The goal of this project

To organize, clean and analyze for the following questions:

is the Loan ammount applied for affected by gender?

Does education affect credit history?

does education affect weekly applicant income?

If you are married do u have a higher weekly applicant income?

if u have a higher weekly applicant income do u get a higher loan ammount?

LOAN DATA PROJECT

The uncleaned dataset was taken from kaggle the link is :
https://www.kaggle.com/datasets/architsharma01/loan-approval-prediction-dataset

What the dataset is used for?

The loan approval dataset is a collection of financial records and associated information used to determine the eligibility of individuals or organizations for obtaining loans from a lending institution.

It includes various factors such as cibil score, income, employment status, loan term, loan amount, assets value, and loan status. This dataset is commonly used in machine

learning and data analysis to develop models and algorithms that predict the likelihood of loan approval based on the given features.

In [170…
```
import pandas as pd
import numpy as np
import math
import matplotlib.pyplot as plt
import seaborn as sns
```

In [171…
```
df=pd.read_csv('data-1.csv')
# read data get familiar with whats missing and whats not.
```

In [172…
```
df.shape
```

Out[172… (367, 12)

Problems Identified early by scoping the dataset.

we can see here a number of things have to be changed.

dependents column 3+ should be 3 and state in footer 3 means more than 3 dependents.

Nan values in self employed change that to Data not provided.

Change loan ammount times 1000 to show real ammount.

loan ammount term shows weekly so rename column.

change 0.0 in credit history to 0.

create a column for yearly, weekly and daily repayments.

missing values in gender dependents self employed loanammount loan ammount term and credit history

In [173…
```
df.head(20)
# we can see here a number of things have to be changed.
# dependents column 3+ should be 3 and state in footer 3 means more than 3 dependents.
# Nan values in self employed change that to Data not provided.
# Change loan ammount times 1000 to show real ammount.
# loan ammount term shows weekly so rename column.
# change 0.0 in credit history to 0.
# create a column for yearly, weekly and daily repayments.
```

Out[173…

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_
0	LP001015	Male	Yes	0	Graduate	No	5720	0	110.0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	126.0	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	208.0	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	100.0	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	78.0	
5	LP001054	Male	Yes	0	Not Graduate	Yes	2165	3422	152.0	
6	LP001055	Female	No	1	Not Graduate	No	2226	0	59.0	
7	LP001056	Male	Yes	2	Not Graduate	No	3881	0	147.0	
8	LP001059	Male	Yes	2	Graduate	NaN	13633	0	280.0	
9	LP001067	Male	No	0	Not Graduate	No	2400	2400	123.0	
10	LP001078	Male	No	0	Not Graduate	No	3091	0	90.0	
11	LP001082	Male	Yes	1	Graduate	NaN	2185	1516	162.0	
12	LP001083	Male	No	3+	Graduate	No	4166	0	40.0	
13	LP001094	Male	Yes	2	Graduate	NaN	12173	0	166.0	
14	LP001096	Female	No	0	Graduate	No	4666	0	124.0	
15	LP001099	Male	No	1	Graduate	No	5667	0	131.0	
16	LP001105	Male	Yes	2	Graduate	No	4583	2916	200.0	
17	LP001107	Male	Yes	3+	Graduate	No	3786	333	126.0	
18	LP001108	Male	Yes	0	Graduate	No	9226	7916	300.0	
19	LP001115	Male	No	0	Graduate	No	1300	3470	100.0	

In [174…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 367 entries, 0 to 366
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            367 non-null    object 
 1   Gender             356 non-null    object 
 2   Married            367 non-null    object 
 3   Dependents         357 non-null    object 
 4   Education          367 non-null    object 
 5   Self_Employed      344 non-null    object 
 6   ApplicantIncome    367 non-null    int64  
 7   CoapplicantIncome  367 non-null    int64  
 8   LoanAmount         362 non-null    float64
 9   Loan_Amount_Term   361 non-null    float64
 10  Credit_History     338 non-null    float64
 11  Property_Area      367 non-null    object 
dtypes: float64(3), int64(2), object(7)
memory usage: 34.5+ KB
```

In [175…

```
#see stats for your data.
df.describe()
```

Out[175…

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	367.000000	367.000000	362.000000	361.000000	338.000000
mean	4805.599455	1569.577657	136.132597	342.537396	0.825444
std	4910.685399	2334.232099	61.366652	65.156643	0.380150
min	0.000000	0.000000	28.000000	6.000000	0.000000
25%	2864.000000	0.000000	100.250000	360.000000	1.000000
50%	3786.000000	1025.000000	125.000000	360.000000	1.000000
75%	5060.000000	2430.500000	158.000000	360.000000	1.000000
max	72529.000000	24000.000000	550.000000	480.000000	1.000000

In [176…
```
# check for missing values in all columns
df.isnull().sum()
```

Out[176…
```
Loan_ID               0
Gender               11
Married               0
Dependents           10
Education             0
Self_Employed        23
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            5
Loan_Amount_Term      6
Credit_History       29
Property_Area         0
dtype: int64
```

In [177…
```
df_copy=df.copy()
```

In [178…
```
df_copy.shape
```

Out[178… (367, 12)

In [179…
```
# find all missing gender values and delete them
df_copy[df_copy['Gender'].isnull()]
```

Out[179…

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan
22	LP001128	NaN	No	0	Graduate	No	3909	0	101.0	
51	LP001287	NaN	Yes	3+	Not Graduate	No	3500	833	120.0	
106	LP001563	NaN	No	0	Graduate	No	1596	1760	119.0	
138	LP001769	NaN	No	NaN	Graduate	No	3333	1250	110.0	
209	LP002165	NaN	No	1	Not Graduate	No	2038	4027	100.0	
231	LP002298	NaN	No	0	Graduate	Yes	2860	2988	138.0	
245	LP002355	NaN	Yes	0	Graduate	No	3186	3145	150.0	
279	LP002553	NaN	No	0	Graduate	No	29167	0	185.0	
296	LP002614	NaN	No	0	Graduate	No	6478	0	108.0	
303	LP002657	NaN	Yes	1	Not Graduate	Yes	570	2125	68.0	
318	LP002775	NaN	No	0	Not Graduate	No	4768	0	125.0	

In [180…
```
# drop rows there the name column has missing nan values.
df_copy = df_copy.dropna(subset=["Gender"])
```

In [181…
```
df_copy[df_copy['Gender'].isnull()]
# there is no null values in gender.
```

Out[181…

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Am

In [182…
```
df_copy.shape
```

Out[182… (356, 12)

In [183…
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 367 entries, 0 to 366
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            367 non-null    object 
 1   Gender             356 non-null    object 
 2   Married            367 non-null    object 
 3   Dependents         357 non-null    object 
 4   Education          367 non-null    object 
 5   Self_Employed      344 non-null    object 
 6   ApplicantIncome    367 non-null    int64  
 7   CoapplicantIncome  367 non-null    int64  
 8   LoanAmount         362 non-null    float64
 9   Loan_Amount_Term   361 non-null    float64
 10  Credit_History     338 non-null    float64
 11  Property_Area      367 non-null    object 
dtypes: float64(3), int64(2), object(7)
memory usage: 34.5+ KB
```

Solutions to clean:

next is dependents

change nan info not provided

dependents column 3+ should be 3 and state in footer 3 means more than 3 dependents.

change dependents to 0 for Nan in dependents. we assume its 0 because no information is given.

now u have changed this change the data type for dependents to numerical so u can analyze this

now we deal with loan ammount drop all the missing entries for loan ammount because the accountant has screwed up obviously and the application needs to be redone.

remove all entries with missing values in loan ammount term as customer will have to redo application

remove all missing values for loan ammount as application will have to be redone.

now we only have missing values for credit history.

change all missing values to 0.

there are some values in credit history with 0.0

replace all instances of 0.0 in credit history with 0.

rename loan ammount term column to weekly loan ammount term

drop the .0 in Loan ammount term by switching to integer.

credit history should also be one integer

applicant income is per week as well as coapplicant income. so rename columns

need to times the loan ammount by a thousand for each loan ammount in whole dataset.

pick the loan ammount column and change to times 1000 answer.

change loan ammount to integer

CREATE 4 NEW COLUMNS WITH DATA CALCULATIONS FOR YEARLY MONTHLY WEEKLY AND DAILY REPAYMENTS FOR THE LOANS.

create a new copy of the changed dataframe, then do a IQR analysis to deal with the error.

after this do graphs to answer the questions.

In [184…
```
# next is dependents
# change nan info not provided
# dependents column 3+ should be 3 and state in footer 3 means more than 3 dependents.
#change dependents to 0 for Nan in dependents. we assume its 0 because no information is given.
df_copy.loc[df_copy['Dependents'].isnull(), 'Dependents'] = '0'
df_copy['Dependents'] = df_copy['Dependents'].replace("3+",3)
# now u have changed this change the data type for dependents to numerical so u can analyze this .
df_copy['Dependents']=df_copy['Dependents'].astype(int)
```

In [185…
```
# next is delf employed
# change all NAn in self employed to no as no data is provided meaning that the customer didnt feel the need to
df_copy.loc[df_copy['Self_Employed'].isnull(), 'Self_Employed'] = 'No'
```

In [186…
```
df_copy.isnull().sum()
```

Out[186…
```
Loan_ID               0
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            5
Loan_Amount_Term      6
Credit_History       29
Property_Area         0
dtype: int64
```

In [187…
```
# now we deal with loan ammount drop all the missing entries for loan ammount because the accountant has screwe
# remove all entries with missing values in loan ammount term as customer will have to redo application
df_copy = df_copy.dropna(subset=["LoanAmount"])
```

In [188…
```
# there are missing values in loan ammount term, in the same vein the application will have to be redone we nee
df_copy = df_copy.dropna(subset=["Loan_Amount_Term"])
```

In [189…
```
df_copy.isnull().sum()
```

Out[189…
```
Loan_ID               0
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term      0
Credit_History       28
Property_Area         0
dtype: int64
```

In [190…
```
# now we only have missing values for credit history.
# change all missing values to 0.
df_copy.loc[df_copy['Credit_History'].isnull(), 'Credit_History'] = '0'
# there are some values in credit history with 0.0
# replace all instances of 0.0 in credit history with 0.
df_copy['Credit_History'] = df_copy['Credit_History'].replace(0.0,0)
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_19124\2315742299.py:3: FutureWarning: Setting an item of incompatible
dtype is deprecated and will raise an error in a future version of pandas. Value '0' has dtype incompatible with
float64, please explicitly cast to a compatible dtype first.
  df_copy.loc[df_copy['Credit_History'].isnull(), 'Credit_History'] = '0'
```

In [191…
```
df_copy.isnull().sum()
# dealt with all missing values and data cleaning lets now look at the data.
```

Out[191…
```
Loan_ID               0
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term      0
Credit_History        0
Property_Area         0
dtype: int64
```

In [192…
```
df_copy.shape
```

Out[192…
```
(345, 12)
```

In [193…
```
df_copy.head(20)
```

Out[193…

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_
0	LP001015	Male	Yes	0	Graduate	No	5720	0	110.0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	126.0	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	208.0	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	100.0	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	78.0	
5	LP001054	Male	Yes	0	Not Graduate	Yes	2165	3422	152.0	
6	LP001055	Female	No	1	Not Graduate	No	2226	0	59.0	
7	LP001056	Male	Yes	2	Not Graduate	No	3881	0	147.0	
8	LP001059	Male	Yes	2	Graduate	No	13633	0	280.0	
9	LP001067	Male	No	0	Not Graduate	No	2400	2400	123.0	
10	LP001078	Male	No	0	Not Graduate	No	3091	0	90.0	
11	LP001082	Male	Yes	1	Graduate	No	2185	1516	162.0	
12	LP001083	Male	No	3	Graduate	No	4166	0	40.0	
13	LP001094	Male	Yes	2	Graduate	No	12173	0	166.0	
14	LP001096	Female	No	0	Graduate	No	4666	0	124.0	
15	LP001099	Male	No	1	Graduate	No	5667	0	131.0	
16	LP001105	Male	Yes	2	Graduate	No	4583	2916	200.0	
17	LP001107	Male	Yes	3	Graduate	No	3786	333	126.0	
18	LP001108	Male	Yes	0	Graduate	No	9226	7916	300.0	
19	LP001115	Male	No	0	Graduate	No	1300	3470	100.0	

In [194…

```
# rename loan ammount term column to weekly loan ammount term
df_copy = df_copy.rename(columns={'Loan_Amount_Term': 'Weekly_Loan_Ammount_Term'})
# drop the .0 in Loan ammount term by switching to integer.
df_copy['Weekly_Loan_Ammount_Term']=df_copy['Weekly_Loan_Ammount_Term'].astype(int)
# credit history should also be one integer
df_copy['Credit_History']=df_copy['Credit_History'].astype(int)
# applicant income is per week as well as coapplicant income. so rename columns
df_copy = df_copy.rename(columns={'ApplicantIncome': 'Weekly_Applicant_Income'})
df_copy = df_copy.rename(columns={'CoapplicantIncome': 'Weekly_Coapplicant_Income'})

# need to times the loan ammount by a thousand for each loan ammount in whole dataset.
df_copy['LoanAmount'] = df_copy['LoanAmount'] * 1000
# pick the loan ammount column and change to times 1000 answer.
# change loan ammount to integer

df_copy['LoanAmount']=df_copy['LoanAmount'].astype(int)
```

In [195…

```
df_copy.head(10)
# columns have now been renamed see below.
```

Out[195…

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Weekly_Applicant_Income	Weekly_Coapplicant_Income	Loa
0	LP001015	Male	Yes	0	Graduate	No	5720	0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	
5	LP001054	Male	Yes	0	Not Graduate	Yes	2165	3422	
6	LP001055	Female	No	1	Not Graduate	No	2226	0	
7	LP001056	Male	Yes	2	Not Graduate	No	3881	0	
8	LP001059	Male	Yes	2	Graduate	No	13633	0	
9	LP001067	Male	No	0	Not Graduate	No	2400	2400	

In [196…

```
# CREATE 4 NEW COLUMNS WITH DATA CALCULATIONS FOR YEARLY MONTHLY WEEKLY AND DAILY REPAYMENTS FOR THE LOANS.
df_copy['Yearly_Loan_Ammount_Term'] = df_copy['Weekly_Loan_Ammount_Term'] / 52

df_copy['Yearly_repayments'] = df_copy['LoanAmount'] / df_copy['Yearly_Loan_Ammount_Term']
df_copy['Monthly'] = ((df_copy['LoanAmount'] / df_copy['Yearly_Loan_Ammount_Term'])/12)
df_copy['Weekly_repayments'] = df_copy['LoanAmount'] / df_copy['Weekly_Loan_Ammount_Term']
df_copy['Daily_repayments'] = ((df_copy['LoanAmount'] / df_copy['Weekly_Loan_Ammount_Term'])/7)
```

In [197…

```
df_copy.head(10)
```

Out[197…

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Weekly_Applicant_Income	Weekly_Coapplicant_Income	Loa
0	LP001015	Male	Yes	0	Graduate	No	5720	0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	
5	LP001054	Male	Yes	0	Not Graduate	Yes	2165	3422	
6	LP001055	Female	No	1	Not Graduate	No	2226	0	
7	LP001056	Male	Yes	2	Not Graduate	No	3881	0	
8	LP001059	Male	Yes	2	Graduate	No	13633	0	
9	LP001067	Male	No	0	Not Graduate	No	2400	2400	

In [198…

```
df = pd.DataFrame(data=df_copy)

# Modify the copy (original DataFrame remains unchanged)
df_copy['Yearly_Loan_Ammount_Term'] = df_copy['Yearly_Loan_Ammount_Term'].apply(lambda x: f"{x:.2f}")

# Display the original and copied DataFrame
# print("Original DataFrame:")
# print(df)
# print("\nCopied DataFrame (formatted):")
# print(df_copy)
```

In [199…

```
df_copy.head(5)
```

Out[199…

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Weekly_Applicant_Income	Weekly_Coapplicant_Income	Loa
0	LP001015	Male	Yes	0	Graduate	No	5720	0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	

In [200…

```
# rename monthly column to Monthly_repayments
df_copy = df_copy.rename(columns={'Monthly': 'Monthly_repayments'})
```

In [201…

```
# Rounded all repayment columns to the nearest 0.10
df_copy['Yearly_repayments'] = df_copy['Yearly_repayments'].round(0)
df_copy['Weekly_repayments'] = df_copy['Weekly_repayments'].round(0)
df_copy['Monthly_repayments'] = df_copy['Monthly_repayments'].round(0)
df_copy['Daily_repayments'] = df_copy['Daily_repayments'].round(0)

# the data is clean now. Lets account for outliers.
```

In [202…

```
df_copy.head(5)
```

Out[202…

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Weekly_Applicant_Income	Weekly_Coapplicant_Income	Loa
0	LP001015	Male	Yes	0	Graduate	No	5720	0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	

In [203…

```
# As we are not testing hypothesis we can account for outliers now
# first remove outliers from only numerical columns using Interquartile range
import pandas as pd

# Step 1: Read data from a CSV file
# Replace 'your_file.csv' with the path to your CSV file
# file_path = 'data-1.csv'

# Read the CSV file into a DataFrame
# df = pd.read_csv('data-1.csv')

df_filtered = pd.DataFrame(data=df_copy)

# Step 2: Specify the columns to analyze
# Replace with the list of columns you want to process
columns_to_analyze = ['Weekly_Applicant_Income','Weekly_Coapplicant_Income']  # Add your column names here

# Ensure the specified columns exist in the DataFrame
for column in columns_to_analyze:
    if column not in df.columns:
        raise ValueError(f"Column '{column}' not found in the CSV file.")

# Step 3: Remove outliers from each specified column
df_filtered = df.copy()  # Create a copy of the original DataFrame to store filtered data

for column in columns_to_analyze:
    # Calculate IQR for the column
    Q1 = df_filtered[column].quantile(0.25)
    Q3 = df_filtered[column].quantile(0.75)
    IQR = Q3 - Q1

    # Define the lower and upper bounds for outliers
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Filter out the outliers for the column
    df_filtered = df_filtered[(df_filtered[column] >= lower_bound) & (df_filtered[column] <= upper_bound)]

# Step 4: Save the filtered DataFrame (optional)
# Uncomment the following line to save the filtered data to a new CSV file
# df_filtered.to_csv('filtered_data.csv', index=False)

# Print the original and filtered DataFrames
```

```
print("Original DataFrame:")
print(df)
print("\nFiltered DataFrame (without outliers):")
print(df_filtered)

# Print the number of rows removed
num_rows_removed = len(df) - len(df_filtered)
print(f"\nNumber of rows removed: {num_rows_removed}")
```

```
Original DataFrame:
      Loan_ID Gender Married  Dependents     Education Self_Employed  \
0    LP001015   Male     Yes           0      Graduate            No
1    LP001022   Male     Yes           1      Graduate            No
2    LP001031   Male     Yes           2      Graduate            No
3    LP001035   Male     Yes           2      Graduate            No
4    LP001051   Male      No           0  Not Graduate            No
..        ...    ...     ...         ...           ...           ...
362  LP002971   Male     Yes           3  Not Graduate           Yes
363  LP002975   Male     Yes           0      Graduate            No
364  LP002980   Male      No           0      Graduate            No
365  LP002986   Male     Yes           0      Graduate            No
366  LP002989   Male      No           0      Graduate           Yes

     Weekly_Applicant_Income  Weekly_Coapplicant_Income  LoanAmount  \
0                       5720                          0      110000
1                       3076                       1500      126000
2                       5000                       1800      208000
3                       2340                       2546      100000
4                       3276                          0       78000
..                       ...                        ...         ...
362                     4009                       1777      113000
363                     4158                        709      115000
364                     3250                       1993      126000
365                     5000                       2393      158000
366                     9200                          0       98000

     Weekly_Loan_Ammount_Term  Credit_History Property_Area  \
0                         360               1         Urban
1                         360               1         Urban
2                         360               1         Urban
3                         360               0         Urban
4                         360               1         Urban
..                        ...             ...           ...
362                       360               1         Urban
363                       360               1         Urban
364                       360               0     Semiurban
365                       360               1         Rural
366                       180               1         Rural

     Yearly_Loan_Ammount_Term  Yearly_repayments      Monthly  \
0                    6.923077       15888.888889  1324.074074
1                    6.923077       18200.000000  1516.666667
2                    6.923077       30044.444444  2503.703704
3                    6.923077       14444.444444  1203.703704
4                    6.923077       11266.666667   938.888889
..                        ...                ...          ...
362                  6.923077       16322.222222  1360.185185
363                  6.923077       16611.111111  1384.259259
364                  6.923077       18200.000000  1516.666667
365                  6.923077       22822.222222  1901.851852
366                  3.461538       28311.111111  2359.259259

     Weekly_repayments  Daily_repayments
0           305.555556         43.650794
1           350.000000         50.000000
2           577.777778         82.539683
3           277.777778         39.682540
4           216.666667         30.952381
..                 ...               ...
362         313.888889         44.841270
363         319.444444         45.634921
364         350.000000         50.000000
365         438.888889         62.698413
366         544.444444         77.777778

[345 rows x 17 columns]

Filtered DataFrame (without outliers):
      Loan_ID Gender Married  Dependents     Education Self_Employed  \
0    LP001015   Male     Yes           0      Graduate            No
1    LP001022   Male     Yes           1      Graduate            No
2    LP001031   Male     Yes           2      Graduate            No
3    LP001035   Male     Yes           2      Graduate            No
4    LP001051   Male      No           0  Not Graduate            No
```

```
..        ...    ...     ...          ...          ...           ...
361  LP002969   Male     Yes           1      Graduate           No
362  LP002971   Male     Yes           3  Not Graduate          Yes
363  LP002975   Male     Yes           0      Graduate           No
364  LP002980   Male      No           0      Graduate           No
365  LP002986   Male     Yes           0      Graduate           No

     Weekly_Applicant_Income  Weekly_Coapplicant_Income  LoanAmount  \
0                       5720                          0      110000
1                       3076                       1500      126000
2                       5000                       1800      208000
3                       2340                       2546      100000
4                       3276                          0       78000
..                       ...                        ...         ...
361                     2269                       2167       99000
362                     4009                       1777      113000
363                     4158                        709      115000
364                     3250                       1993      126000
365                     5000                       2393      158000

     Weekly_Loan_Ammount_Term  Credit_History Property_Area  \
0                         360               1         Urban
1                         360               1         Urban
2                         360               1         Urban
3                         360               0         Urban
4                         360               1         Urban
..                        ...             ...           ...
361                       360               1     Semiurban
362                       360               1         Urban
363                       360               1         Urban
364                       360               0     Semiurban
365                       360               1         Rural

     Yearly_Loan_Ammount_Term  Yearly_repayments      Monthly  \
0                    6.923077       15888.888889  1324.074074
1                    6.923077       18200.000000  1516.666667
2                    6.923077       30044.444444  2503.703704
3                    6.923077       14444.444444  1203.703704
4                    6.923077       11266.666667   938.888889
..                        ...                ...          ...
361                  6.923077       14300.000000  1191.666667
362                  6.923077       16322.222222  1360.185185
363                  6.923077       16611.111111  1384.259259
364                  6.923077       18200.000000  1516.666667
365                  6.923077       22822.222222  1901.851852

     Weekly_repayments  Daily_repayments
0           305.555556         43.650794
1           350.000000         50.000000
2           577.777778         82.539683
3           277.777778         39.682540
4           216.666667         30.952381
..                 ...               ...
361         275.000000         39.285714
362         313.888889         44.841270
363         319.444444         45.634921
364         350.000000         50.000000
365         438.888889         62.698413

[311 rows x 17 columns]

Number of rows removed: 34
```

In [204…

```
df_filtered
```

Out[204…

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Weekly_Applicant_Income	Weekly_Coapplicant_Income	L
0	LP001015	Male	Yes	0	Graduate	No	5720	0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	
...	...	...	...	...	...	...	...	...	
361	LP002969	Male	Yes	1	Graduate	No	2269	2167	
362	LP002971	Male	Yes	3	Not Graduate	Yes	4009	1777	
363	LP002975	Male	Yes	0	Graduate	No	4158	709	
364	LP002980	Male	No	0	Graduate	No	3250	1993	
365	LP002986	Male	Yes	0	Graduate	No	5000	2393	

311 rows × 17 columns

In [205…

```
# adjust for changes that didnt reflect in df filtered.
# rename monthly column to Monthly_repayments
df_filtered = df_filtered.rename(columns={'Monthly': 'Monthly_repayments'})

# Rounded all repayment columns to the nearest 0.10
df_filtered['Yearly_repayments'] = df_filtered['Yearly_repayments'].round(0)
df_filtered['Weekly_repayments'] = df_filtered['Weekly_repayments'].round(0)
df_filtered['Monthly_repayments'] = df_filtered['Monthly_repayments'].round(0)
df_filtered['Daily_repayments'] = df_filtered['Daily_repayments'].round(0)
```

In [206…

```
df_filtered.head(5)
```

Out[206…

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Weekly_Applicant_Income	Weekly_Coapplicant_Income	Loa
0	LP001015	Male	Yes	0	Graduate	No	5720	0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	

In [207…

```
df_filtered.isnull().sum()
```

Out[207…

```
Loan_ID                     0
Gender                      0
Married                     0
Dependents                  0
Education                   0
Self_Employed               0
Weekly_Applicant_Income     0
Weekly_Coapplicant_Income   0
LoanAmount                  0
Weekly_Loan_Ammount_Term    0
Credit_History              0
Property_Area               0
Yearly_Loan_Ammount_Term    0
Yearly_repayments           0
Monthly_repayments          0
Weekly_repayments           0
Daily_repayments            0
dtype: int64
```

In [208…

```
df_filtered.shape
```

Out[208…

```
(311, 17)
```

In [209…

```
df_filtered.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 311 entries, 0 to 365
Data columns (total 17 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Loan_ID                    311 non-null    object
 1   Gender                     311 non-null    object
 2   Married                    311 non-null    object
 3   Dependents                 311 non-null    int32
 4   Education                  311 non-null    object
 5   Self_Employed              311 non-null    object
 6   Weekly_Applicant_Income    311 non-null    int64
 7   Weekly_Coapplicant_Income  311 non-null    int64
 8   LoanAmount                 311 non-null    int32
 9   Weekly_Loan_Ammount_Term   311 non-null    int32
 10  Credit_History             311 non-null    int32
 11  Property_Area              311 non-null    object
 12  Yearly_Loan_Ammount_Term   311 non-null    float64
 13  Yearly_repayments          311 non-null    float64
 14  Monthly_repayments         311 non-null    float64
 15  Weekly_repayments          311 non-null    float64
 16  Daily_repayments           311 non-null    float64
dtypes: float64(5), int32(4), int64(2), object(6)
memory usage: 38.9+ KB
```

In [210…

```
# 302 is bigger than 30 therefore we pay attention to z test.
# if the sample size was smaller than 30 we pay attention to the t test.
```

In [211…

```
import pandas as pd
import numpy as np
from scipy.stats import ttest_ind, norm

sample1 = df_filtered['LoanAmount']
Sample2 = df_filtered['Weekly_Applicant_Income']

def z_test(sample1, sample2):

    # df = pd.DataFrame(df_filtered)
    """
    Perform a z-test for two independent samples.
    """
    n1 = len(sample1)
    n2 = len(sample2)
    mean1 = np.mean(sample1)
    mean2 = np.mean(sample2)
    std1 = np.std(sample1, ddof=1)  # Sample standard deviation
    std2 = np.std(sample2, ddof=1)

    # Pooled standard error
    pooled_se = np.sqrt((std1**2 / n1) + (std2**2 / n2))

    # Z-statistic
    z_statistic = (mean1 - mean2) / pooled_se

    # P-value (two-tailed)
    p_value = 2 * (1 - norm.cdf(abs(z_statistic)))

    return z_statistic, p_value

def perform_tests(df_filtered, LoanAmount, Weekly_Applicant_Income, alpha=0.05):
    """
    Perform t-test and z-test on two columns from a CSV file.
    """
    # Load data from CSV
    # df = pd.DataFrame(df_filtered)

    # Extract the two columns
    group1 = df_filtered['LoanAmount']
    group2 = df_filtered['Weekly_Applicant_Income']

    # Perform t-test
    t_statistic, p_value_t = ttest_ind(group1, group2)

    # Perform z-test
    z_statistic, p_value_z = z_test(group1, group2)

    # Print results
    print("T-Test Results:")
    print(f"T-statistic: {t_statistic}")
    print(f"P-value: {p_value_t}")
    if p_value_t < alpha:
        print("Reject the null hypothesis (significant difference between groups).")
    else:
```

```
        print("Fail to reject the null hypothesis (no significant difference between groups).")

    print("\nZ-Test Results:")
    print(f"Z-statistic: {z_statistic}")
    print(f"P-value: {p_value_z}")
    if p_value_z < alpha:
        print("Reject the null hypothesis (significant difference between groups).")
    else:
        print("Fail to reject the null hypothesis (no significant difference between groups).")

# Example usage
csv_file = 'data.csv'  # Replace with your CSV file path
col1 = 'Group1'        # Replace with the first column name
col2 = 'Group2'        # Replace with the second column name

perform_tests(df_filtered, 'LoanAmount', 'Weekly_Applicant_Income')
```

```
T-Test Results:
T-statistic: 49.76178401070807
P-value: 1.0884762280372716e-218
Reject the null hypothesis (significant difference between groups).

Z-Test Results:
Z-statistic: 49.76178401070804
P-value: 0.0
Reject the null hypothesis (significant difference between groups).
```

In [212…

```
df_filtered
```

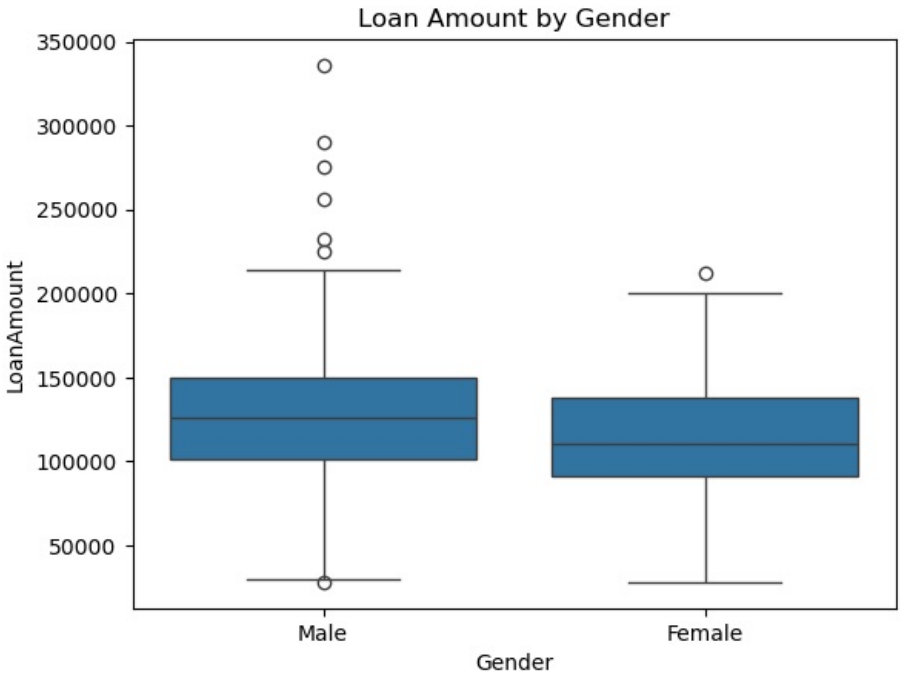
Out[212…

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Weekly_Applicant_Income	Weekly_Coapplicant_Income	L
0	LP001015	Male	Yes	0	Graduate	No	5720	0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	
...	...	...	...	...	...	...	...	...	
361	LP002969	Male	Yes	1	Graduate	No	2269	2167	
362	LP002971	Male	Yes	3	Not Graduate	Yes	4009	1777	
363	LP002975	Male	Yes	0	Graduate	No	4158	709	
364	LP002980	Male	No	0	Graduate	No	3250	1993	
365	LP002986	Male	Yes	0	Graduate	No	5000	2393	

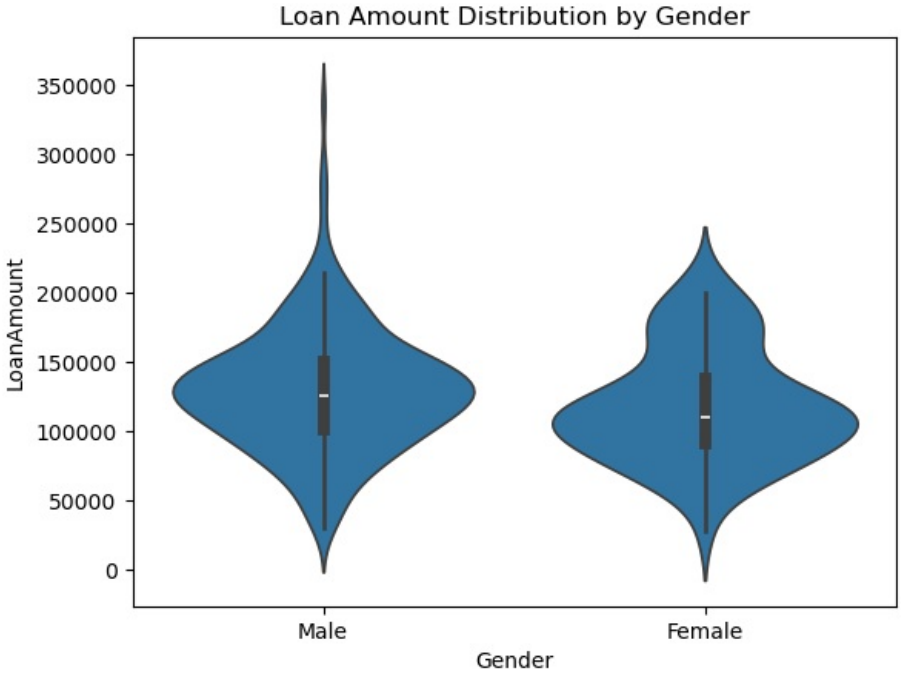
311 rows × 17 columns

In [213…

```
# now for charts.
# Assuming df is your DataFrame with 'Gender' and 'Loan Amount' columns
sns.boxplot(x='Gender', y='LoanAmount', data=df_filtered)
plt.title('Loan Amount by Gender')
plt.show()
```

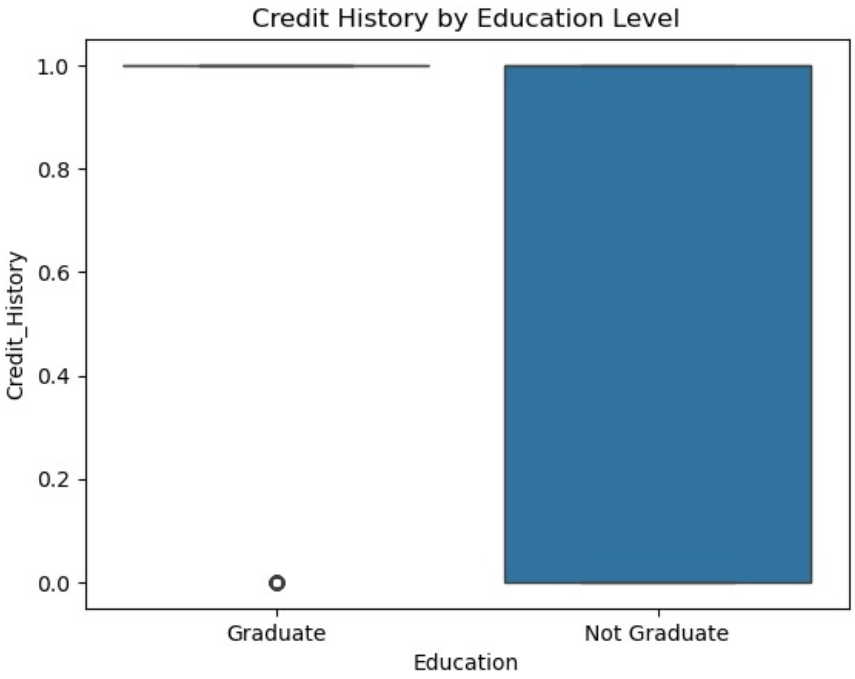


In [214…
```
sns.violinplot(x='Gender', y='LoanAmount', data=df_filtered)
plt.title('Loan Amount Distribution by Gender')
plt.show()
```

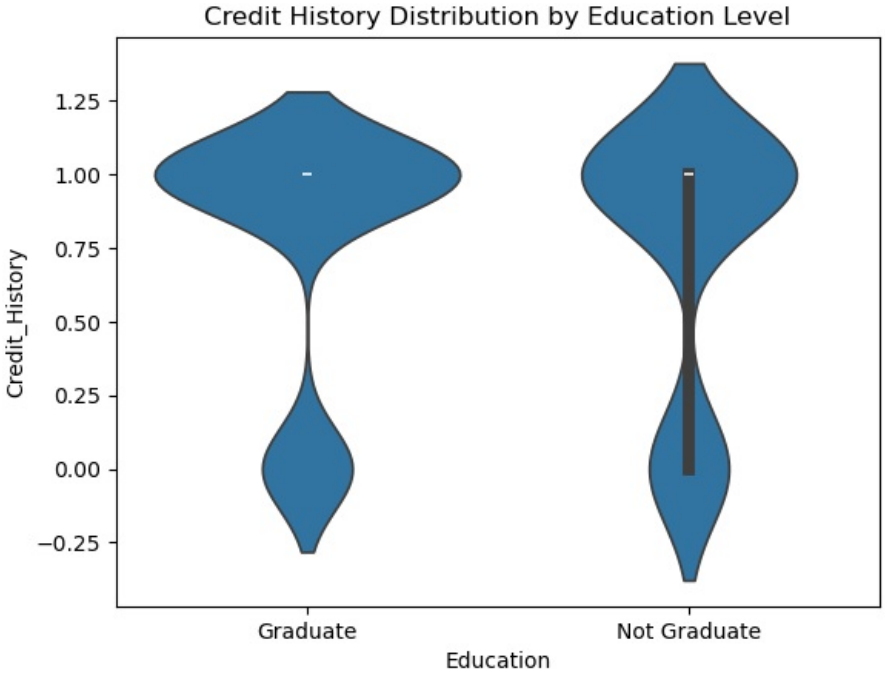


In [215…
```
# change credit history from object to numerical
df_filtered['Credit_History']=df_filtered['Credit_History'].astype(float)
```

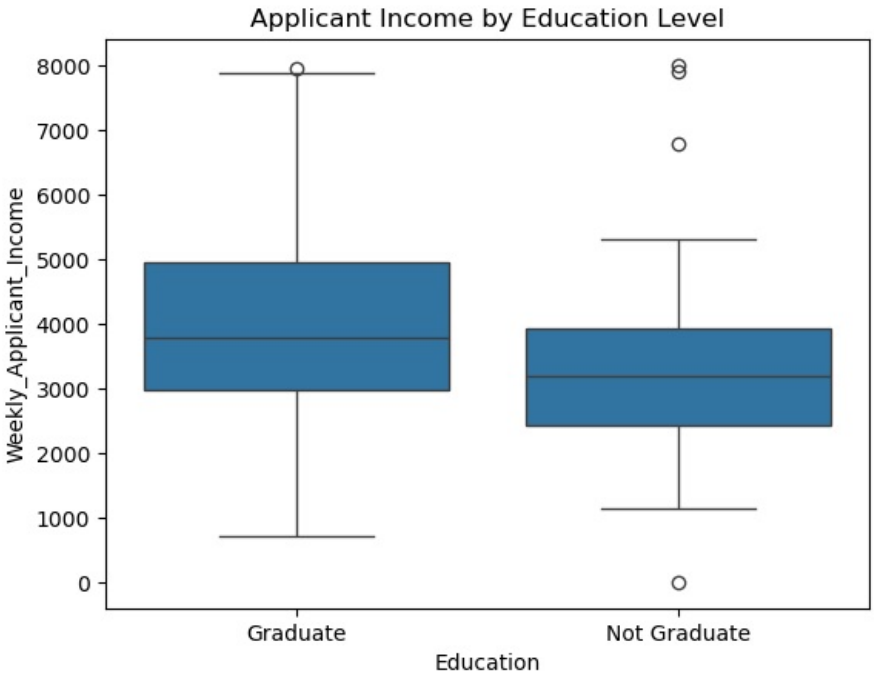
In [216…
```
sns.boxplot(x='Education', y='Credit_History', data=df_filtered)
plt.title('Credit History by Education Level')
plt.show()
```



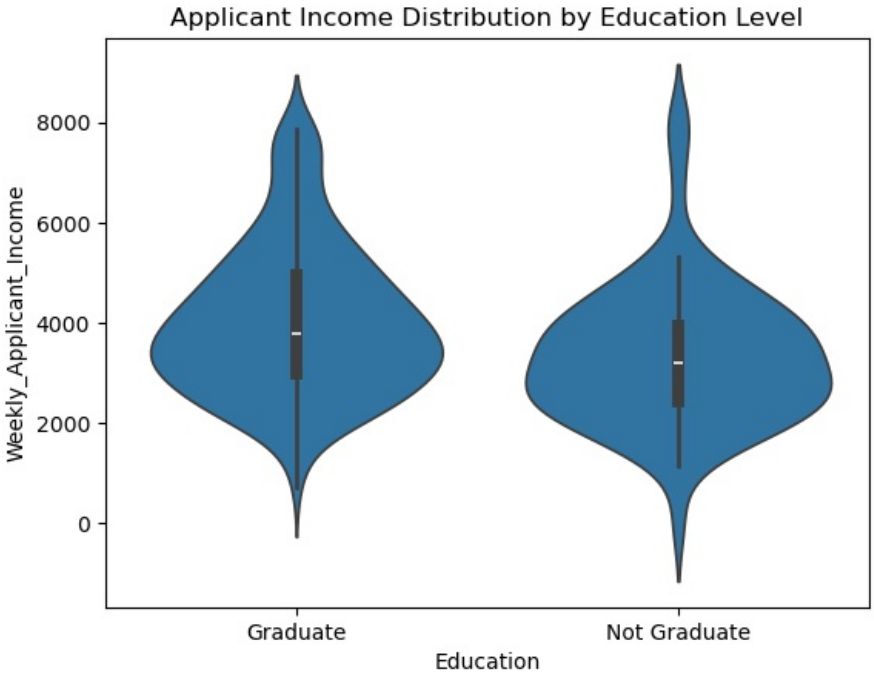
In [217…
```
sns.violinplot(x='Education', y='Credit_History', data=df_filtered)
plt.title('Credit History Distribution by Education Level')
plt.show()
```



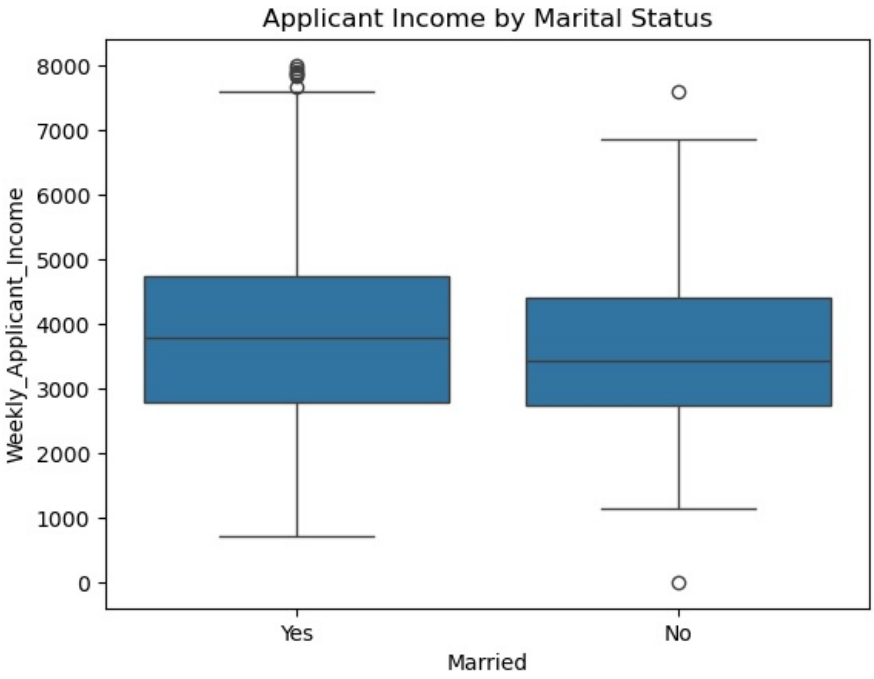
In [218…
```
sns.boxplot(x='Education', y='Weekly_Applicant_Income', data=df_filtered)
plt.title('Applicant Income by Education Level')
plt.show()
```



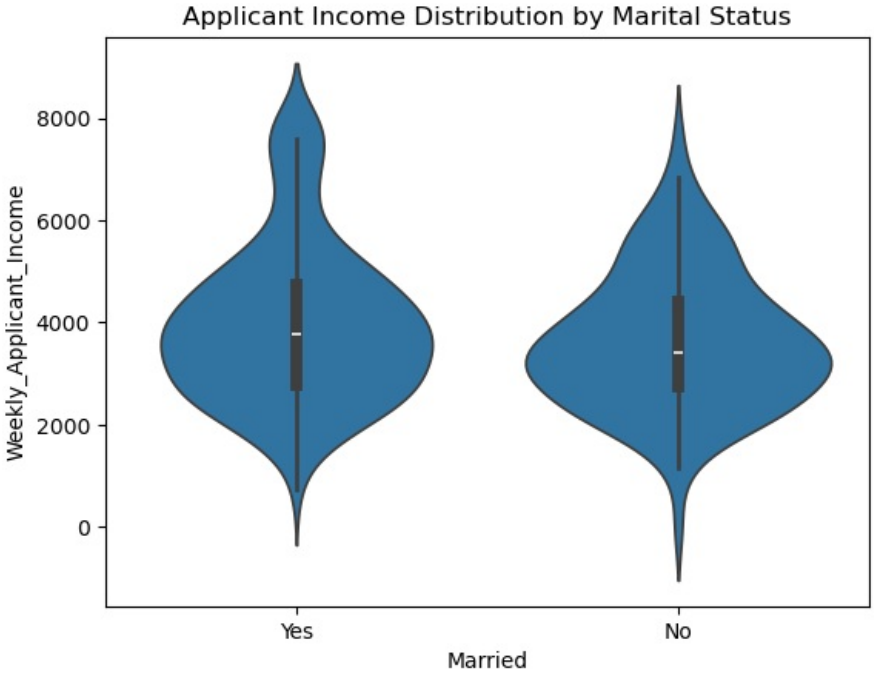
In [219…
```
sns.violinplot(x='Education', y='Weekly_Applicant_Income', data=df_filtered)
# can do boxplot and violin plot with one cateogorical and one numerical.
plt.title('Applicant Income Distribution by Education Level')
plt.show()
```



In [220…
```
sns.boxplot(x='Married', y='Weekly_Applicant_Income', data=df_filtered)
plt.title('Applicant Income by Marital Status')
plt.show()
```

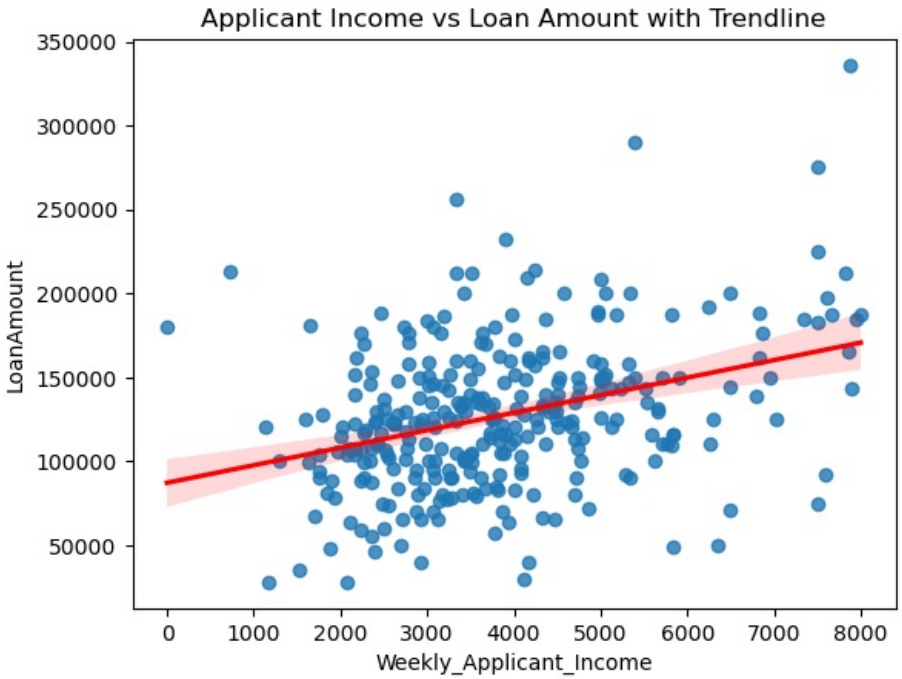


In [222…
```
sns.violinplot(x='Married', y='Weekly_Applicant_Income', data=df_filtered)
plt.title('Applicant Income Distribution by Marital Status')
plt.show()
```



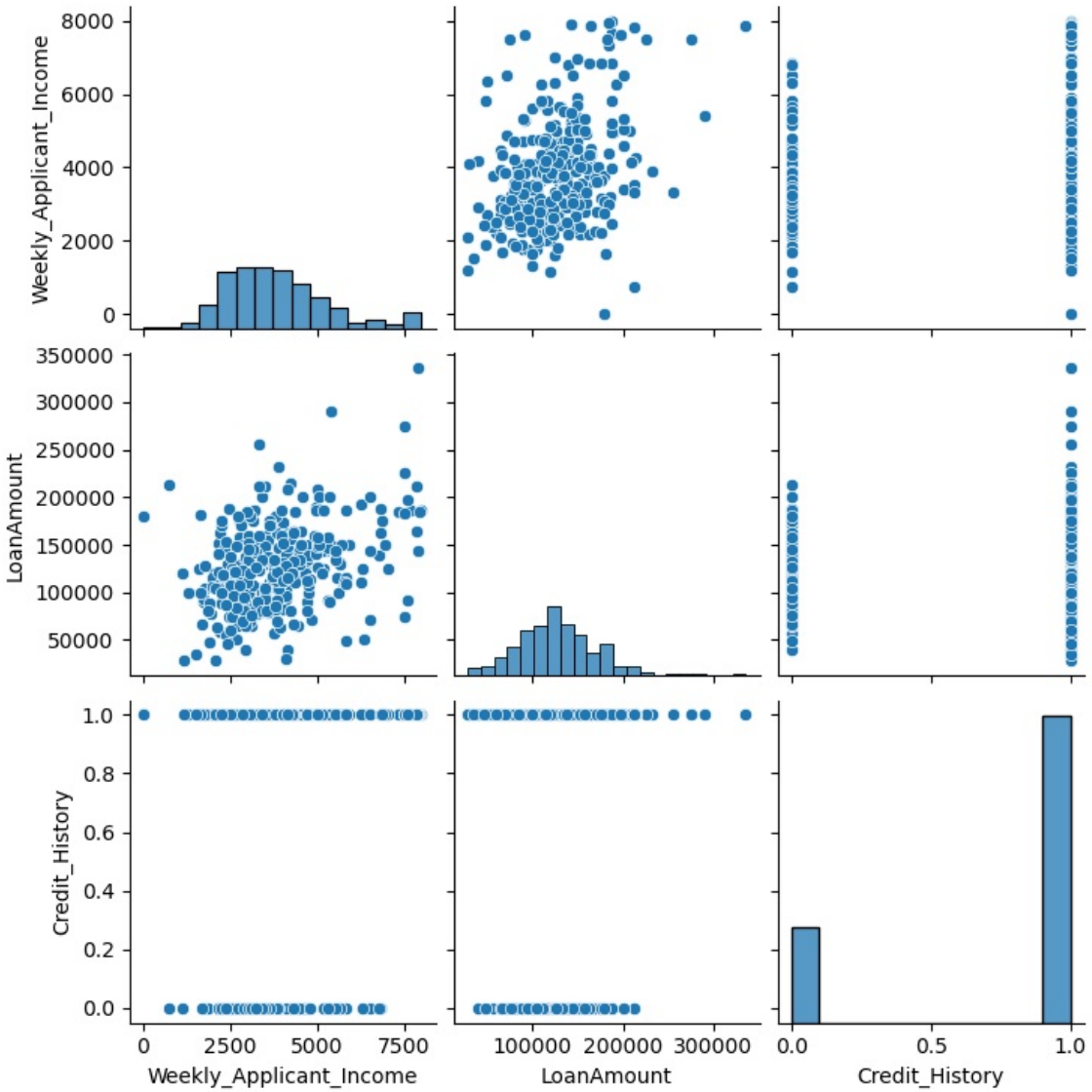
In [ ]:
```
sns.regplot(x='Weekly_Applicant_Income', y='LoanAmount', data=df_filtered,
            scatter=True, line_kws={'color': 'red'})

plt.title('Applicant Income vs Loan Amount with Trendline')
plt.show()
```



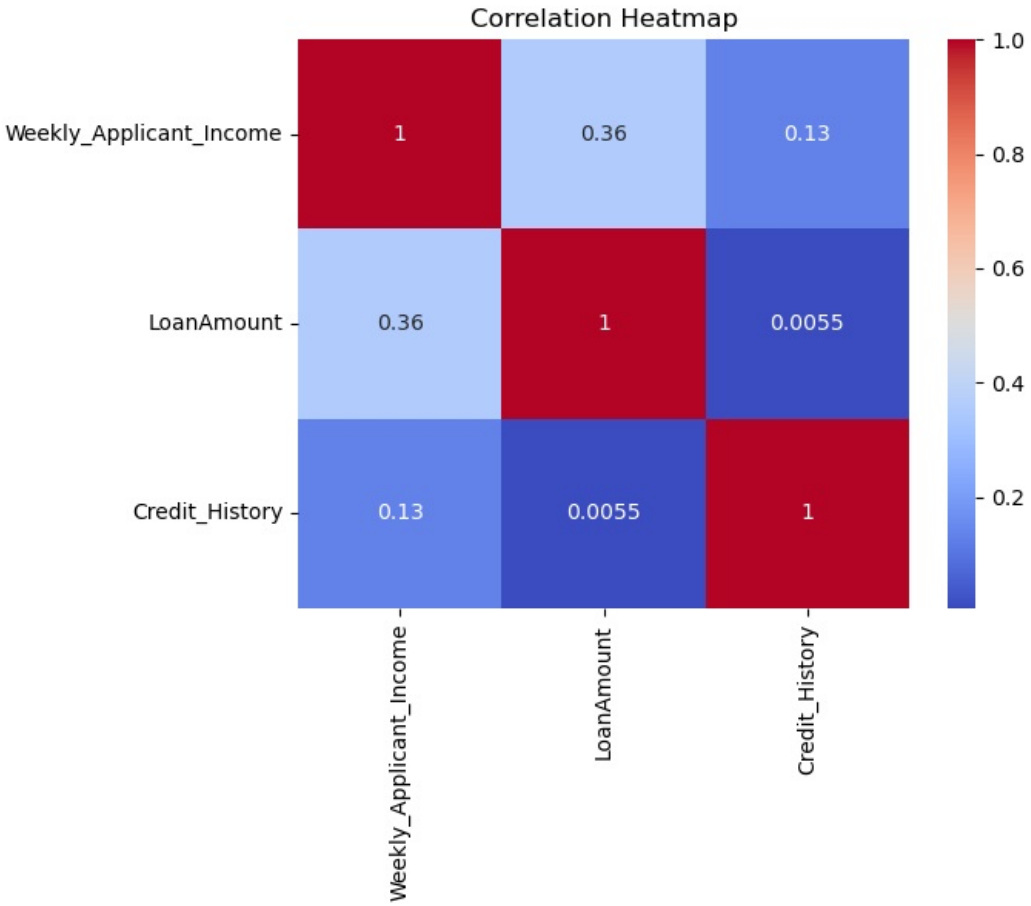
In [224…

```
sns.pairplot(df_filtered[['Weekly_Applicant_Income', 'LoanAmount', 'Credit_History']])
# can only do regression and pairplot with numerical variables.
# you can see a number of trends here.
### Applicant Income
# applicant Income has a slightly positive relationship with Loan ammount given (the more income u have the bet
# customers with a 1 credit history have a higher applicant income.
### LOAN AMMOUNT GIVEN
# Loan ammount given doesnt have a relationship with applicant income. As it depends on applicant income.
# credit history affects your loan ammount from the bank
### CREDIT HISTORY.
# the better your credit history the higher the applicant income.
# the better the credit history the higher the loan ammount given.
plt.show()
```



In [225…

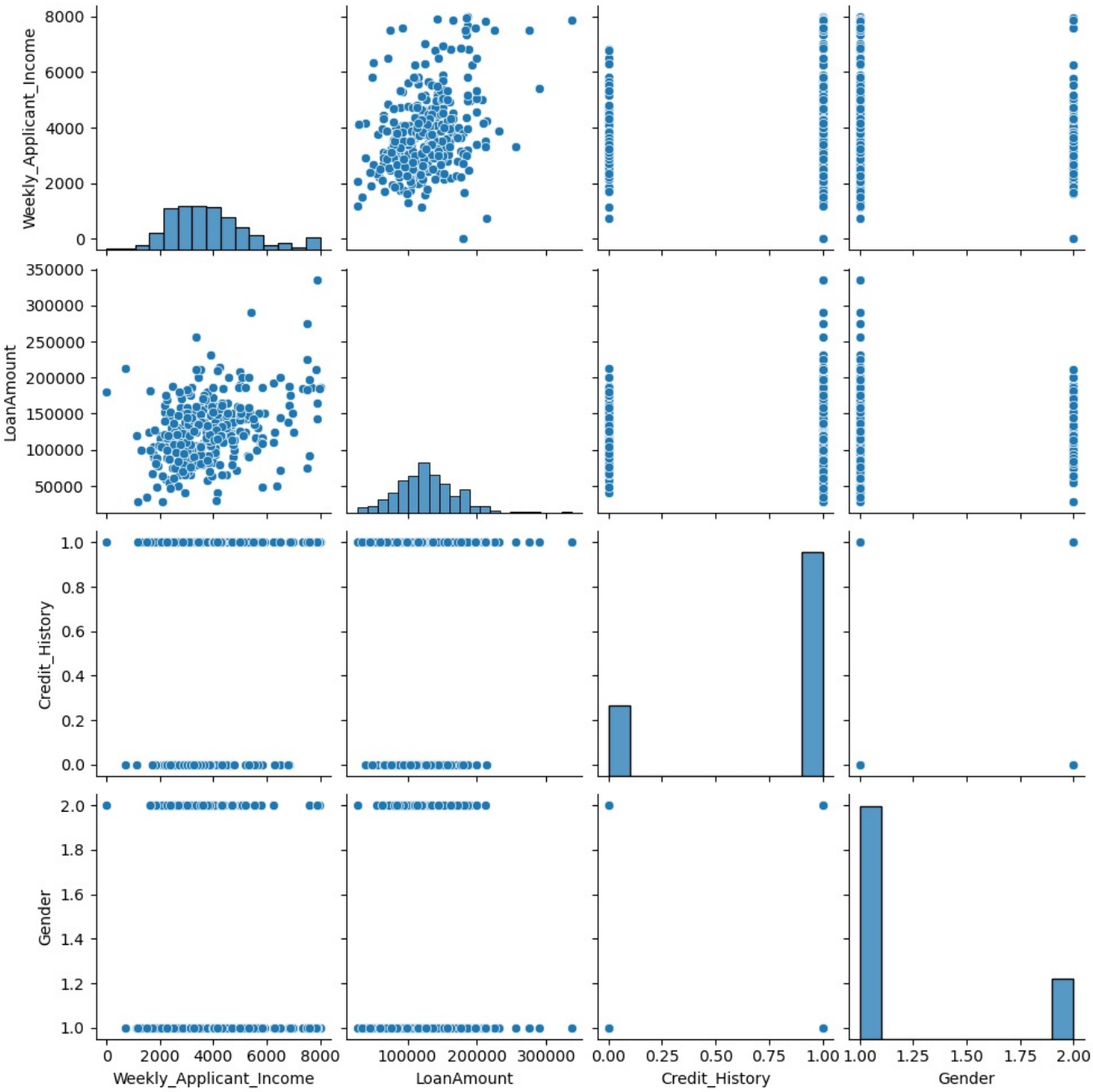
```
corr = df_filtered[['Weekly_Applicant_Income', 'LoanAmount', 'Credit_History']].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



In [226…
```
# Change gender datatype to 0 and 1 to be seen
df_filtered['Gender'] = df_filtered['Gender'].map({'Male': 1, 'Female': 2})
```

In [227…
```
sns.pairplot(df_filtered[['Weekly_Applicant_Income','LoanAmount','Credit_History','Gender']])
plt.show
```

Out[227…
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



ANSWER THE Original Questions of this project

is the Loan ammount applied for affected by gender?

In the graph above 1 is male and 2 is female. Males clearly burrow more notice the extra data pieces in the 300 000 range.

Does education affect credit history?

Yes refer to the violin plot the data is concentrated at a credit history of 1. Meaning that there is a positive correlation between eduction vs credit history.

does education affect weekly applicant income?

Yes refer to box plot Applicant income vs eduction level, the average is higher.

If you are married do u have a higher weekly applicant income?

Refer to Applicant income by Marital status viloin plot. The average and distribution at 8000 is higher. Yes if u are married u have a higher weekly applicant income.

if u have a higher weekly applicant income do u get a higher loan ammount?

Refer to Applicant Income vs Loan Amount with Trendline. There is a positive correlation if u have a higher weekly applicant income u can apply for a higher loan ammount.