Exploratory Data Analysis (EDA) Report – Loan Dataset

Platform: Microsoft Azure Databricks
Language: PySpark (in Databricks notebooks)

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1. Dataset Overview

The dataset contains information about loan applicants, their demographic and financial details, and the status of their loan approval.

Column	Type	Description
Loan_ID	String	Unique identifier for the loan
Gender	String	Applicant's gender
Married	String	Marital status
Dependents	String	Number of dependents (0, 1, 2, 3+)
Education	String	Graduate or Not Graduate
Self_Employed	String	Employment status
ApplicantIncome	Integer	Income of the primary applicant
CoapplicantIncome	Double	Income of the co-applicant
LoanAmount	Integer	Loan amount requested (in thousands)
Loan_Amount_Term	Integer	Term of loan in months
Credit_History	Integer	Credit history (1 = good, 0 = bad)
Property_Area	String	Area where property is located (Urban/Rural/etc)
Loan_Status	String	Target variable (Y = Approved, N = Rejected)

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2. Data Loading & Preparation

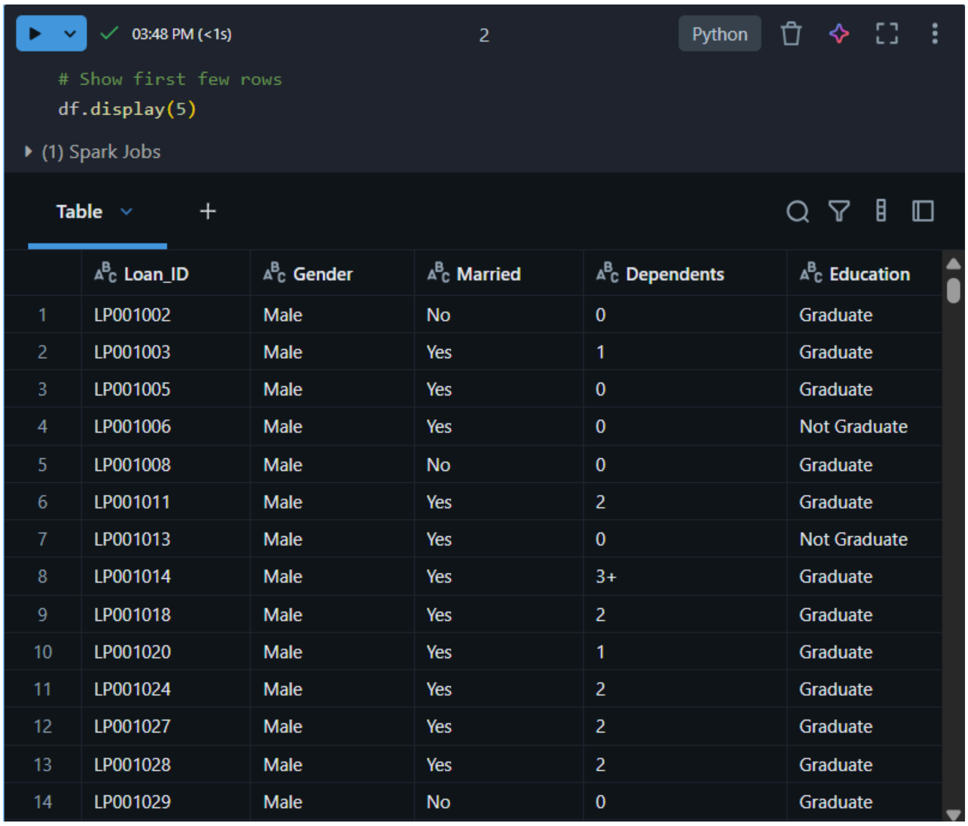
File was uploaded using Databricks UI → `/FileStore/tables/LoanData__1_-1.csv`

Loaded with PySpark using:

```
df = spark.read.csv("/FileStore/tables/LoanData__1_-1.csv", header=True,
inferSchema=True)
```

Show the first few rows

```
df.display(5)
```



	Loan_ID	Gender	Married	Dependents	Education
1	LP001002	Male	No	0	Graduate
2	LP001003	Male	Yes	1	Graduate
3	LP001005	Male	Yes	0	Graduate
4	LP001006	Male	Yes	0	Not Graduate
5	LP001008	Male	No	0	Graduate
6	LP001011	Male	Yes	2	Graduate
7	LP001013	Male	Yes	0	Not Graduate
8	LP001014	Male	Yes	3+	Graduate
9	LP001018	Male	Yes	2	Graduate
10	LP001020	Male	Yes	1	Graduate
11	LP001024	Male	Yes	2	Graduate
12	LP001027	Male	Yes	2	Graduate
13	LP001028	Male	Yes	2	Graduate
14	LP001029	Male	No	0	Graduate

The schema was verified using `df.printSchema()`.

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# Schema
df.printSchema()
```

```
root
 |-- Loan_ID: string (nullable = true)
 |-- Gender: string (nullable = true)
 |-- Married: string (nullable = true)
 |-- Dependents: string (nullable = true)
 |-- Education: string (nullable = true)
 |-- Self_Employed: string (nullable = true)
 |-- ApplicantIncome: integer (nullable = true)
 |-- CoapplicantIncome: double (nullable = true)
 |-- LoanAmount: integer (nullable = true)
 |-- Loan_Amount_Term: integer (nullable = true)
 |-- Credit_History: integer (nullable = true)
 |-- Property_Area: string (nullable = true)
 |-- Loan_Status: string (nullable = true)
```

Missing values and data consistency were checked using:

```
df.select([sum(col(c).isNull().cast("int")).alias(c) for c in
df.columns]).display()
```

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# 3. Null Values
from pyspark.sql.functions import col, sum

df.select([sum(col(c).isNull().cast("int")).alias(c) for c in df.columns]).display
()
```

(2) Spark Jobs

Table

	Loan_ID	Gender	Married	Dependents	Education
1	0	13	3	15	0

Duplicates removed and basic cleaning done (e.g., converting "3+" dependents to numeric value).

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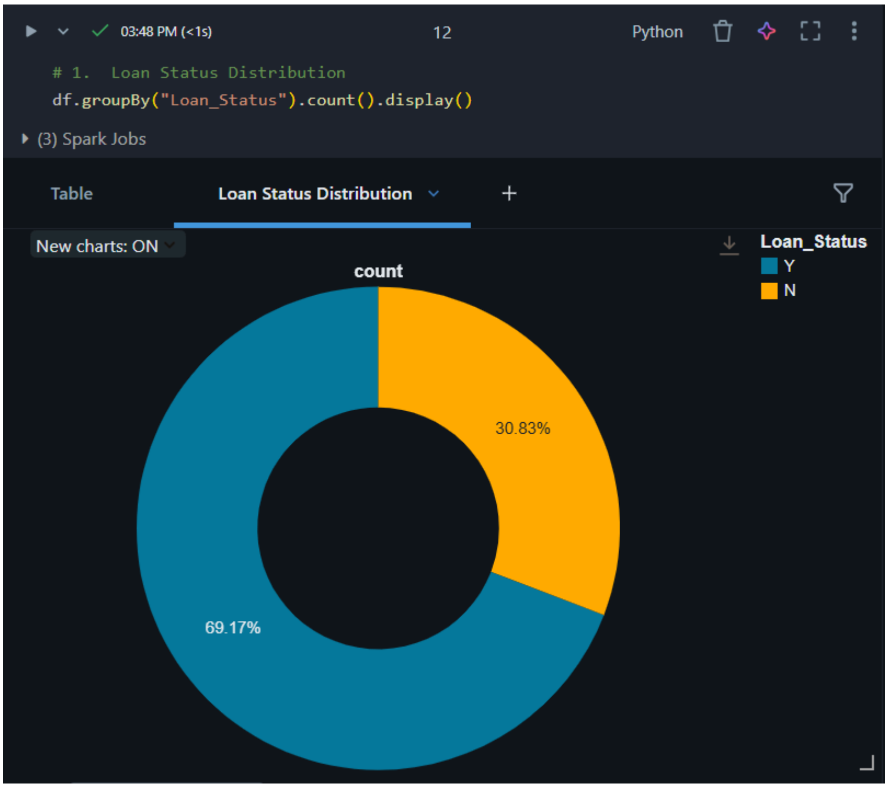
3. Visualizations and Insights

Databricks built-in visualizations were used via `display()` and `groupBy().count().show()` methods.

3.1 Loan Status Distribution

- **Goal:** Understand the overall distribution of loan approvals vs rejections.
- **Chart:** Pie Chart (or Bar Chart)
- **Insight:** Majority of the applicants in the dataset had their loans approved (`Loan_Status = Y`), indicating a favorable approval rate.

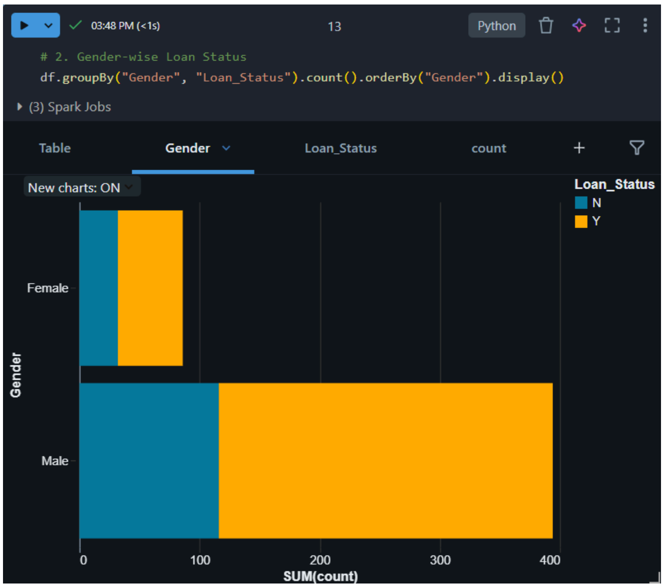
```
df.groupBy("Loan_Status").count().display()
```

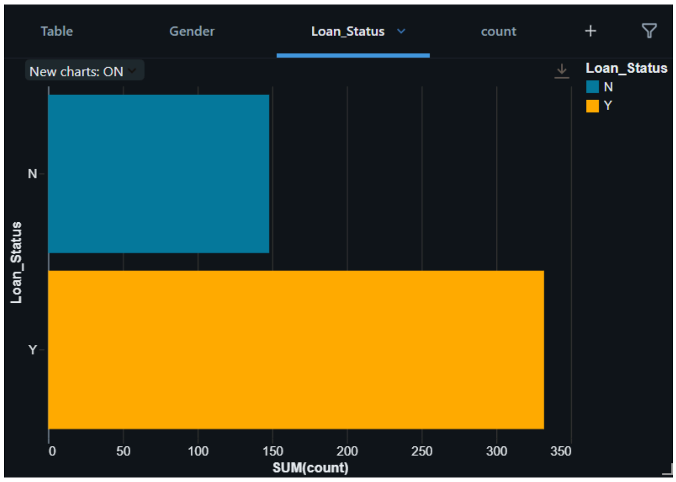


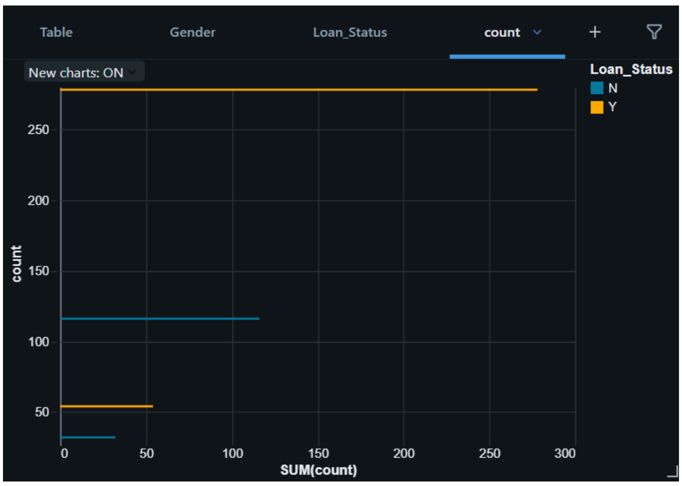
3.2 Gender-wise Loan Approval

- **Goal:** Analyze whether gender has any effect on loan approval.
- **Chart:** Grouped Bar Chart
- **Insight:** Males apply for more loans than females. The approval rate is roughly similar across genders, but male applicants dominate in volume.

```
df.groupBy("Gender", "Loan_Status").count().orderBy("Gender").display()
```



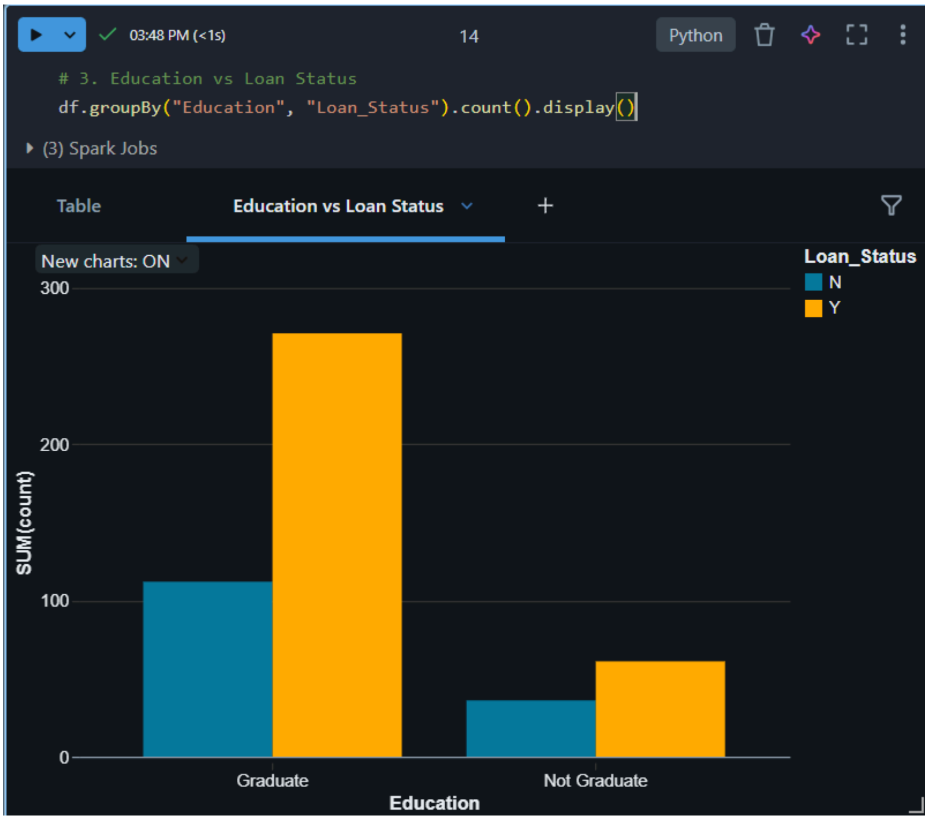




3.3 Education vs Loan Status

- **Goal:** Explore the impact of education level on loan approval.
- **Chart:** Grouped Bar Chart
- **Insight:** Graduate applicants have a higher number of approved loans, suggesting that education might have a positive impact on loan approval.

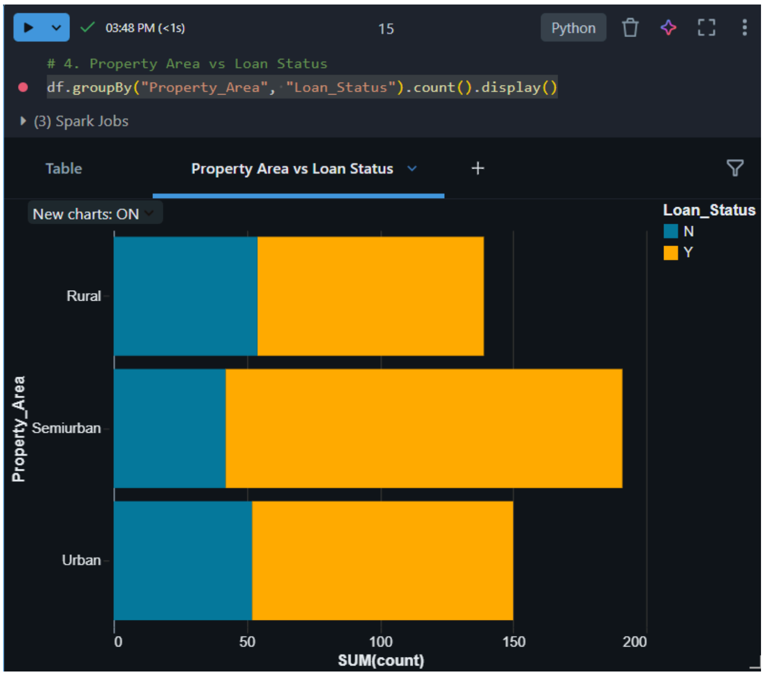
```
df.groupBy("Education", "Loan_Status").count().display()
```



3.4 Property Area vs Loan Status

- **Goal:** Understand how the loan approval rate varies by property location.
- **Chart:** Grouped Bar Chart
- **Insight:** Applicants from semiurban areas have a noticeably higher approval rate, followed by urban, with rural areas seeing the least approvals.

```
df.groupBy("Property_Area", "Loan_Status").count().display()
```



3.5 Applicant Income vs Loan Amount

- **Goal:** Analyze if there's a relationship between applicant income and the loan amount they request.
- **Chart:** Scatter Plot
- **Insight:** There is no strong correlation between income and loan amount. Some high-income applicants request low loans and vice versa, suggesting that loan size may depend on other factors too.

```
df.select("ApplicantIncome", "LoanAmount").display()
```

3.6 Histogram – Income Distribution

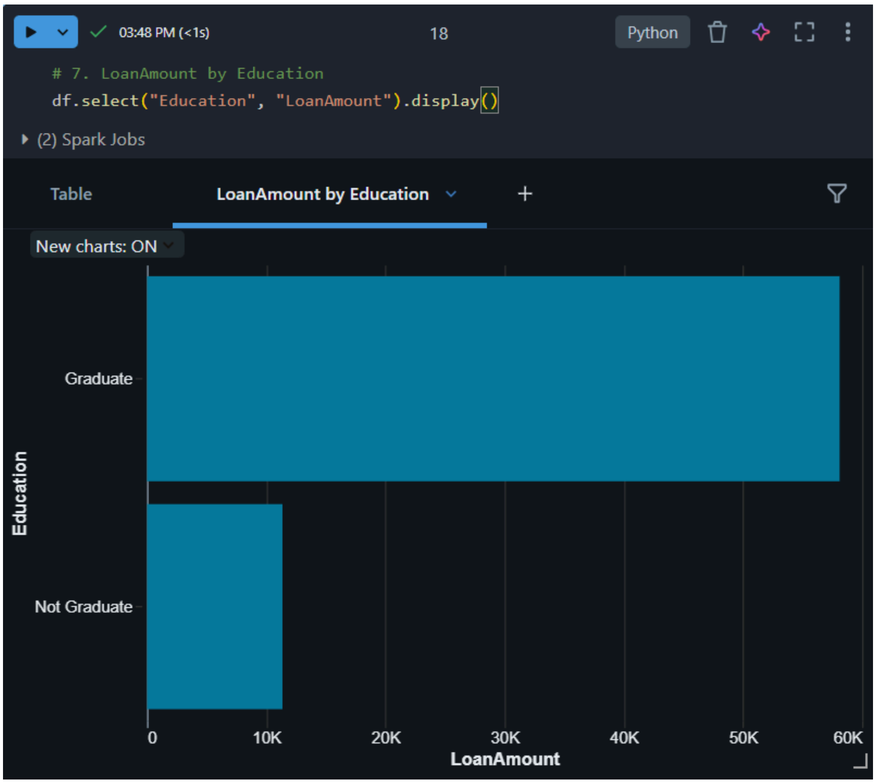
- **Goal:** Understand how applicant income is distributed.
- **Chart:** Histogram
- **Insight:** The income distribution is right-skewed, with a few outliers having very high incomes. Most applicants fall within a moderate income range.

```
df.select("ApplicantIncome").display()
```

3.7 Box Plot – LoanAmount by Education

- **Goal:** Compare loan amount distribution between graduates and non-graduates.
- **Chart:** Box Plot
- **Insight:** Graduates tend to apply for slightly higher loans, but both groups have outliers. There's slightly more variation among graduates.

```
df.select("Education", "LoanAmount").display()
```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Python
# 7. LoanAmount by Education
df.select("Education", "LoanAmount").display()
(2) Spark Jobs
Table
LoanAmount by Education
New charts: ON
Graduate
Not Graduate
Education
0
10K
20K
30K
40K
50K
60K
LoanAmount