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Loan Dataset Analysis

Profiling and Analyzing the Loan Dataset

Introduction:

This project centers on performing an in-depth exploratory data analysis (EDA) on a loan applicant dataset. The dataset comprises crucial financial attributes such as gender, marital status, education, income particulars, loan amounts, credit history, and others. The primary objective is to extract actionable insights into the financial profiles of loan applicants and discern the key determinants influencing loan approval.

Objective:

The central aim of this project is to meticulously explore and analyze the loan applicant dataset to glean invaluable insights into demographics, financial profiles, and pertinent factors impacting loan approval. Through a systematic approach involving targeted inquiries, alongside adept data manipulation, visualization, and statistical analysis, our goal is to reveal latent patterns, emerging trends, and significant correlations inherent within the dataset.

Project Description:

Through a comprehensive series of 30 inquiries, we delve into the loan dataset utilizing diverse techniques including data filtering, grouping, sorting, and visualization. Each question focuses on specific facets of the dataset, spanning from income distribution and loan approval rates to demographic trends and financial ratios.

Commencing with meticulous data preprocessing to ensure data integrity and uniformity, we proceed to apply exploratory data analysis techniques to unveil insights within the dataset. Visual representations such as bar plots are harnessed to depict the data visually, simplifying the interpretation of trends and patterns.

Key revelations from the analysis encompass insights into income distribution, loan approval rates across various parameters, demographic trends among applicants, and interrelations among attributes such as income, loan amount, and credit history. Statistical metrics like mean, median, and percentiles are leveraged to offer quantitative insights into the data.

The culmination of the project entails the presentation of results, wherein findings are succinctly summarized and effectively communicated. This comprehensive analysis yields valuable insights, enhancing our understanding of loan applicant characteristics and the factors shaping loan approval decisions.

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Dataset/Column Explanations

Column #1: Gender – Gender of Applicant for loan. (Object; “Male” or “Female”)

Column #2: Married – Whether Applicant is Married or not. Being married suggests that the applicant shares financial responsibility and income with their spouse. (Object; “Yes” or “No”)

Column #3: Dependents – Number of Individuals who rely on Applicants financial support. (int)

Column #4: Education – Education Level attained by Applicant. (Object; “Graduated” or “Not Graduated”)

Column #5: Self Employed – Applicant who runs their own business or works as an independent contractor rather than being employed by another company or organization. (Object; “Yes” or “No”)

Column #6: Applicant Income – Represents the income of the primary applicant of the loan. Income is a critical factor in assessing loan applications as it directly influences the applicants ability to pay back a loan. (int; USD)

Column #7: Co-Applicant Income – Represents the income of the Co-Applicant, if applicable, who is jointly applying for the loan with the primary applicant. (int; USD)

Column #8: Loan Amount – The amount of money that the loan applicant is requesting or has been approved for. (int; USD)

Columns #9: Term – Represents the duration of the loan, commonly referred to as the loan term. This term specifies the length of time over which the borrower is expected to repay the loan amount to the lender. (float; months)

Column #10: Credit History – The Credit History of the loan applicant. This is a crucial factor considered by lenders when assessing loan applicants as it provides insight into the applicant’s past credit behavior and repayment patterns. (float; 1.0 = Acceptable Credit History, 0.0 = No/Non-Acceptable Credit History)

Column #11: Area – The geographical area or location associated with the loan applicants. (String; “Urban”, “Semiurban”, “Rural”)

Columns added from ‘Data Preprocessing’

Column #12: Household Income – The total income of the household to which the loan applicant belongs. This column provides a comprehensive view of the financial resources available to the applicant and their family. Household Income = Applicant Income + Co-applicant Income (int; USD)

Column #13: Total Yearly Debt – The sum of all the borrower’s debts over the course of a year. This column provides insight into the borrower’s overall debt burden and financial obligations. Total Yearly Debt = Loan Amount / (Term / 12) (float; USD)

Column #14: Debt to Income Ratio – The ratio of the borrower’s total yearly debt to their household income. This ratio is a fundamental metric used by lenders to evaluate the borrower’s ability to manage debt relative to their income level.

Debt to Income Ratio = Total Yearly Debt / Household Income (float)

Column #15: Risk Level – The risk associated with each loan application. This column is determined based on specific criteria, such as credit history and debt-to-income ratio, to categorize the level of risk posed by each applicant. (String; “Low”, “Medium”, “High”)

Loan Dataset Analysis – Python Script and Outputs

Import Libraries and CSV File

- i. Import libraries: Pandas for analysis, Matplotlib for Visualization
- ii. Import Dataset: Import CSV file using Pandas

```
# Import Libraries
import pandas as pd
import matplotlib.pyplot as plt

# Import Dataset and View
df= pd.read_csv('loan.csv')
df.head(5)
```

	Gender	Married	Dependents	Education	Self_Employed	Applicant_Income	Coapplicant_Income	Loan_Amount	Term	Credit_History	Area
0	Male	Yes	0.0	Graduate	No	572000	0	220000	360.0	1.0	Urban
1	Male	Yes	1.0	Graduate	No	307600	150000	252000	360.0	1.0	Urban
2	Male	Yes	2.0	Graduate	No	500000	180000	416000	360.0	1.0	Urban
3	Male	Yes	2.0	Graduate	No	234000	254600	200000	360.0	NaN	Urban
4	Male	No	0.0	Not Graduate	No	327600	0	156000	360.0	1.0	Urban

Dataset Preprocessing

- iii. View Datatypes before analyzation

```
# View data types for each column
df.dtypes
```

```
Gender                object
Married               object
Dependents            float64
Education             object
Self_Employed         object
Applicant_Income      int64
Coapplicant_Income    int64
Loan_Amount           int64
Term                 float64
Credit_History        float64
Area                 object
dtype: object
```

- iv. All missing (NaN) values in the Credit History Column will be treated as a Credit History of zero.

```
# Change all NaN values in Credit History to 0
# 1.0 represents a Credit History meeting a specified criteria
# 0.0 represents a Credit History as not meeting a specified criteria or no Credit History
df['Credit_History'].fillna(0, inplace = True)
df['Credit_History']
```

```
0      1.0
1      1.0
2      1.0
3      0.0
4      1.0
...
362    1.0
363    1.0
364    0.0
365    1.0
366    1.0
Name: Credit_History, Length: 367, dtype: float64
```

- v. Calculate Household Income Column, by adding the Applicant Income and Co-Applicant Income

```
# Create column to represent the entire Household Income
df['Household Income'] = 0
df['Household Income'] = df['Applicant Income'] + df['Coapplicant Income']
df.head(5)
```

- vi. Calculate new columns, 'Debt to Income Ratio' & 'Risk Level', these metrics will be used to judge whether a loan was approved or not

```
# Create Debt to Income Ratio & Risk Level column to help assess Loan Approval

#Debt to Income Ratio
# Calculate Total Monthly Debt
df['Total Yearly Debt'] = df['Loan Amount'] / (df['Term'] / 12)

# Calculate Debt to Income Ratio
df['Debt to Income Ratio'] = df['Total Yearly Debt'] / (df['Household Income'])

#Risk Level Assessment
df['Risk Level'] = 'Low'
df.loc[(df['Credit History'] < 0.5) | (df['Debt to Income Ratio'] > 0.3), 'Risk Level'] = 'High'
df.loc[(df['Credit History'] >= 0.5) & (df['Debt to Income Ratio'] <= 0.3), 'Risk Level'] = 'Medium'
```

- vii. Identify two thresholds used for Loan Approval; Credit History Threshold set to 0.5 and Debt to Income Ratio Threshold to 0.3.
- viii. Three columns for Loan Approval were taken into consideration; Credit History, Debt to Income Ratio and the Risk Calculated.
- ix. A Loan is approved if either the Credit History or the Debt-to-Income Ratio were above their respective thresholds and the Risk Level calculated was not High. All other loans were not approved.
- x. Among 367 applicants, 75.7% were approved.

```
# Create a column to represent Loan Approval Status

# Threshold
credit_history_threshold = 0.5
dti_ratio_threshold = 0.3
# Risk Level must be Low or Medium

# Calculate Loan Approval Column
df['Approval Status'] = 'No'
df.loc[(df['Credit History'] > credit_history_threshold) | (df['Debt to Income Ratio'] > dti_ratio_threshold) & (df['Risk Level'] != 'High'),
'Approval Status'] = 'Yes'

# Calculate number of Loans Approved and not
loan_approved = len(df.loc[df['Approval Status'] == 'Yes'])
loan_not_approved = len(df.loc[df['Approval Status'] == 'No'])

print(f"Number of Loans Approved: {loan_approved}")
print(f"Number of Loans not Approved: {loan_not_approved}")

# Calculate percentage of Approved Loans
percentage_approved = (loan_approved/(loan_approved + loan_not_approved))*100
print(f"The percentage of loans that were approved: {percentage_approved}%")

Number of Loans Approved: 278
Number of Loans not Approved: 89
The percentage of loans that were approved: 75.74931880108991%
```

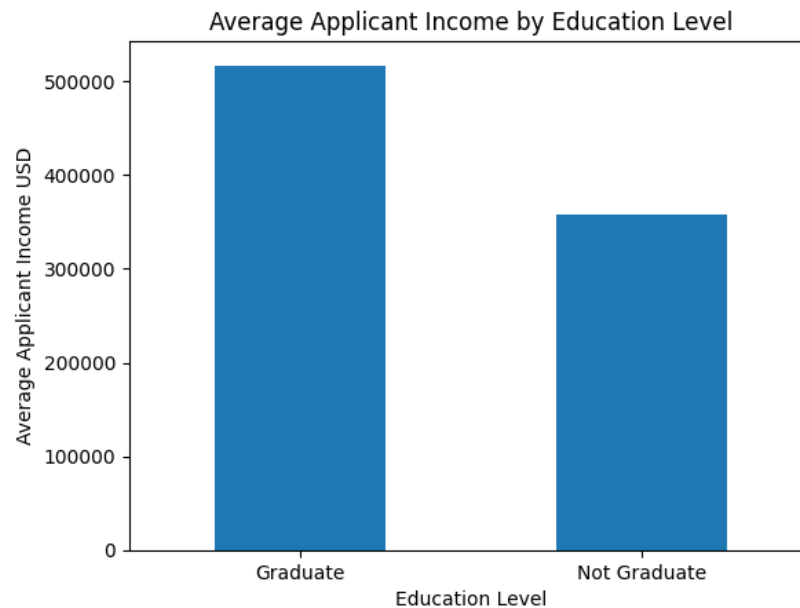
Dataset Analysis

Plotting

```
#1. What is the average 'Applicant Income' of individuals grouped by their 'Education' level?  
avg_inc_by_ed = df.groupby('Education')['Applicant Income'].mean()  
print(f"Output \n{avg_inc_by_ed}")
```

```
# Plot  
avg_inc_by_ed.plot(kind = 'bar')  
plt.title("Average Applicant Income by Education Level")  
plt.xlabel("Education Level")  
plt.xticks(rotation=0)  
plt.ylabel("Average Applicant Income USD")  
plt.show()
```

Output
Education
Graduate 516994.346290
Not Graduate 357810.714286
Name: Applicant Income, dtype: float64

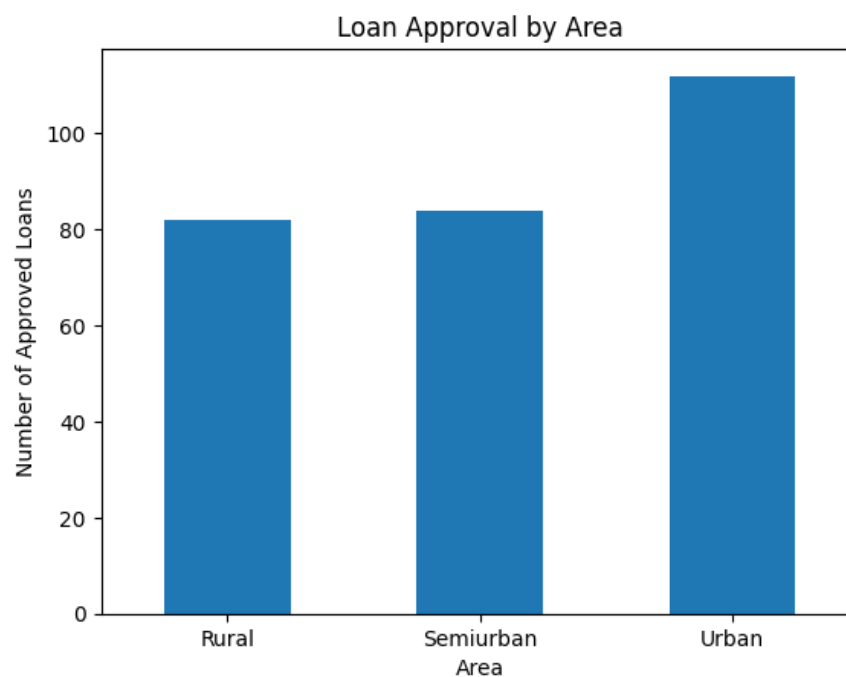



```
#2. How many individuals in each 'Area' have been approved for a loan?
loan_app_by_area = df.loc[df['Approval Status'] == 'Yes'].groupby('Area').size()
print(f"Output \n{loan_app_by_area}")

# Plot
loan_app_by_area.plot(kind = 'bar')
plt.title("Loan Approval by Area")
plt.xlabel("Area")
plt.xticks(rotation=0)
plt.ylabel("Number of Approved Loans")
plt.show()
```

Output

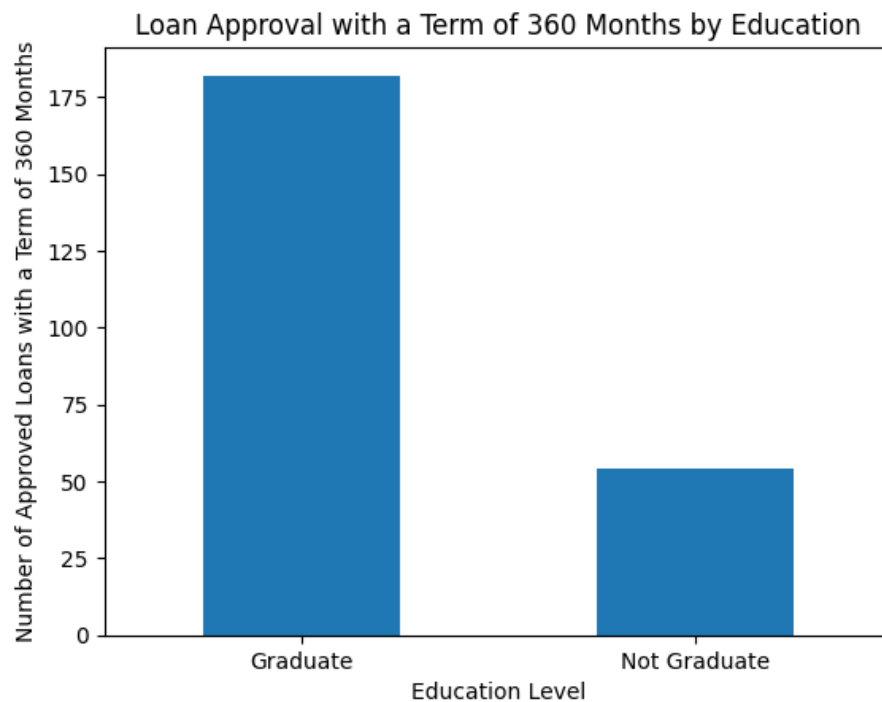
```
Area
Rural      82
Semiurban  84
Urban     112
dtype: int64
```



```
#3. How many individuals in each 'Education' level have been approved for a loan and have a 'Term' of 360?
app_loans_term_360_by_ed = df.loc[(df['Approval Status'] == 'Yes') & (df['Term'] == 360.0)].groupby('Education')['Approval Status'].count()
print(f"Output \n{app_loans_term_360_by_ed}")

# Plot
app_loans_term_360_by_ed.plot(kind = 'bar')
plt.title("Loan Approval with a Term of 360 Months by Education")
plt.xlabel("Education Level")
plt.xticks(rotation=0)
plt.ylabel("Number of Approved Loans with a Term of 360 Months")
plt.show()
```

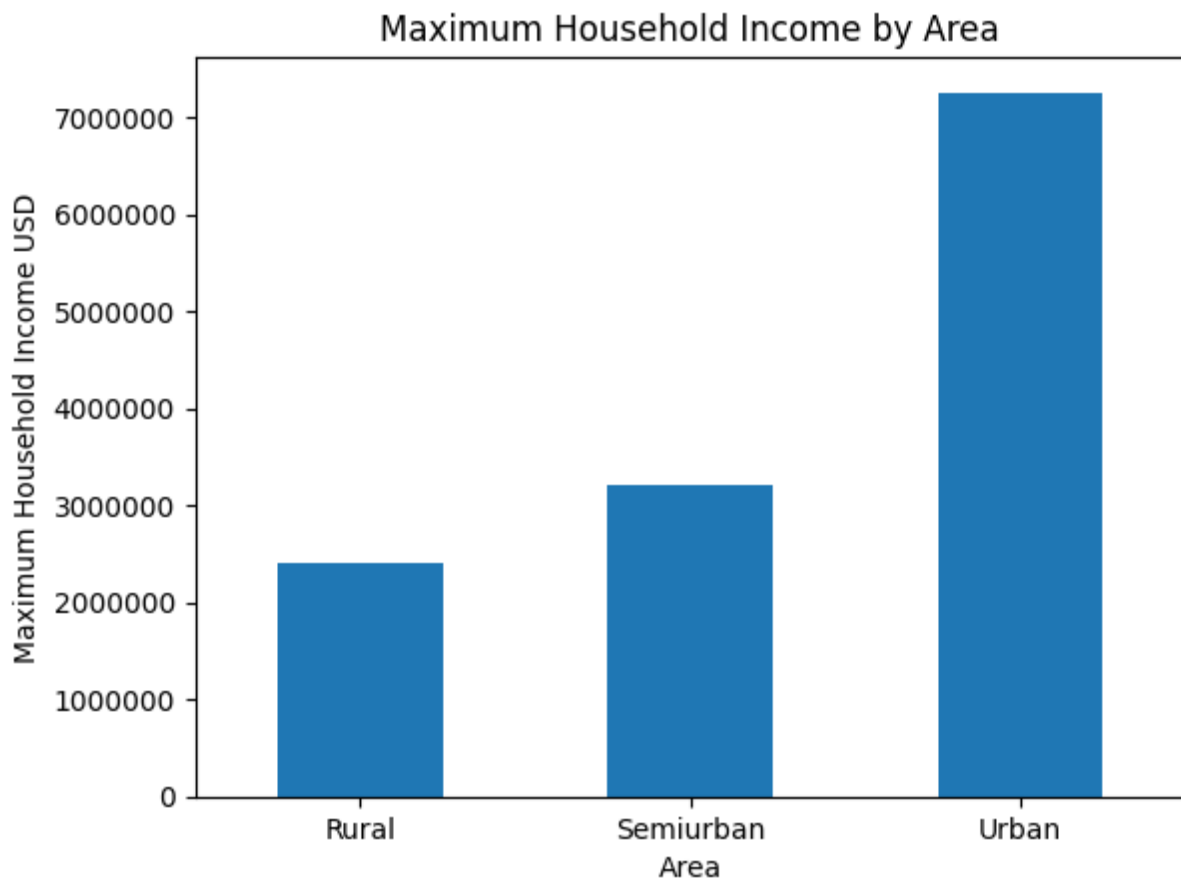
```
Output
Education
Graduate      182
Not Graduate   54
Name: Approval Status, dtype: int64
```



```
#4. What is the maximum 'Household Income' in each 'Area'?
household_inc_by_area = df.groupby('Area')['Household Income'].max()
print(f"Output \n{household_inc_by_area}")

# Plot
household_inc_by_area.plot(kind = 'bar')
plt.title("Maximum Household Income by Area")
plt.xlabel("Area")
plt.xticks(rotation=0)
plt.ylabel("Maximum Household Income USD")
plt.ticklabel_format(style='plain', axis='y')
plt.show()
```

```
Output
Area
Rural      2400000
Semiurban  3200000
Urban      7252900
Name: Household Income, dtype: int64
```



#5. How many individuals in each 'Area' have a 'Loan Amount' greater than the 75th percentile of 'Loan Amount' and a 'Credit History' of 1.0?

Calculate Percentiles

```
loan_75 = df['Loan Amount'].quantile(q = 0.75)
```

Filter

```
num_ind = df.loc[(df['Loan Amount'] > loan_75) & (df['Credit History'] == 1.0)].groupby('Area').size()
```

```
print(f"Output: {num_ind}")
```

Plot

```
num_ind.plot(kind = 'bar')
```

```
plt.title("Number of Individuals with a Loan Amount greater than 75th percentile and Credit History of 1 by Area")
```

```
plt.xlabel("Area")
```

```
plt.xticks(rotation=0)
```

```
plt.ylabel("Number of Individuals")
```

```
plt.ticklabel_format(style='plain', axis='y')
```

```
plt.show()
```

Output: Area

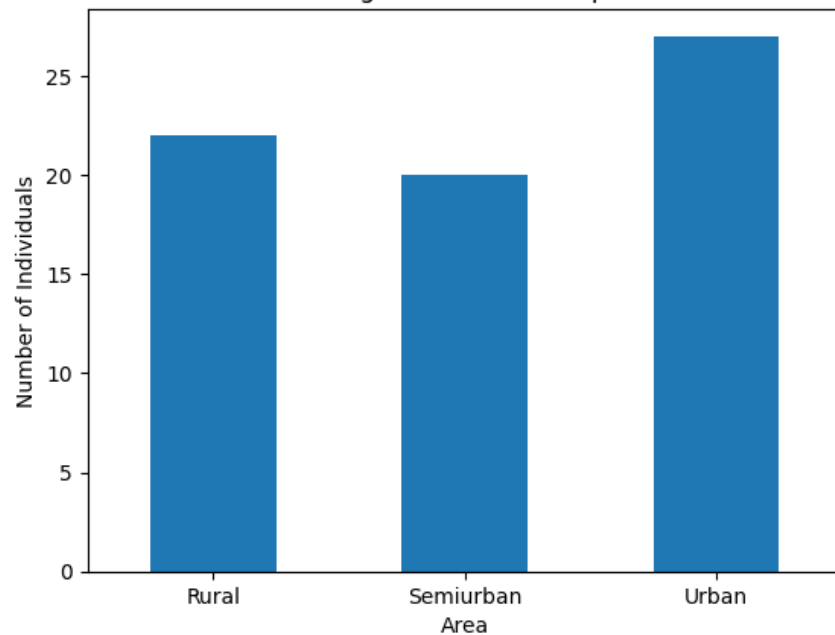
Rural 22

Semiurban 20

Urban 27

dtype: int64

Number of Individuals with a Loan Amount greater than 75th percentile and Credit History of 1 by Area



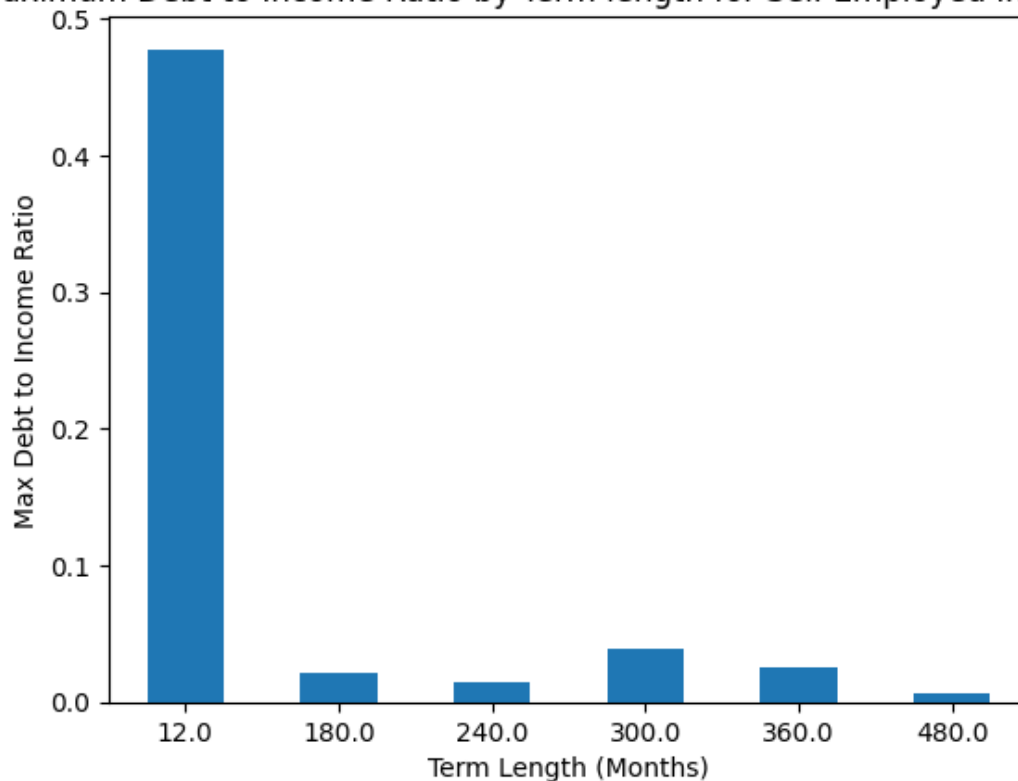
```
#6. Among self-employed applicants, what is the maximum 'Debt to Income Ratio' for each term length?
self_emp_dti_by_term = df.loc[df['Self Employed'] == 'Yes'].groupby('Term')['Debt to Income Ratio'].max()
print(f"Output: \n{self_emp_dti_by_term}")
```

```
# Plot
self_emp_dti_by_term.plot(kind = 'bar')
plt.title("Maximum Debt to Income Ratio by Term length for Self-Employed Individuals")
plt.xlabel("Term Length (Months)")
plt.xticks(rotation=0)
plt.ylabel("Max Debt to Income Ratio")
plt.ticklabel_format(style='plain', axis='y')
plt.show()
```

Output:

```
Term
12.0      0.477502
180.0     0.021823
240.0     0.015223
300.0     0.039199
360.0     0.025804
480.0     0.006203
Name: Debt to Income Ratio, dtype: float64
```

Maximum Debt to Income Ratio by Term length for Self-Employed Individuals



Filtering

```
#7. How many individuals have a 'Dependents' count of 0 and a 'Loan Amount' less than 500000?
num_ind = len(df.loc[(df['Dependents'] == 0) & (df['Loan Amount'] < 500000)])
print(f"Output: {num_ind} Individuals")
```

Output: 194 Individuals

```
#8. What is the average 'Coapplicant Income' for individuals who are not self-employed and have a 'Credit History' of 1.0?
avg_coapp_inc = df.loc[(df['Self Employed'] == 'No') & (df['Credit History'] == 1.0)][['Coapplicant Income']].mean()
print(f"Output: ${avg_coapp_inc}")
```

Output: \$142303.43347639486

```
#9. What is the median 'Household Income' for individuals with 'Dependents' greater than 0 and a 'Term' of 360?
med_household_inc = df.loc[(df['Dependents'] > 0) & (df['Term'] == 360.0)][['Household Income']].median()
print(f"Output: ${med_household_inc}")
```

Output: \$570500.0

```
#10. What is the maximum 'Loan Amount' for individuals who are not self-employed and have a 'Credit History' of 1.0?
max_loan_amount = df.loc[(df['Self Employed'] == 'No') & (df['Credit History'] == 1.0)][['Loan Amount']].max()
print(f"Output: ${max_loan_amount}")
```

Output: \$920000

```
#11. What is the average 'Household Income' for individuals who have a 'Loan Amount' greater than the median 'Loan Amount' in the dataset?

#Median Loan Amount
median_loan = df['Loan Amount'].median()
#Filter
avg_household_inc_above_median = df.loc[df['Loan Amount'] > median_loan][['Household Income']].mean()
print(f"Output: ${avg_household_inc_above_median}")
```

Output: \$777361.4525139665

```
#12. How many individuals have an 'Applicant Income' greater than the mean 'Applicant Income' and a 'Loan Amount' less than the median 'Loan Amount'?

# Calculate Mean and Median Values
app_mean = df['Applicant Income'].mean()
loan_med = df['Loan Amount'].median()

#Filter
num_ind = len(df.loc[(df['Applicant Income'] > app_mean) & (df['Loan Amount'] < loan_med)])
print(f"Output: {num_ind} Individuals")
```

Output: 28 Individuals

```
#13. What is the median 'Household Income' for individuals with 'Dependents' greater than or equal to 2 and a 'Term' of 360?
med_household_inc = df.loc[(df['Dependents'] >= 2) & (df['Term'] == 360.0)][['Household Income']].median()
print(f"Output: ${med_household_inc}")
```

Output: \$561300.0

```
#14. What is the median 'Debt to Income Ratio' ratio for individuals who are not self-employed and have a 'Credit History' of 1.0?
med_dti = df.loc[(df['Self Employed'] == 'No') & (df['Credit History'] == 1.0)]['Debt to Income Ratio'].median()
print(f"Output: {med_dti}")
```

Output: 0.016909347111319868

```
#15. What is the maximum household income among married applicants with more than one dependent?
max_household_inc = df.loc[(df['Married'] == 'Yes') & (df['Dependents'] > 1)]['Household Income'].max()
print(f"Output: ${max_household_inc}")
```

Output: \$7252900

```
#16. How many applicants in semiurban areas, who are married and have no dependents, have been approved for a loan with a term less than 240 days?
num_app = len(df.loc[(df['Area'] == 'Semiurban') & (df['Married'] == 'Yes') & (df['Dependents'] == 0) & (df['Approval Status'] == 'Yes')
                  & (df['Term'] < 240)])
print(f"Output: {num_app} Applicants")
```

Output: 3 Applicants

```
#17. Among self-employed applicants, what is the median household income for each combination of gender and education level?
med_household_inc = df.loc[df['Self Employed'] == 'Yes'].groupby(['Gender', 'Education'])['Household Income'].median()
print(f"Output: \n{med_household_inc}")
```

Output:

Gender	Education	
Female	Graduate	621650.0
Male	Graduate	691050.0
	Not Graduate	558700.0

Name: Household Income, dtype: float64

```
#18. What is the maximum coapplicant income for each combination of gender and education level, among applicants with a credit history of 1.0
# and household income greater than 500,000?
max_coapp_inc = df.loc[(df['Credit History'] == 1.0) & (df['Household Income'] > 500000)].groupby(['Gender', 'Education'])['Coapplicant Income'].max()
print(f"Output: \n{max_coapp_inc}")
```

Output:

Gender	Education	
Female	Graduate	1166600
	Not Graduate	357500
Male	Graduate	1450700
	Not Graduate	1398300

Name: Coapplicant Income, dtype: int64

Filtering by Percentile

#19. How many individuals have an 'Applicant Income' greater than the 75th percentile of 'Applicant Income' and a 'Coapplicant Income' greater than the 90th percentile of 'Coapplicant Income'?

```
# Calculate Percentiles
app_75 = df['Applicant Income'].quantile(q = 0.75)
coapp_90 = df['Coapplicant Income'].quantile(q = 0.9)

# Filter
num_ind = len(df.loc[(df['Applicant Income'] > app_75) & (df['Coapplicant Income'] > coapp_90)])
print(f"Output: {num_ind} Individuals")
```

Output: 10 Individuals

#20. How many individuals have a 'Loan Amount' greater than the 90th percentile of 'Loan Amount' and a 'Term' of 360, and are self-employed?

```
# Calculate Percentile
loan_90 = df['Loan Amount'].quantile(q = 0.9)

# Filter and Count
num_ind = len(df.loc[(df['Loan Amount'] > loan_90) & (df['Term'] == 360.0) & (df['Self Employed'] == 'Yes')])
print(f"Output: {num_ind} Individuals")
```

Output: 6 Individuals

#21. How many individuals in each 'Area' have a 'Term' less than the 25th percentile of 'Debt to Income Ratio' and an 'Approval Status' of 'Yes'?

```
dti_25 = df['Debt to Income Ratio'].quantile(q = 0.25)

df.loc[(df['Debt to Income Ratio'] < dti_25) & (df['Approval Status'] == 'Yes')].groupby('Area').size()
```

```
Area
Rural      21
Semiurban  18
Urban      25
dtype: int64
```

Grouping and Sorting

#22. What is the average 'Loan Amount' for individuals who are self-employed and have a 'Credit History' of 1.0, grouped by their 'Education' level?

```
avg_loan_amount = df.loc[(df['Self Employed'] == 'Yes') & (df['Credit History'] == 1.0)].groupby('Education')['Loan Amount'].mean()
print(f"Output: ${avg_loan_amount}")
```

```
Output: $Education
Graduate      283846.153846
Not Graduate   228857.142857
Name: Loan Amount, dtype: float64
```


#23. Can you provide the top 3 records with the highest 'Debt to Income Ratio' , sorted in descending order?

```
dti_sorted = df.sort_values('Debt to Income Ratio', ascending = False)
dti_top_3 = dti_sorted.head(3)
print(dti_top_3)
```

	Gender	Married	Dependents	Education	Self Employed	Applicant Income
325	Male	No	0.0	Graduate	No	287500 \
144	Male	Yes	2.0	Graduate	Yes	1089000
216	Male	Yes	0.0	Not Graduate	No	274700

	Coapplicant Income	Loan Amount	Term	Credit History	Area
325	241600	190000	6.0	0.0	Semiurban \
144	0	520000	12.0	1.0	Rural
216	245800	236000	36.0	1.0	Semiurban

	Household Income	Total Yearly Debt	Debt to Income Ratio	Risk Level
325	529100	380000.000000	0.718201	High \
144	1089000	520000.000000	0.477502	High
216	520500	78666.666667	0.151137	Medium

	Approval Status
325	No
144	No
216	Yes

#24. What is the median household income for each area, sorted in descending order?

```
med_household_inc_by_area = df.groupby('Area')['Household Income'].median().sort_values(ascending = False)
print(f"Output: \n{med_household_inc_by_area}")
```

Output:

```
Area
Rural      547400.0
Urban      529850.0
Semiurban  487550.0
Name: Household Income, dtype: float64
```

#25. What is the median coapplicant income for each combination of gender, education level, and credit history category, sorted in descending order of median coapplicant income?

```
med_coapp_inc = df.groupby(['Gender', 'Education', 'Credit History'])['Coapplicant Income'].median().sort_values(ascending = False)
print(f"Output: \n{med_coapp_inc}")
```

Output:

Gender	Education	Credit History	
Female	Graduate	0.0	200000.0
	Not Graduate	0.0	170000.0
Male	Graduate	0.0	140850.0
	Not Graduate	1.0	135000.0
	Graduate	1.0	134050.0
	Not Graduate	0.0	52800.0
Female	Graduate	1.0	0.0
	Not Graduate	1.0	0.0

Name: Coapplicant Income, dtype: float64

#26. What is the average loan amount for each combination of gender, education level, and self-employed status?

```
avg_loan_amount = df.groupby(['Gender', 'Education', 'Self Employed'])['Loan Amount'].mean()
print(f"Output: \n{avg_loan_amount}")
```

Output:

Gender	Education	Self Employed	
Female	Graduate	No	248448.979592
		Yes	342000.000000
	Not Graduate	No	229000.000000
Male	Graduate	No	280340.659341
		Yes	311250.000000
	Not Graduate	No	228867.924528
		Yes	266285.714286

Name: Loan Amount, dtype: float64

#27. Among individuals with 'Self Employed' status, what is the median 'Total Yearly Debt' for each 'Risk Level', grouped by 'Education'?

```
self_emp_ind = df.loc[df['Self Employed'] == 'Yes'].groupby(['Risk Level', 'Education'])['Total Yearly Debt'].median()
print(f"Output: \n{self_emp_ind}")
```

Output:

Risk Level	Education	
High	Graduate	24566.666667
	Not Graduate	13266.666667
Medium	Graduate	10000.000000
	Not Graduate	7533.333333

Name: Total Yearly Debt, dtype: float64

```
#28. What is the average debt-to-income ratio for individuals grouped by their 'Education' level?
dti_by_ed = df.groupby('Education')['Debt to Income Ratio'].mean()
print(f"Output: \n{dti_by_ed}")
```

Output:

Education

Graduate 0.021600

Not Graduate 0.020416

Name: Debt to Income Ratio, dtype: float64

```
#29. How many individuals with a debt-to-income ratio above 0.05 have been approved for a loan
# ('Approval Status' = 'Yes'), grouped by their 'Gender'?
num_ind = df.loc[(df['Debt to Income Ratio'] > 0.05) & (df['Approval Status'] == 'Yes')].groupby('Gender').size()
print(f"Output: \n{num_ind}")
```

Output:

Gender

Female 2

Male 4

dtype: int64

```
#30. Among individuals with 'Self Employed' status, what is the median debt-to-income ratio for each
# 'Dependents' category?
med_dti = df.loc[df['Self Employed'] == 'Yes'].groupby('Dependents')['Debt to Income Ratio'].median()
print(f"Output: \n{med_dti}")
```

Output:

Dependents

0.0 0.015150

1.0 0.015223

2.0 0.016800

3.0 0.013020

4.0 0.015111

Name: Debt to Income Ratio, dtype: float64