

Loan Analysis & Insights for Risk Identification

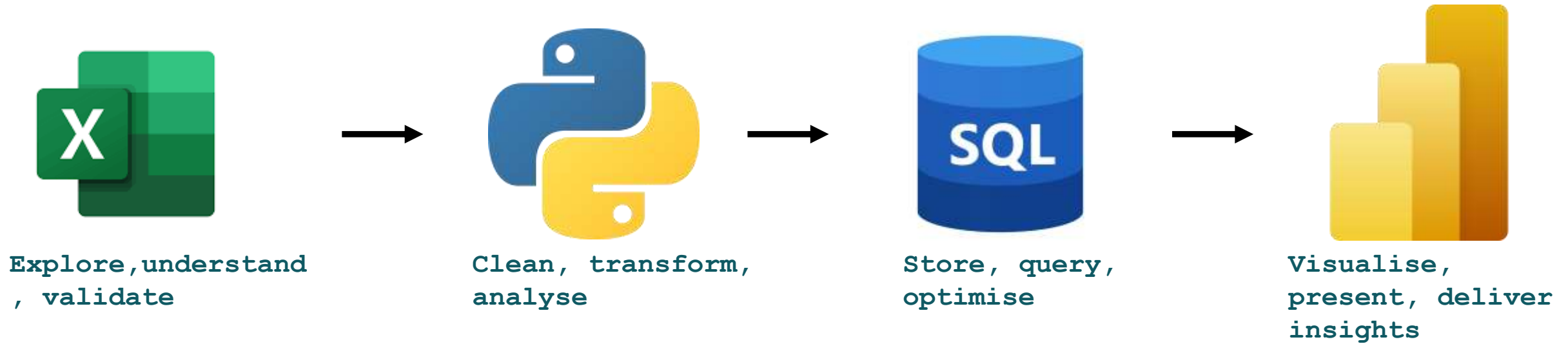
By - Sandeep Kumar

Tools Used:

Python | Pandas | NumPy | Seaborn | SQL | Power BI | Excel

End-to-End Data Analysis Workflow

(Excel → Python → SQL → Power BI)



Raw Data → Processing & Analysis → Database → Dashboard & Insights

Problem Statement

Banks give loans to many customers, but some customers do not repay, which causes financial loss.

This project aims to:

- Analyze customer and loan-related data
- Identify key factors that influence default
- Detect high-risk borrower profiles
- Provide actionable insights that help minimize losses
- Support better credit decision-making using data

Business Impact

- Improve approval quality
- Reduce risk exposure
- Enhance credit policies using data-backed insights



Excel – Initial Data Understanding

Before moving to Python, the dataset was first explored in Excel to perform basic validation and early insights.

1. Data Import & Structure Check

- Loaded the raw dataset into Excel
- Verified total rows, columns, and header format
- Ensured no misaligned or broken columns

2. Basic Data Quality Checks

- Used **filters** to spot blank cells, inconsistent values
- Checked for **duplicate rows** using *Remove Duplicates*



Excel – Initial Data Understanding

3. Quick Summary Using Excel Tools

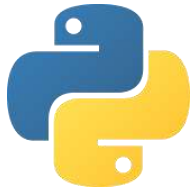
- Created **Pivot Tables** to review:
 - Loan Status distribution (Good vs Default)
 - Loan Purpose counts
 - Grade-wise loan distribution
 - Loan amount ranges

4. Initial Trend & Pattern Identification

- Created quick charts:
 - Loan Amount histogram
 - Interest Rate distribution
 - Loan Purpose bar chart

5. Export for Python

- Cleaned file saved as **.xlsx / .csv**
- Handed over to Python for advanced cleaning & EDA



Data Summary

Dataset Overview

The dataset contains information about customers, their loan details, and their repayment status. It helps us understand the factors that influence whether a loan is repaid or defaulted.

Dataset Size

- Total Rows: 38576
- Total Columns: 24

Key Columns Include

- Customer Information:** age, income, employment type
- Loan Details:** loan amount, interest rate, loan term
- Financial Indicators:** credit score, debt-to-income ratio
- Loan Status:** Good loan / default



Data Cleaning & Preparation

1. Missing Values Handling

- Checked missing values in all columns
- The column **emp_title** had missing values
- Filled missing emp_title with **"Unknown"**

2. Duplicate Records

- Verified for duplicated entries
- **Total duplicate rows: 0**

3. Outlier Detection

- Identified outliers using boxplots
- Outliers were **not removed**, kept for analysis to avoid data loss

4. Fixing Data Types

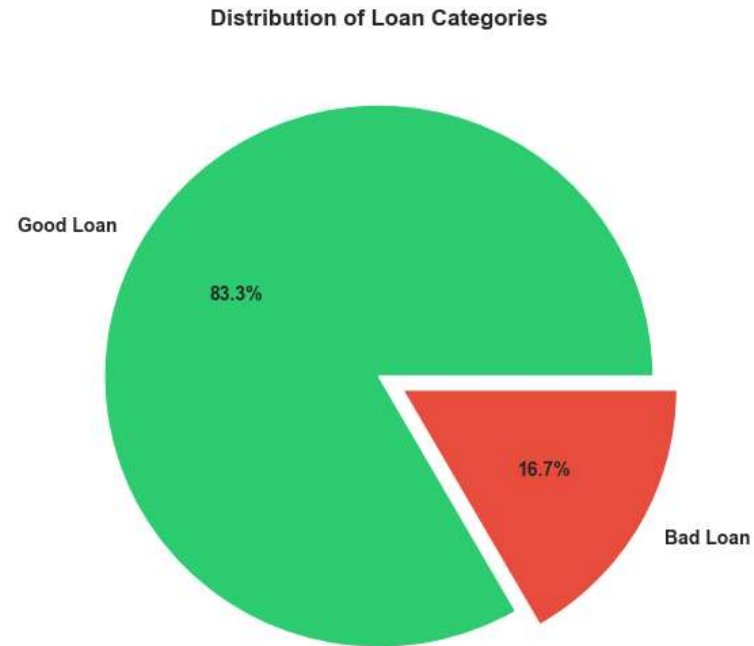
- Converted date-related columns into proper datetime format:
 - issue_date
 - last_credit_pull_date
 - last_payment_date
 - next_payment_date

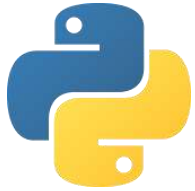


Dependent Variable

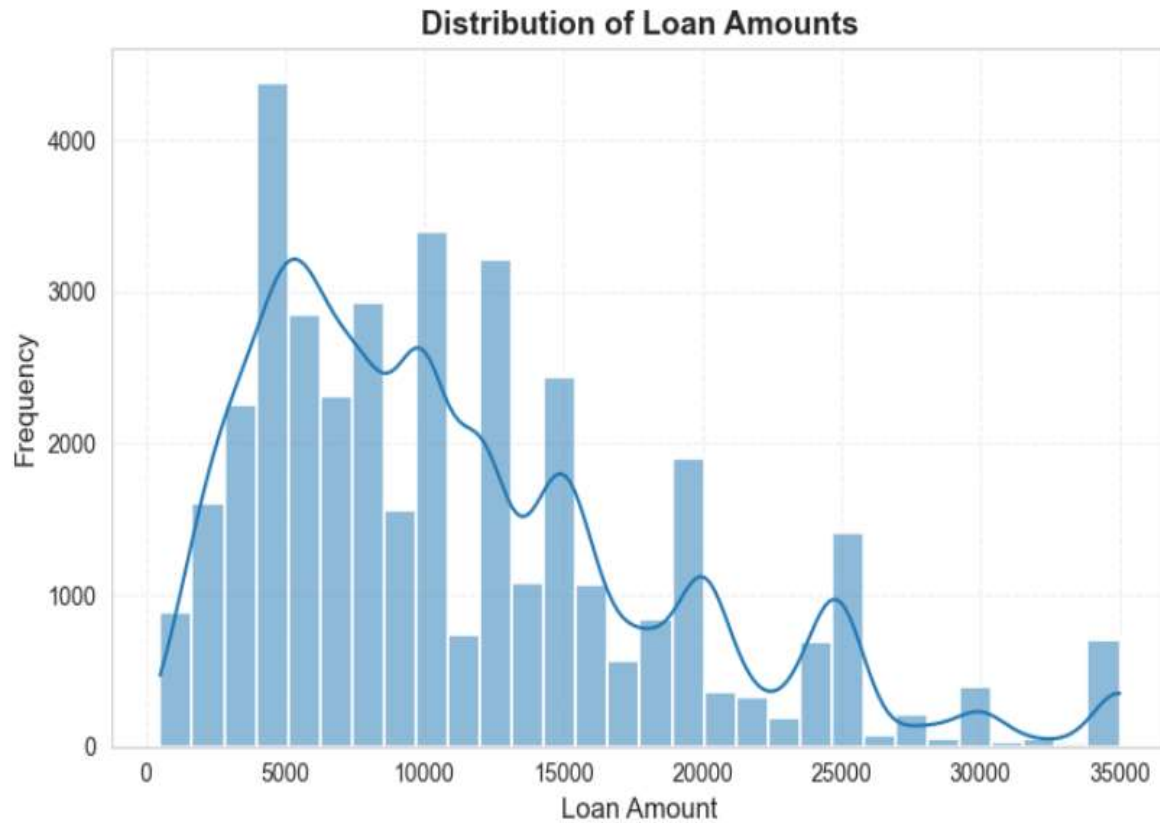
★ `loan_status` (Good Loan vs Default Loan)

This column tells you whether a borrower **repaid the loan** or **defaulted**.





Exploratory Data Analysis (EDA)

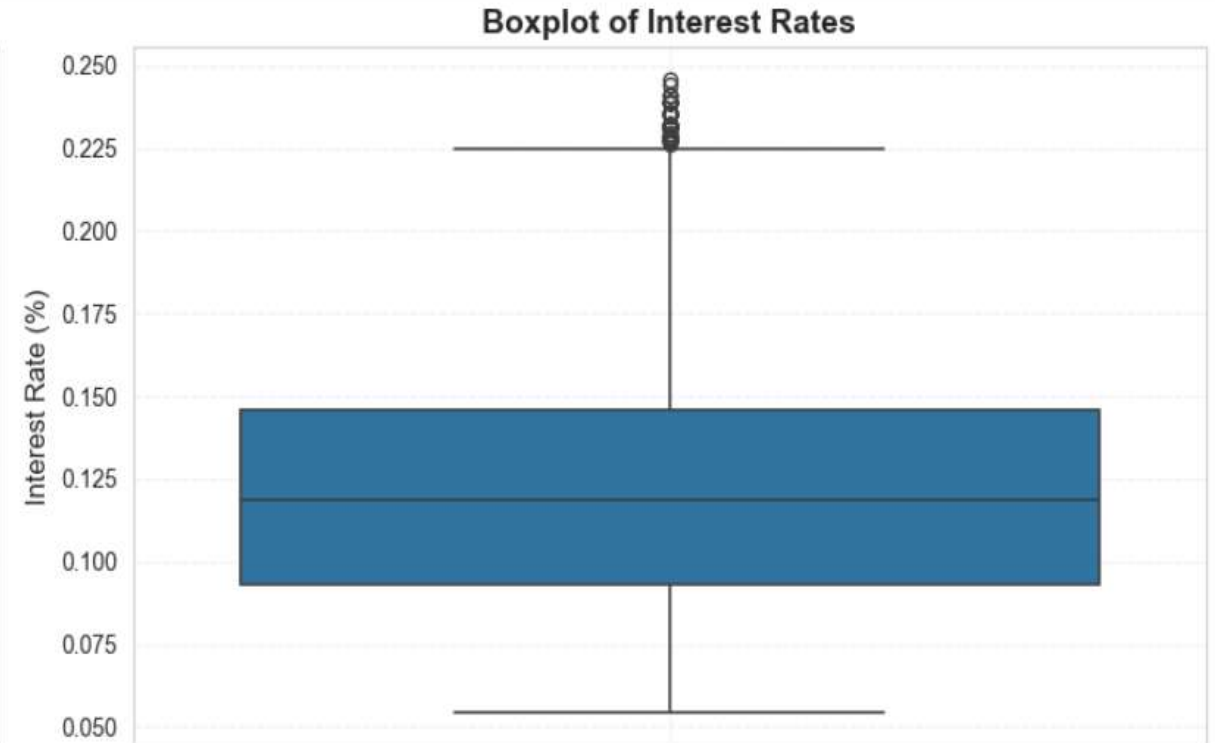
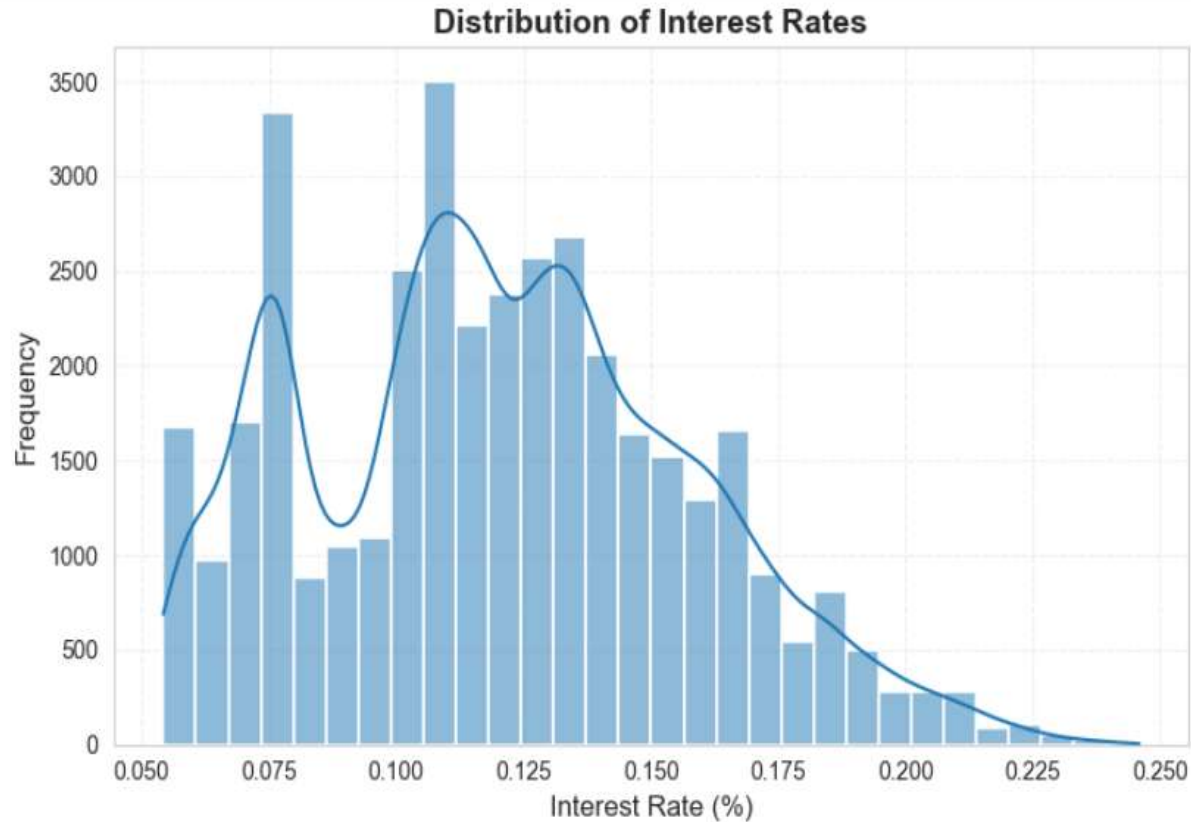


Loan Amount

- Most loan amounts lie between **\$5,000 and \$15,000**.
- The distribution is **right-skewed**, meaning some customers take very high loan amounts.
- Boxplot shows **clear outliers**, but we did **not remove them** because they represent real high-value loans



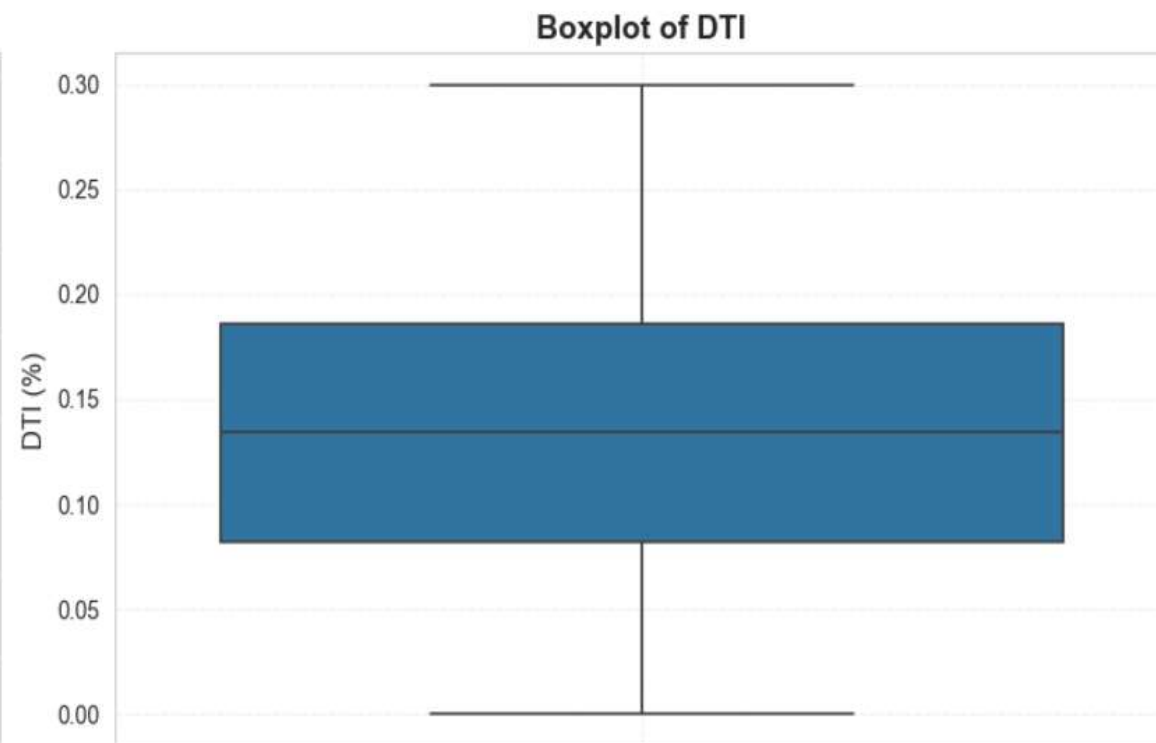
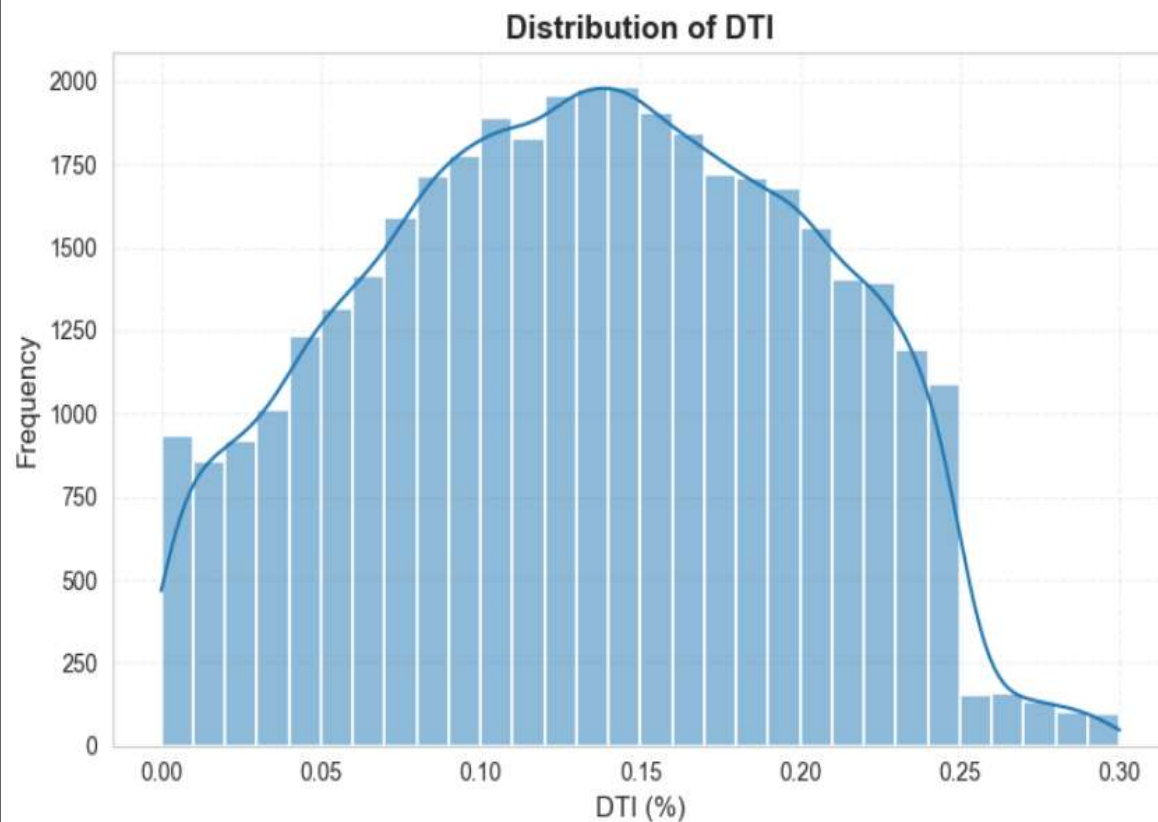
Exploratory Data Analysis (Continued)



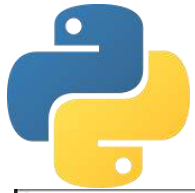
- Interest rates are mostly between **8% and 14%**.
- The distribution is **slightly right-skewed**, with a few customers getting higher interest rates.
- Outliers are present at the upper end (18%-24%).
- These outliers are expected due to risk-based pricing.



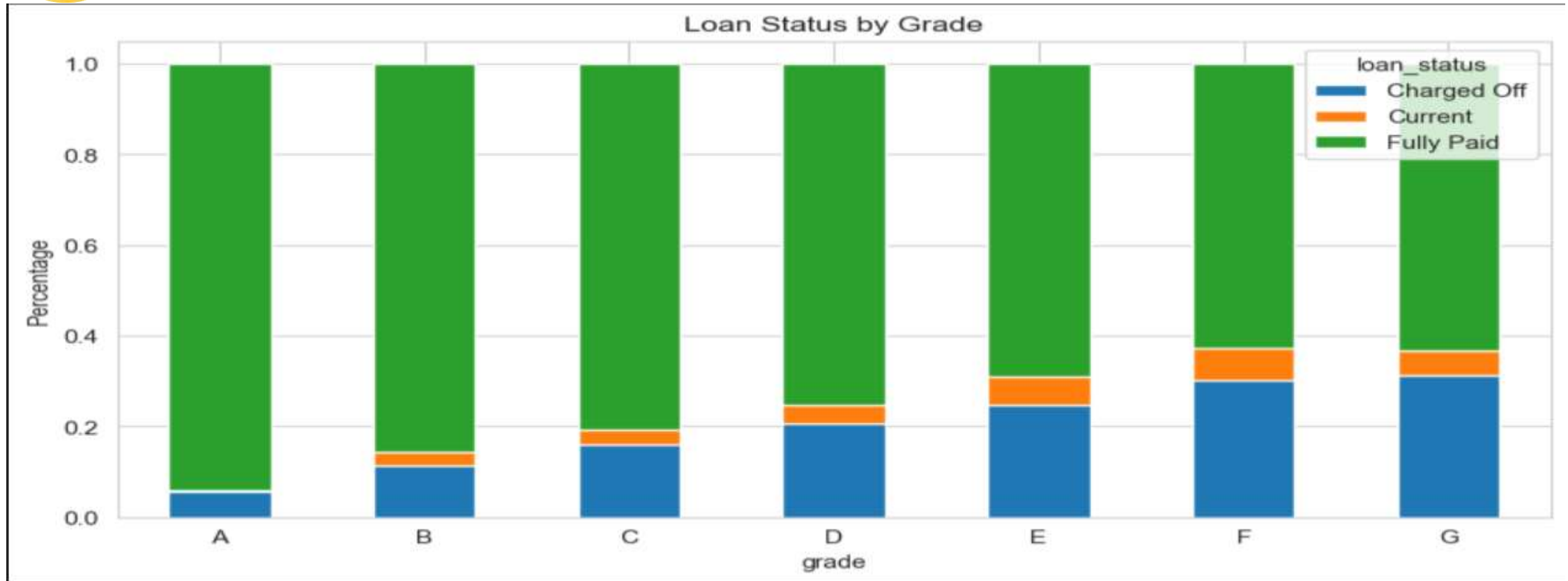
Exploratory Data Analysis (Continued)



- Most DTI values lie between **8%–18%**.
- Distribution is **slightly right-skewed**.
- **Median DTI \approx 13%**.
- Few **high DTI cases**, but **no major outliers**



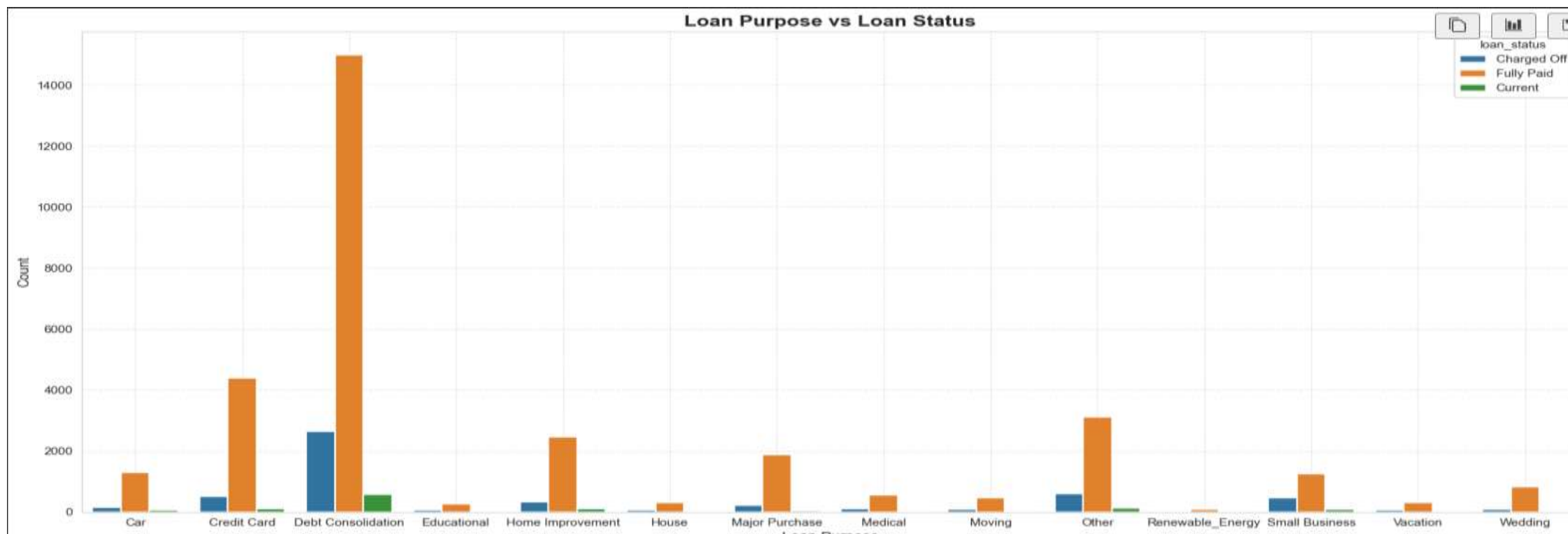
Exploratory Data Analysis (Continued)



- Higher grades (A, B, C) have **very low Charged-Off rates**.
- Lower grades (D, E, F, G) show **increasing default (Charged-Off) percentages**.
- Most loans across all grades are **Fully Paid**, but risk clearly increases as grade decreases.
- This confirms that **loan grade is strongly linked to credit risk**.



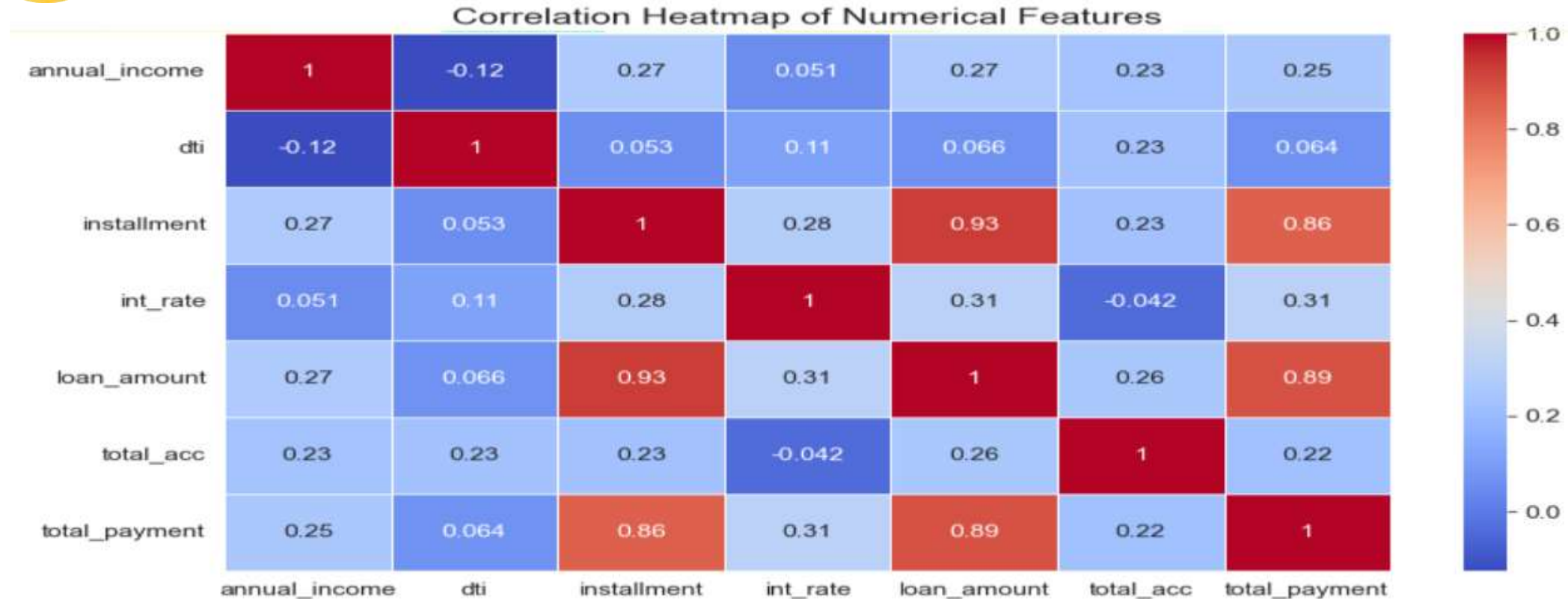
Exploratory Data Analysis (Continued)



- **Debt Consolidation** is the most common loan purpose; it also has a high number of **Charged-Off** loans.
- Credit Card, Home Improvement, and Other categories also show moderate levels of default.
- Very few loans across all categories remain in **Current** status.
- Loan purpose can help identify **high-risk borrower segments**.



Exploratory Data Analysis (Continued)



- **Installment** and **Loan Amount** show **very high correlation**.
- **Total Payment** is strongly correlated with both **Loan Amount** and **Installment**.
- **Annual Income**, **DTI**, and **Interest Rate** have **weak correlations** with other features.
- No strong multicollinearity issues except the **Loan Amount** ↔ **Installment** pair



Key Insights from EDA

Loan Status

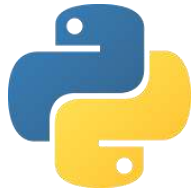
- Dataset is **imbalanced** → ~83% Good Loans, ~17% Bad Loans.

Loan Amount

- Most loan amounts fall between **\$5K–\$15K**.
- Higher loan amounts** are more common in **Current** loans.
- Borrowers with **higher loan amounts** are more likely to be **Charged Off**.

Interest Rate

- Charged-off loans** have **higher interest rates**.
- Fully Paid** loans have **lower interest rates**.
- Higher interest rates increase the chance of **default**.



Key Insights from EDA

DTI (Debt-to-Income Ratio)

- **Charged-off borrowers** have **higher DTI** than Fully Paid borrowers.
- Higher DTI increases the likelihood of **loan default**.

Loan Grade

- Lower grades (**E, F, G**) show **higher default rates**.
- Higher grades (**A, B, C**) indicate **lower risk**.

Loan Purpose

- **Debt Consolidation** is the largest category and has the **most defaults**.
- Other risky purposes: **Credit Card, Home Improvement, Other**.

Correlation Insights

- **Loan Amount ↔ Installment** show **very high correlation**.
- All other numerical features show **weak correlation → no multicollinearity issues**.



Feature Engineering

1. Date Feature Extraction

- Extracted `issue_year` and `issue_month` from the loan issue date
→ helps analyze trends over time.

2. Income Bucketing

- Grouped annual income into **Low**, **Medium**, **High**, and **Very High** categories
→ simplifies analysis and improves model interpretability.

3. Income-to-Loan Ratio

- Created a new feature: `income_to_loan_ratio = annual_income / loan_amount`
→ captures borrower repayment capacity more effectively.

4. DTI Bucketing

- Converted continuous DTI values into risk buckets
→ **Low DTI**, **Medium DTI**, **High DTI** groups.

5. Interest Rate Bucketing

- Converted continuous interest rates into labeled buckets such as:
Low ($\leq 10\%$), **Medium (10–15%)**, **High ($> 15\%$)**
- Helps group borrowers based on the cost of borrowing, making it easier to analyze default patterns.



SQL Data Storage & Querying

Why SQL?

After cleaning and preparing the dataset in Python, the final DataFrame was uploaded into a SQL database for:

- Efficient querying
- KPI calculations
- Portfolio segmentation
- Data validation
- Power BI connection

Database Setup:

- `CREATE DATABASE Bank loan data;`
- `USE Bank loan data;`



SQL Analysis & KPIs

Table Creation:

```
CREATE TABLE loans_cleaned AS  
SELECT * FROM loans_python_clean;
```

1. Portfolio Overview:

```
SELECT  
    COUNT(*) AS total_loans,  
    SUM(CASE WHEN loan_status='Good' THEN 1 END) AS good_loans,  
    SUM(CASE WHEN loan_status='Bad' THEN 1 END) AS bad_loans  
FROM loans_cleaned;
```

2. Good vs Bad Loan Percentage:

```
SELECT  
    loan_status,  
    ROUND(100 * COUNT(*) / (SELECT COUNT(*) FROM loans_clean), 2) AS percent  
FROM loans_cleaned  
GROUP BY loan_status;
```



SQL Analysis & KPIs

3. Grade-wise Risk:

```
SELECT
    grade,
    SUM(CASE WHEN loan_status='Bad' THEN 1 END) AS bad_loans
FROM loans_cleaned
GROUP BY grade;
```

4. Interest Rate Trend Using Window Function:

```
SELECT
    issue_date,
    COUNT(*) AS loans_issued,
    SUM(COUNT(*)) OVER (ORDER BY issue_date) AS cumulative_loans
FROM loans_clean
GROUP BY issue_date;
```



SQL Analysis & KPIs

5. CTE for High-Risk Segments:

```
WITH risky AS (  
    SELECT *  
    FROM loans_clean  
    WHERE dti > 20 AND interest_rate > 15  
)  
SELECT COUNT(*) AS high_risk_borrowers  
FROM risky;
```

"The cleaned SQL table served as the data source for Power BI, enabling real-time updates, dynamic filtering, and smooth KPI dashboards."



Visual Insights from Dashboards





Visual Insights from Dashboards (Continued)

Insights from Summary Dashboard

1. High Loan Success Rate

- **86.18% of all loans issued are Good Loans**, indicating strong repayment behavior.

2. Default Level is Moderate but Significant

- **13.82% loans are in default**, resulting in **\$65.53M** total defaulted amount.

3. Good Loans Drive Most of the Revenue

- Good loans recovered **\$435.79M**, far higher than other segments.

4. Interest Rate Difference Explains Risk

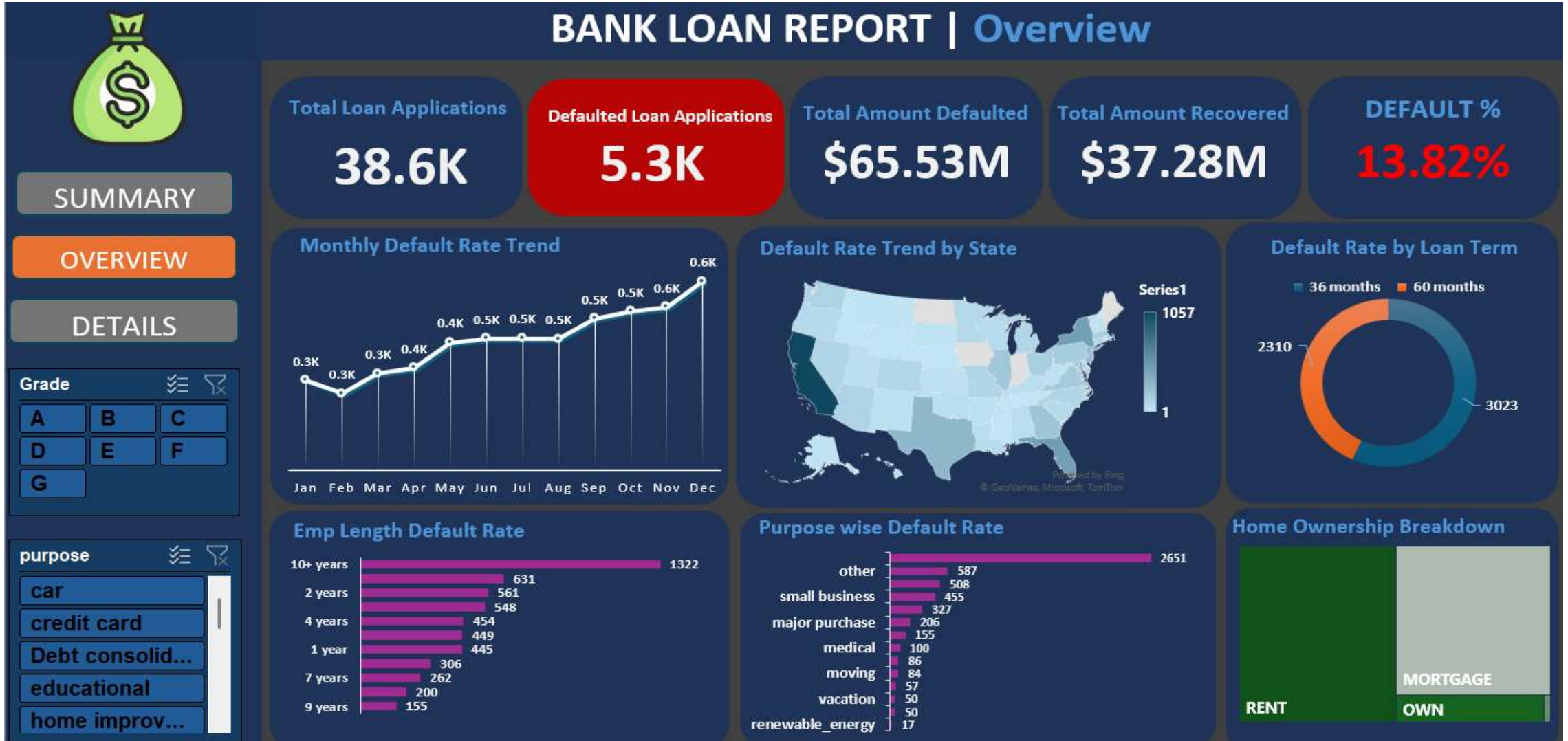
- Charged-off loans have **higher interest rates** (13.88%+) compared to Fully Paid (11.64%).

5. Loan Purpose & Grade Affect Risk Profile

- Filters (Grade & Purpose) allow identifying high-risk segments like **lower grades** and **Debt Consolidation** loans.



Visual Insights from Dashboards (Continued)





Visual Insights from Dashboards (Continued)

Insights from Overview Dashboard

1. Default Rate is Gradually Increasing

- Monthly trend shows defaults rising from **0.3K in Jan to 0.6K in Dec** → consistent upward risk pattern.

2. State-wise Defaults Vary Significantly

- Some states show **very high default concentration**, while others remain low → geographic risk differences.

3. Longer Loan Terms Have Higher Default Rates

- **60-month loans** default more than **36-month loans** → longer commitments increase risk.

4. Certain Loan Purposes Are High Risk

- Highest defaults come from **Other, Small Business, and Debt Consolidation** categories.

5. Employment Length Doesn't Guarantee Low Risk

- Even borrowers with **10+ years experience** show high defaults → stability doesn't always mean safe borrowing.

Final Recommendations

- **Tighten loan approval rules** for high-risk segments (low grades: E, F, G) .
- **Increase interest rates** or add stricter checks for borrowers with **high DTI** or **high loan amounts**.
- **Strengthen verification** for high-risk loan purposes (Debt Consolidation, Small Business, Other)
- **Promote shorter loan terms** (36-month) to reduce default probability.
- **Use automated alerts** for risky profiles (high DTI, high interest rate, long loan term) .

Conclusion

- This project analyzed **loan applications, borrower profiles, and repayment behavior** using Python and Power BI.
- Clear patterns emerged: higher **DTI**, higher **interest rates**, lower **grades**, and certain **loan purposes** increase default risk.
- Insights help the business **improve approval policies, identify high-risk customers, and reduce default losses**.
- Overall, the analysis supports **smarter credit decisions** and better **portfolio risk management**.