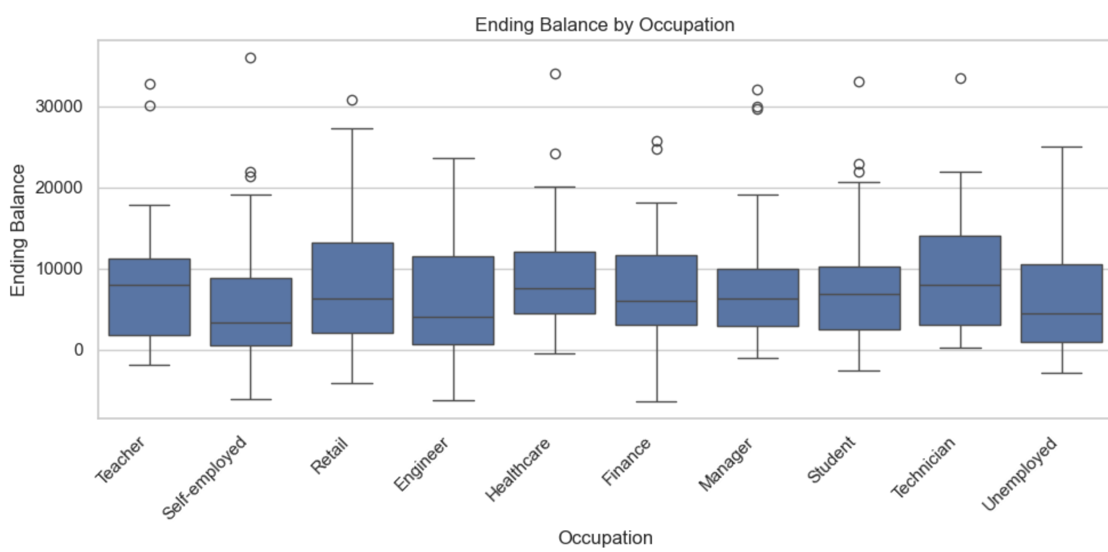
```python
# Age distribution
sns.histplot(df_eda['age'].dropna(), bins=20, kde=True)
plt.title('Customer Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()

# Credit score change distribution
if 'final_credit_score' in df_eda.columns and 'initial_credit_score' in df_eda.
 ↪columns:
    score_change = df_eda['final_credit_score'] - df_eda['initial_credit_score']
    sns.histplot(score_change.dropna(), bins=20, kde=True)
    plt.title('Credit Score Change Distribution')
    plt.xlabel('Final - Initial Credit Score')
    plt.ylabel('Count')
    plt.show()

# Scatter: monthly_income vs. monthly_debit
sns.scatterplot(x='monthly_income', y='monthly_debit', data=df_eda)
plt.title('Monthly Income vs. Monthly Debit')
plt.xlabel('Monthly Income')
plt.ylabel('Monthly Debit')
plt.show()

# Boxplot: ending_balance by occupation
if 'occupation' in df_eda.columns:
    plt.figure(figsize=(10,5))
    sns.boxplot(x='occupation', y='ending_balance', data=df_eda)
    plt.title('Ending Balance by Occupation')
    plt.xlabel('Occupation')
    plt.ylabel('Ending Balance')
    plt.xticks(rotation=45, ha='right')
    plt.tight_layout()
    plt.show()

# Scatter: monthly_invest_return_pct vs. final_credit_score
if 'monthly_invest_return_pct' in df_eda.columns and 'final_credit_score' in␣
 ↪df_eda.columns:
    sns.scatterplot(x='monthly_invest_return_pct', y='final_credit_score',␣
 ↪data=df_eda)
    plt.title('Investment Return % vs. Final Credit Score')
    plt.xlabel('Monthly Investment Return (%)')
    plt.ylabel('Final Credit Score')
    plt.show()

# Outlier highlighting for ending_balance and monthly_debit (top/bottom 1%)
def highlight_outliers(series, quantile=0.01):
```

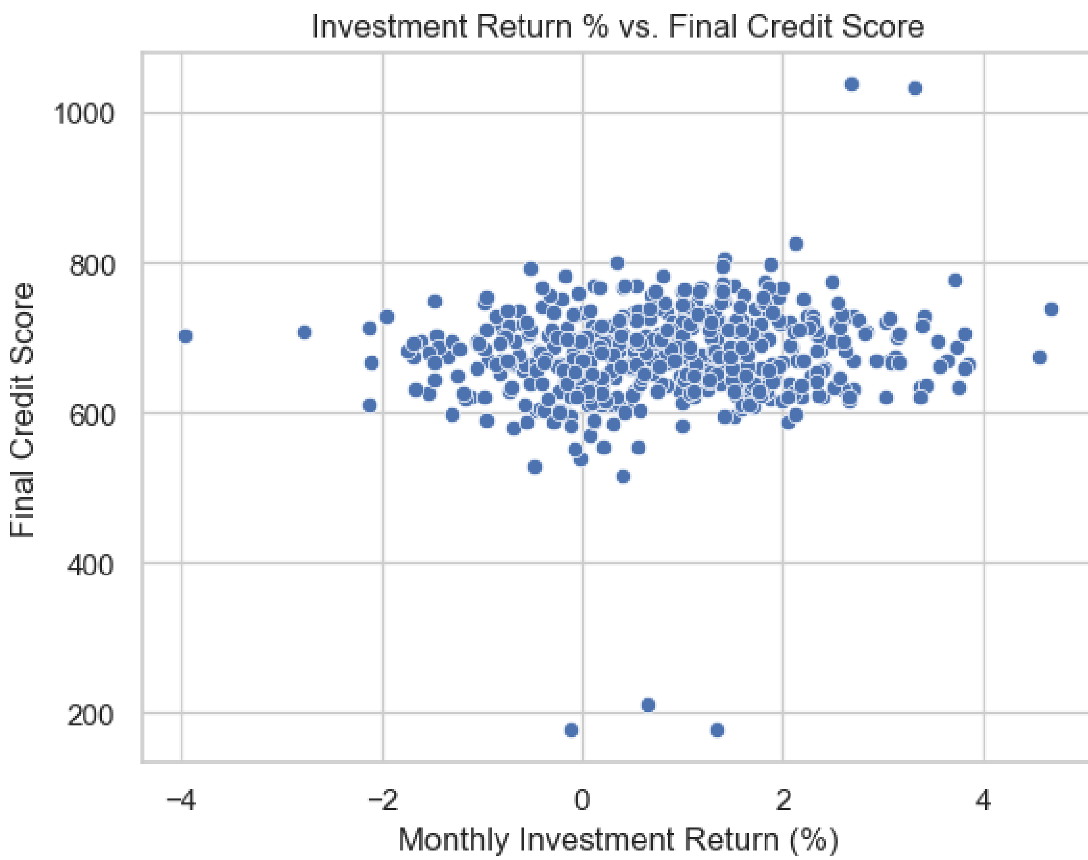
```
    lower = series.quantile(quantile)
    upper = series.quantile(1-quantile)
    return (series < lower) | (series > upper)

for col in ['ending_balance', 'monthly_debit']:
    if col in df_eda.columns:
        outlier_mask = highlight_outliers(df_eda[col])
        plt.figure(figsize=(8,2))
        sns.stripplot(x=df_eda[col], color='gray', alpha=0.5)
        sns.stripplot(x=df_eda.loc[outlier_mask, col], color='red', alpha=0.8)
        plt.title(f'Outliers in {col} (red = top/bottom 1%)')
        plt.xlabel(col)
        plt.show()
```

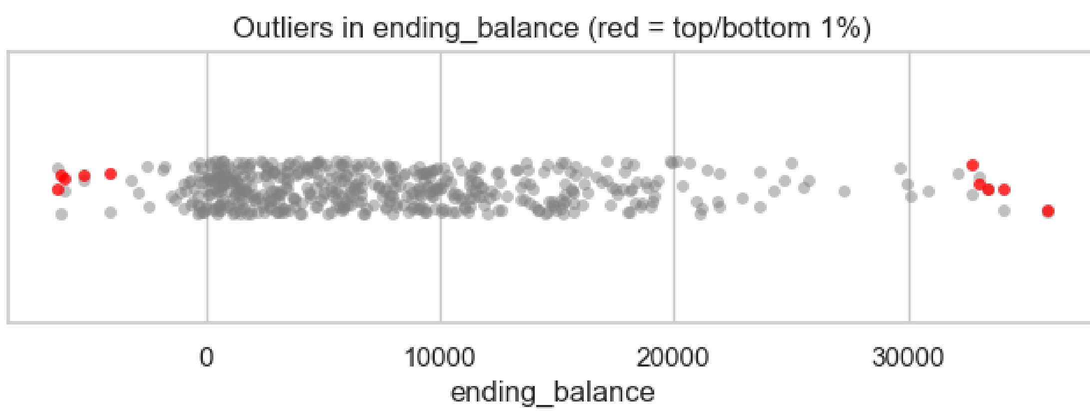


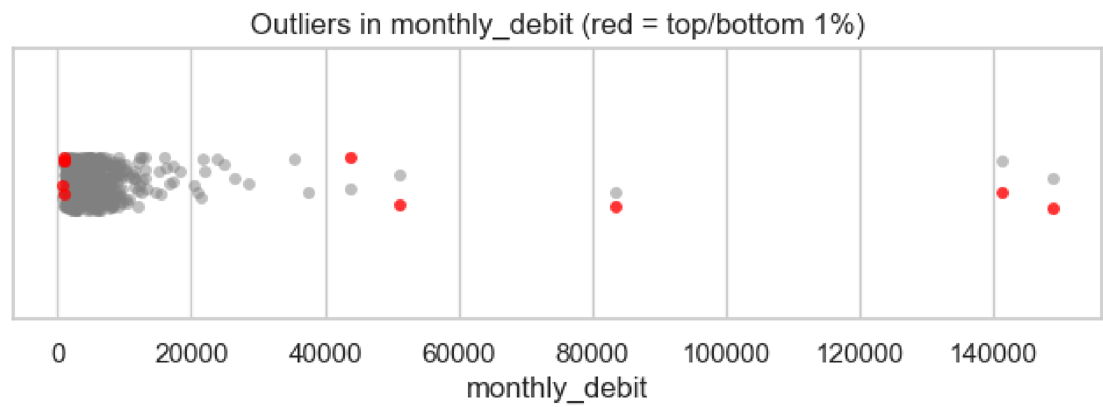
Credit Score Change Distribution
Count
500
400
300
200
100
0
−400
−200
0
200
400
Final - Initial Credit Score


Monthly Income vs. Monthly Debit
Monthly Debit
0
20000
40000
60000
80000
100000
120000
140000
2000
4000
6000
8000
10000
Monthly Income


Ending Balance by Occupation
Ending Balance
0
10000
20000
30000
Teacher
Self-employed
Retail
Engineer
Healthcare
Finance
Manager
Student
Technician
Unemployed
Occupation


Investment Return % vs. Final Credit Score
Final Credit Score
Monthly Investment Return (%)
1000
800
600
400
200
−4
−2
0
2
4


Outliers in ending_balance (red = top/bottom 1%)
ending_balance
0
10000
20000
30000



0.3 Part 2.2: AI-generated summaries

[3]:
```
# This cell provides consolidated EDA helpers and an AI-assisted summarizer.

from pathlib import Path

OUT_DIR = Path('data')
OUT_DIR.mkdir(parents=True, exist_ok=True)

def summary_statistics(df: pd.DataFrame):
    numeric_cols = df.select_dtypes(include=["number"]).columns.tolist()
    cat_cols = df.select_dtypes(include=["object"]).columns.tolist()
    stats = {"rows": len(df), "numeric": {}, "categorical_top": {}}
    if numeric_cols:
        stats['numeric'] = df[numeric_cols].describe().to_dict()
    for c in cat_cols:
        stats['categorical_top'][c] = df[c].value_counts(dropna=False).head(10).
 ↪to_dict()
    return stats


def detect_anomalies(df: pd.DataFrame, numeric_cols: list) -> pd.DataFrame:
    if not numeric_cols:
        return pd.DataFrame()
    num = df[numeric_cols].copy()
    mu = num.mean()
    sigma = num.std(ddof=0).replace(0, np.nan)
    z = (num - mu) / sigma
    z_abs = z.abs()
    z_mask = (z_abs > 3).any(axis=1)

    iqr_mask = pd.Series(False, index=df.index)
```

```
    for c in numeric_cols:
        col = df[c]
        if col.dropna().empty:
            continue
        q1 = col.quantile(0.25); q3 = col.quantile(0.75)
        iqr = q3 - q1
        low = q1 - 1.5 * iqr; high = q3 + 1.5 * iqr
        iqr_mask = iqr_mask | ((col < low) | (col > high))

    combined = z_mask | iqr_mask
    anomalies = df[combined].copy()
    if not anomalies.empty:
        anomalies['_max_abs_z'] = z_abs.loc[anomalies.index].max(axis=1)
    return anomalies


def generate_ai_summaries(stats, corr_matrix, anomalies, df):
    # Build a short prompt-like summary for Gemini to consume
    lines = [f"rows: {stats.get('rows')}"]
    numeric = stats.get('numeric', {})
    for col in ['monthly_income','monthly_credit','monthly_debit','ending_balance','monthly_invest_return_
        try:
            m = numeric[col]['mean']
            lines.append(f"mean_{col}: {m:.2f}")
        except Exception:
            pass

    corr_lines = []
    try:
        if corr_matrix is not None:
            pairs = []
            cols = corr_matrix.columns.tolist()
            for i,a in enumerate(cols):
                for j,b in enumerate(cols):
                    if i>=j: continue
                    v = corr_matrix.iloc[i,j]
                    if abs(v) >= 0.4:
                        pairs.append((a,b,float(v)))
            pairs = sorted(pairs, key=lambda x: -abs(x[2]))
            for a,b,v in pairs[:6]:
                corr_lines.append(f"{a} vs {b}: {v:.2f}")
    except Exception:
        pass
```

```
    prompt_body = "\n".join(lines + ["--- correlations ---"] + corr_lines +␣
↪[f"anomalies_count: {len(anomalies)}"])

    # Primary path: use Google GenAI (Gemini) if SDK and API key are present
    if 'genai' in globals() and genai is not None and 'types' in globals() and␣
↪types is not None and os.getenv('GOOGLE_API_KEY'):
        try:
            client = genai.Client(api_key=os.getenv('GOOGLE_API_KEY'))
            system = (
                "You are a data analyst. Based on the stats and correlations␣
↪provided, produce up to 6 short plain-English insights. "
                "Return a JSON array of objects with keys 'topic' and 'insight'.
↪ Each insight should be 1-2 sentences."
            )
            contents = [system + "\n\n" + prompt_body]
            response = client.models.generate_content(
                model="gemini-2.5-flash",
                contents=contents,
                config=types.GenerateContentConfig(system_instruction=system)
            )
            text = _extract_text(response)
            # Extract JSON substring if the model wraps the output
            start = text.find('[')
            end = text.rfind(']')
            if start != -1 and end != -1 and end > start:
                json_text = text[start:end+1]
                parsed = json.loads(json_text)
                out_lines = []
                for o in parsed[:6]:
                    topic = o.get('topic') or o.get('title') or 'insight'
                    insight = o.get('insight') or o.get('text') or o.
↪get('feedback') or ''
                    out_lines.append(f"- {topic}: {insight}")
                return "\n".join(out_lines)
            # fallback: return raw text if JSON not found
            return text
        except Exception as e:
            print(f"GenAI call failed: {e} - falling back to heuristic␣
↪summarizer")

    # Fallback heuristic (used only if GenAI not available)
    insights = []
    try:
        if 'monthly_income' in df.columns and 'monthly_invest_return_pct' in df.
↪columns:
```

```
            c = df[['monthly_income','monthly_invest_return_pct']].dropna().
↪corr().iloc[0,1]
            if math.isnan(c): c = 0.0
            if c>0.2:
                insights.append('Higher income weakly associates with higher␣
↪investment return pct.')
            elif c<-0.2:
                insights.append('Higher income tends to have lower investment␣
↪return pct in this sample.')
            else:
                insights.append('No strong relationship between income and␣
↪investment return pct.')
    except Exception:
        pass

    try:
        if 'monthly_income' in df.columns and 'ending_balance' in df.columns:
            c = df[['monthly_income','ending_balance']].dropna().corr().
↪iloc[0,1]
            if c>0.5:
                insights.append('Monthly income strongly correlates with ending␣
↪balance.')
            elif c>0.2:
                insights.append('Monthly income moderately correlates with␣
↪ending balance.')
            else:
                insights.append('Weak relationship between income and ending␣
↪balance.')
    except Exception:
        pass

    try:
        if 'monthly_debit' in df.columns and 'ending_balance' in df.columns:
            c = df[['monthly_debit','ending_balance']].dropna().corr().iloc[0,1]
            if c<-0.5:
                insights.append('Higher debits strongly associate with lower␣
↪ending balances.')
            elif c<-0.2:
                insights.append('Debits moderately negatively associate with␣
↪ending balance.')
            else:
                insights.append('No strong negative relationship between debits␣
↪and ending balance.')
    except Exception:
        pass
```

```
    try:
        if 'transaction_category_major' in df.columns:
            top = df['transaction_category_major'].value_counts().head(3).
↪to_dict()
            top_str = ', '.join([f"{k}({v})" for k,v in top.items()])
            insights.append(f"Top categories: {top_str}.")
    except Exception:
        pass

    try:
        if len(anomalies)==0:
            insights.append('Very few extreme outliers detected across numeric␣
↪fields.')
        else:
            s = anomalies.head(3)
            insights.append(f"Detected {len(anomalies)} anomalous rows. Sample␣
↪IDs: {', '.join(map(str, s.get('customer_id', s.index).tolist()[:3]))}.")
    except Exception:
        pass

    try:
        if 'initial_credit_score' in df.columns and 'final_credit_score' in df.
↪columns:
            changes = (df['final_credit_score'] - df['initial_credit_score']).
↪dropna()
            if not changes.empty:
                mean_change = changes.mean()
                if mean_change>2:
                    insights.append('Credit scores increased slightly on␣
↪average.')
                elif mean_change<-2:
                    insights.append('Credit scores decreased slightly on␣
↪average.')
                else:
                    insights.append('Average credit score change is small.')
    except Exception:
        pass

    insights = insights[:6]
    return '\n'.join([f"- {s}" for s in insights])
```

[7]:
```
# Run the consolidated EDA + AI summary on the dataframe `df_eda` if present␣
↪(falls back to `df`)
try:
    working_df = df_eda
except NameError:
```

```
    working_df = globals().get('df', None)

if working_df is None:
    raise RuntimeError('Could not find a dataframe to run EDA on (no df_eda or␣
 ↪df in notebook scope).')

stats = summary_statistics(working_df)
with open(OUT_DIR / 'eda_combined_stats.json', 'w', encoding='utf-8') as f:
    json.dump(stats, f, indent=2, default=lambda x: str(x))

numeric_cols = working_df.select_dtypes(include=['number']).columns.tolist()
# correlation
corr = None
if len(numeric_cols) >= 2:
    corr = working_df[numeric_cols].corr()
    # save a CSV of correlations for quick inspection
    corr.to_csv(OUT_DIR / 'correlations.csv')

# anomalies
anoms = detect_anomalies(working_df, numeric_cols)
anoms.to_csv(OUT_DIR / 'anomalies_combined.csv', index=False)

# AI or heuristic summary
ai_text = generate_ai_summaries(stats, corr, anoms, working_df)
with open(OUT_DIR / 'ai_summary.txt', 'w', encoding='utf-8') as f:
    f.write(ai_text)

print('\n=== Data Anomalies ===\n')
if anoms.empty:
    print('No anomalies detected.')
else:
    print(anoms.head(10).to_string(index=False))

print('\n=== AI / heuristic insights ===\n')
print(ai_text)
print(f"\nWrote combined EDA outputs to: {OUT_DIR.resolve()}")
```

```
=== Data Anomalies ===

customer_id       date  age    occupation  monthly_income  monthly_credit
monthly_debit  starting_balance  ending_balance  monthly_invest_gain
monthly_invest_return_pct  initial_credit_score  final_credit_score
transaction_category_major
customer_feedback  _max_abs_z
  CUST00008 2025-01-31   44       Finance         7823.06         8723.14
7201.270000          24270.85        25792.72               494.00
1.52                   759                  769                   education
```

```
Education investment continues; strong savings too.    2.604607
  CUST00011 2025-01-31   55       Student         3110.72         4170.34
22035.915826           2123.53         2634.51               121.59
1.97                   728                718                     dining
Dining was a treat, but aiming for higher savings.    1.440865
  CUST00012 2025-01-31   22       Manager         6930.78         8292.94
2132.040000          23506.19        29667.09                 0.00
-0.40                   731                741                 groceries
Groceries managed well; excellent progress on savings!    3.042570
  CUST00021 2025-01-31   36       Student         6495.48         8196.25
3628.920000          17371.65        21938.99               833.55
3.37                   638                633                 education
Education expenses met, excellent financial position overall.    4.338740
  CUST00023 2025-01-31   45       Finance         8577.36         9518.93
8448.620000          15233.93        16304.24               482.97
1.99                   673                668                 education
Education expenses are significant, but manageable with income.    2.384194
  CUST00036 2025-01-31   55       Finance         4359.44         7750.06
13107.640000          10704.38         5346.80                58.87
0.32                   656                646             entertainment
Entertainment costs very high, significantly impacted balance.    1.436190
  CUST00040 2025-01-31   23    Unemployed         4748.96         7150.13
2980.340000           9902.44        14072.24               614.77
3.74                   699                689                 education
Education expenses met; strong savings continue this month.    2.995034
  CUST00045 2025-01-31   27       Manager         6963.33         8055.31
4041.690000          25977.81        29991.42               270.10
0.80                   778                783                 groceries
Groceries managed; phenomenal savings, very well done!    3.087369
  CUST00047 2025-01-31   44       Finance         4936.63         5946.68
16739.800000           4445.26        -6347.86                 0.00
-0.01                   645                640                healthcare
Serious overspending, especially on healthcare. Immediate action needed.
1.932135
  CUST00049 2025-01-31   35 Self-employed         7775.38         9735.37
18380.080000           8361.95         -282.76                 0.00
-1.06                   704                694             entertainment
Entertainment spending excessive, resulted in an overdrawn account.    1.978276

=== AI / heuristic insights ===

- Income and Credit Activity: There is a very strong positive correlation (0.94)
between monthly income and monthly credit activity. This indicates that higher-
income individuals tend to have substantially more credit flowing into their
accounts.
- Account Balance Stability: An individual's starting balance is a powerful
predictor of their ending balance, with a correlation of 0.91. This suggests
that account balances are relatively stable or follow a consistent trend over
```

```
the period observed.
- Data Quality/Anomalies: A significant 15.2% of the records contain anomalies
(76 out of 500 rows). This high number warrants further investigation into
potential data quality issues or unusual financial behaviors.
- Spending vs. Income: Average monthly debits (6235.75) significantly exceed
both average monthly income (3866.87) and credit (4757.02). This suggests that
many individuals are spending more than their current income and credit inflows,
potentially relying on savings or other financial resources.
- Credit Score Predictability: An individual's initial credit score is a strong
predictor of their final credit score, with a correlation of 0.70. While some
change is possible, credit scores tend to show considerable stability over time.
- Income's Impact on Balances: Higher monthly income is strongly correlated with
a higher starting account balance (0.68). This indicates that a greater income
generally contributes to a stronger foundational financial position.

Wrote combined EDA outputs to: C:\Users\Jonas\OneDrive - Universiti
Malaya\UM2025-26\code\wie3007_indiv\data
```

0.4 Part 3: Data-preprocessing

[32]:
```python
# Use Gemini for sentiment and topic classification
def generate_sentiment_topic_gemini_batch(feedbacks, n_requests=10,␣
 ↪model="gemini-2.5-flash-lite", max_retries=3, retry_delay=5,␣
 ↪batch_delay_seconds=4):
    """Send feedbacks to Gemini in batches and return sentiment and topic maps.

    feedbacks: list of dicts, each with 'customer_id' and 'feedback'.
    Returns: {customer_id: {'sentiment': str, 'topic': str}}
    """
    if 'genai' not in globals() or genai is None or 'types' not in globals() or␣
 ↪types is None:
        raise RuntimeError("Google GenAI SDK not available.")

    GOOGLE_API_KEY = os.getenv("GOOGLE_API_KEY")
    if not GOOGLE_API_KEY:
        raise ValueError("GOOGLE_API_KEY not found.")

    client = genai.Client(api_key=GOOGLE_API_KEY)

    result_map = {}
    total = len(feedbacks)
    if total == 0:
        return result_map

    batch_size = max(1, math.ceil(total / n_requests))

    for i in range(0, total, batch_size):
```

```
        batch = feedbacks[i:i+batch_size]
        items_text = []
        for f in batch:
            items_text.append(f"ID: {f['customer_id']} | Feedback: {f['feedback']}")
        prompt_body = "\n".join(items_text)
        prompt = (
            "You are given multiple customer feedbacks (one per line in the format 'ID: <id> | Feedback: <text>').\n"
            "For each feedback, classify the sentiment as 'positive', 'neutral', or 'negative', and detect the topic as one of: 'savings', 'loan', 'investment', 'credit', 'dining', 'healthcare', 'utilities', 'shopping', 'education', 'transport', 'groceries', 'entertainment'.\n"
            "Return a JSON array of objects with fields {\"customer_id\": <id>, \"sentiment\": <sentiment>, \"topic\": <topic>} and NOTHING ELSE.\n"
            "Respond with valid JSON only.\n\n"
            f"Feedbacks:\n{prompt_body}"
        )

        attempt = 0
        resp_text = None
        last_exception = None
        while attempt < max_retries:
            try:
                print(f"Sending Gemini batch request for feedbacks {i} to {i+len(batch)-1}...")
                response = client.models.generate_content(
                    model=model,
                    contents=[prompt],
                    config=types.GenerateContentConfig(system_instruction="Classify sentiment and topic for customer feedbacks.")
                )
                resp_text = _extract_text(response)
                if resp_text:
                    break
                else:
                    raise RuntimeError('Empty response from Gemini')
            except Exception as e:
                last_exception = e
                attempt += 1
                wait = retry_delay * (2 ** (attempt - 1))
                print(f"Gemini batch request failed (attempt {attempt}/{max_retries}): {e}. Retrying in {wait}s...")
                time.sleep(wait)
```

```
        if resp_text is None:
            raise RuntimeError(f"Gemini failed for batch starting at index {i}␣
↪after {max_retries} attempts.") from last_exception

        if resp_text.startswith('```json') and resp_text.endswith('```'):
            resp_text = resp_text[7:-3].strip()
        elif resp_text.startswith('```') and resp_text.endswith('```'):
            resp_text = resp_text[3:-3].strip()
        try:
            parsed = json.loads(resp_text)
        except Exception:
            start = resp_text.find('[')
            end = resp_text.rfind(']')
            if start != -1 and end != -1:
                parsed = json.loads(resp_text[start:end+1])

        if not isinstance(parsed, list):
            raise ValueError(f"Invalid response for batch {i}.")

        for obj in parsed:
            cid = obj.get('customer_id')
            sent = obj.get('sentiment')
            top = obj.get('topic')
            if cid and sent and top:
                result_map[str(cid)] = {'sentiment': str(sent), 'topic':␣
↪str(top)}

        time.sleep(batch_delay_seconds)

    return result_map
```

[33]:
```
# Data Preprocessing using LLMs / SLMs

# Copy df_eda to df_preproc and drop ID columns
df_preproc = df_eda.copy()
df_preproc = df_preproc.drop(columns=['customer_id'])

# 1. Handle missing values
num_cols = df_preproc.select_dtypes(include=['number']).columns
cat_cols = df_preproc.select_dtypes(include=['object']).columns.tolist()

# Exclude text fields from categorical encoding
text_fields = ['customer_feedback']
cat_encode_cols = [col for col in cat_cols if col not in text_fields]

# Impute numerics with median
if len(num_cols) > 0:
```

```
    num_imputer = SimpleImputer(strategy='median')
    df_preproc[num_cols] = num_imputer.fit_transform(df_preproc[num_cols])

# Impute categoricals with mode
if len(cat_encode_cols) > 0:
    cat_imputer = SimpleImputer(strategy='most_frequent')
    df_preproc[cat_encode_cols] = cat_imputer.
 ↪fit_transform(df_preproc[cat_encode_cols])

# 2. Normalize numerical features
if len(num_cols) > 0:
    scaler = StandardScaler()
    df_preproc[num_cols] = scaler.fit_transform(df_preproc[num_cols])

# 3. Encode categorical variables (excluding text fields)
if len(cat_encode_cols) > 0:
    for col in cat_encode_cols:
        le = LabelEncoder()
        df_preproc[col] = le.fit_transform(df_preproc[col].astype(str))

# 4. Process text fields (customer_feedback)
# Impute missing feedback with 'No feedback provided'
if 'customer_feedback' in df_preproc.columns:
    df_preproc['customer_feedback'] = df_preproc['customer_feedback'].
 ↪fillna('No feedback provided')

    # Prepare feedbacks for Gemini
    feedback_list = []
    for idx, row in df_preproc.iterrows():
        feedback_list.append({'customer_id': row.get('customer_id', idx),␣
 ↪'feedback': row['customer_feedback']})

    # Get sentiments and topics from Gemini
    st_map = generate_sentiment_topic_gemini_batch(feedback_list,␣
 ↪n_requests=10, batch_delay_seconds=4)
    df_preproc['feedback_sentiment'] = df_preproc.apply(lambda row: st_map.
 ↪get(str(row.get('customer_id', row.name)),{}).get('sentiment', 'neutral'),␣
 ↪axis=1)
    df_preproc['feedback_topic'] = df_preproc.apply(lambda row: st_map.
 ↪get(str(row.get('customer_id', row.name)), {}).get('topic', 'other'), axis=1)


print('Preprocessing complete. Sample:')
display(df_preproc.head())
```

```
Sending Gemini batch request for feedbacks 0 to 49…
Sending Gemini batch request for feedbacks 50 to 99…
```

```
Sending Gemini batch request for feedbacks 100 to 149…
Sending Gemini batch request for feedbacks 150 to 199…
Sending Gemini batch request for feedbacks 200 to 249…
Sending Gemini batch request for feedbacks 250 to 299…
Sending Gemini batch request for feedbacks 300 to 349…
Sending Gemini batch request for feedbacks 350 to 399…
Sending Gemini batch request for feedbacks 400 to 449…
Sending Gemini batch request for feedbacks 450 to 499…
Preprocessing complete. Sample:

   date       age  occupation  monthly_income  monthly_credit  monthly_debit  \
0   0.0  0.531674    0.939857       -0.072768       -0.376958      -0.343048
1   0.0 -1.639164    0.939857        0.720964        0.591754       0.060636
2   0.0  0.531674    0.210154       -0.196258       -0.262615      -0.059628
3   0.0  0.983932    0.210154        0.038221        0.144418       0.022654
4   0.0 -0.644196   -0.154697        0.940283        0.532908      -0.372229

   starting_balance  ending_balance  monthly_invest_gain  \
0          0.525168        0.675998            -0.304163
1          0.682625        0.547825             1.155685
2         -0.698189       -0.769307            -0.414899
3         -0.120381       -0.248586             0.847304
4          0.371673        0.903423             1.031620

   monthly_invest_return_pct  initial_credit_score  final_credit_score  \
0                  -0.268976             -0.239284           -0.077399
1                   0.702920             -0.960144           -0.606704
2                  -0.053884              0.337403            0.119199
3                   1.077339              1.408395            1.132439
4                   0.782584              0.522767            0.330921

   transaction_category_major  customer_feedback feedback_sentiment  \
0                   -1.511365          -1.152617           negative
1                    0.140400          -0.119693            neutral
2                   -1.511365          -1.173554           negative
3                    1.792165           1.471567           positive
4                   -1.511365          -0.719906           negative

  feedback_topic
0         dining
1         dining
2         dining
3         dining
4         dining
```