```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Import Required Libraries

```
from pyspark.sql import SparkSession
from pyspark.sql.functions import col
from pyspark.sql.functions import regexp_extract, col, isnan, when, count
from pyspark.sql.types import DoubleType
```

```
# Start Spark session
spark = SparkSession.builder.appName("LoanDataPrediction").getOrCreate()
```

```
# Load dataset
df = spark.read.csv("/content/drive/MyDrive/Lending_Data/lending_club_loan_two.csv", header=True, inferSchema=True)
```

```
df.printSchema()
```

```
root
 |-- loan_amnt: string (nullable = true)
 |-- term: string (nullable = true)
 |-- int_rate: double (nullable = true)
 |-- installment: double (nullable = true)
 |-- grade: string (nullable = true)
 |-- sub_grade: string (nullable = true)
 |-- emp_title: string (nullable = true)
 |-- emp_length: string (nullable = true)
 |-- home_ownership: string (nullable = true)
 |-- annual_inc: double (nullable = true)
 |-- verification_status: string (nullable = true)
 |-- issue_d: string (nullable = true)
 |-- loan_status: string (nullable = true)
 |-- purpose: string (nullable = true)
 |-- title: string (nullable = true)
 |-- dti: string (nullable = true)
 |-- earliest_cr_line: string (nullable = true)
 |-- open_acc: string (nullable = true)
 |-- pub_rec: double (nullable = true)
 |-- revol_bal: double (nullable = true)
 |-- revol_util: double (nullable = true)
 |-- total_acc: double (nullable = true)
 |-- initial_list_status: string (nullable = true)
 |-- application_type: string (nullable = true)
 |-- mort_acc: string (nullable = true)
 |-- pub_rec_bankruptcies: double (nullable = true)
 |-- address: string (nullable = true)
```

```
df.show(5)
```

```
+-----------+----------+--------+-----------+-----+---------+---------------+----------+--------------+----------+-------------------+-
|  loan_amnt|      term|int_rate|installment|grade|sub_grade|      emp_title|emp_length|home_ownership|annual_inc|verification_status|
+-----------+----------+--------+-----------+-----+---------+---------------+----------+--------------+----------+-------------------+-
|    10000.0| 36 months|   11.44|     329.48|    B|       B4|      Marketing| 10+ years|          RENT|  117000.0|       Not Verified|J
|Mendozaberg| OK 22690"|    NULL|       NULL| NULL|     NULL|           NULL|      NULL|          NULL|      NULL|               NULL|
|     8000.0| 36 months|   11.99|     265.68|    B|       B5|Credit analyst |   4 years|      MORTGAGE|   65000.0|       Not Verified|J
| Loganmouth| SD 05113"|    NULL|       NULL| NULL|     NULL|           NULL|      NULL|          NULL|      NULL|               NULL|
|    15600.0| 36 months|   10.49|     506.97|    B|       B3|   Statistician|  < 1 year|          RENT|   43057.0|    Source Verified|J
+-----------+----------+--------+-----------+-----+---------+---------------+----------+--------------+----------+-------------------+-
only showing top 5 rows
```

```
df.describe()
```

```
DataFrame[summary: string, loan_amnt: string, term: string, int_rate: string, installment: string, grade: string, sub_grade: string,
emp_title: string, emp_length: string, home_ownership: string, annual_inc: string, verification_status: string, issue_d: string,
loan_status: string, purpose: string, title: string, dti: string, earliest_cr_line: string, open_acc: string, pub_rec: string,
revol_bal: string, revol_util: string, total_acc: string, initial_list_status: string, application_type: string, mort_acc: strir
pub_rec_bankruptcies: string, address: string]
```

Feature Engineering

```
# 1. Extract zipcode from address
df = df.withColumn("zip_code", regexp_extract(col("address"), r'([A-Z]{2}\s*\d{5})$', 1))
```

```
df.printSchema()
```

```
root
 |-- loan_amnt: string (nullable = true)
 |-- term: string (nullable = true)
 |-- int_rate: double (nullable = true)
 |-- installment: double (nullable = true)
 |-- grade: string (nullable = true)
 |-- sub_grade: string (nullable = true)
 |-- emp_title: string (nullable = true)
 |-- emp_length: string (nullable = true)
 |-- home_ownership: string (nullable = true)
 |-- annual_inc: double (nullable = true)
 |-- verification_status: string (nullable = true)
 |-- issue_d: string (nullable = true)
 |-- loan_status: string (nullable = true)
 |-- purpose: string (nullable = true)
 |-- title: string (nullable = true)
 |-- dti: string (nullable = true)
 |-- earliest_cr_line: string (nullable = true)
 |-- open_acc: string (nullable = true)
 |-- pub_rec: double (nullable = true)
 |-- revol_bal: double (nullable = true)
 |-- revol_util: double (nullable = true)
 |-- total_acc: double (nullable = true)
 |-- initial_list_status: string (nullable = true)
 |-- application_type: string (nullable = true)
 |-- mort_acc: string (nullable = true)
 |-- pub_rec_bankruptcies: double (nullable = true)
 |-- address: string (nullable = true)
 |-- zip_code: string (nullable = true)
```

Data Cleaning

```
# 4. Drop rows with missing values in key columns
df = df.dropna(subset=['emp_length', 'mort_acc', 'pub_rec_bankruptcies'])
```

```
# 5. Filter out rows where important columns are zero
df = df.filter((col('annual_inc') != 0) &
               (col('revol_bal') != 0) &
               (col('revol_util') != 0))
```

```
# 6. Remove 'NONE' and 'OTHER' values from home_ownership
df = df.filter(~col('home_ownership').isin(['NONE', 'OTHER']))
```

```
print(f"Number of rows: {df.count()}")
print(f"Number of columns: {len(df.columns)}")
```

```
Number of rows: 339433
Number of columns: 28
```

Plot Outliers

```
numeric_cols = df.columns[2:]
numeric_cols
```

```
['int_rate',
 'installment',
 'grade',
 'sub_grade',
 'emp_title',
 'emp_length',
 'home_ownership',
 'annual_inc',
```

```
    'verification_status',
    'issue_d',
    'loan_status',
    'purpose',
    'title',
    'dti',
    'earliest_cr_line',
    'open_acc',
    'pub_rec',
    'revol_bal',
    'revol_util',
    'total_acc',
    'initial_list_status',
    'application_type',
    'mort_acc',
    'pub_rec_bankruptcies',
    'address',
    'zip_code']
```

```
from pyspark.sql import functions as f
from pyspark.sql.types import IntegerType, DoubleType # Import DoubleType

# List of columns that should be treated as numeric
true_numeric_cols = ['int_rate', 'installment', 'annual_inc', 'revol_bal', 'revol_util', 'pub_rec', 'total_acc', 'pub_rec_bankruptcies']

for column in true_numeric_cols:
    df = df.withColumn(column,f.col(column).cast(DoubleType()))

# Keep other columns as they are (including those incorrectly cast to int previously)
# The find_outliers function will filter for numeric types based on the schema after this casting
```

```
df.printSchema()
```

```
root
 |-- loan_amnt: string (nullable = true)
 |-- term: string (nullable = true)
 |-- int_rate: double (nullable = true)
 |-- installment: double (nullable = true)
 |-- grade: string (nullable = true)
 |-- sub_grade: string (nullable = true)
 |-- emp_title: string (nullable = true)
 |-- emp_length: string (nullable = true)
 |-- home_ownership: string (nullable = true)
 |-- annual_inc: double (nullable = true)
 |-- verification_status: string (nullable = true)
 |-- issue_d: string (nullable = true)
 |-- loan_status: string (nullable = true)
 |-- purpose: string (nullable = true)
 |-- title: string (nullable = true)
 |-- dti: string (nullable = true)
 |-- earliest_cr_line: string (nullable = true)
 |-- open_acc: string (nullable = true)
 |-- pub_rec: double (nullable = true)
 |-- revol_bal: double (nullable = true)
 |-- revol_util: double (nullable = true)
 |-- total_acc: double (nullable = true)
 |-- initial_list_status: string (nullable = true)
 |-- application_type: string (nullable = true)
 |-- mort_acc: string (nullable = true)
 |-- pub_rec_bankruptcies: double (nullable = true)
 |-- address: string (nullable = true)
 |-- zip_code: string (nullable = true)
```

```
original_numerical_df = df.select(*true_numeric_cols).toPandas()
```

```
original_numerical_df.head(10)
```

	int_rate	installment	annual_inc	revol_bal	revol_util	pub_rec	total_acc	pub_rec_bankruptcies
0	11.44	329.48	117000.0	36369.0	41.8	0.0	25.0	0.0
1	11.99	265.68	65000.0	20131.0	53.3	0.0	27.0	0.0
2	10.49	506.97	43057.0	11987.0	92.2	0.0	26.0	0.0
3	6.49	220.65	54000.0	5472.0	21.5	0.0	13.0	0.0
4	17.27	609.33	55000.0	24584.0	69.8	0.0	43.0	0.0
5	13.33	677.07	86788.0	25757.0	100.6	0.0	23.0	0.0
6	5.32	542.07	125000.0	4178.0	4.9	0.0	25.0	0.0
7	11.14	426.47	46000.0	13425.0	64.5	0.0	15.0	0.0
8	10.99	410.84	103000.0	18637.0	32.9	0.0	40.0	0.0
9	16.29	928.40	115000.0	22171.0	82.4	0.0	37.0	0.0

```python
from pyspark.sql.types import IntegerType, DoubleType # Import DoubleType

def find_outliers(df):
    from pyspark.sql.functions import col, when, lit, count, isnan # Import specific functions

    # Identifying the numerical columns in a spark dataframe
    # Filter for columns that are actually numeric types after casting
    numeric_columns = [column[0] for column in df.dtypes if column[1] in ('int', 'double')]

    # Using the `for` loop to create new columns by identifying the outliers for each feature
    for column in numeric_columns:
        print(f"Processing column: {column}") # Add this print statement
        # Check if the column has non-null values before calculating quantiles
        if df.filter(col(column).isNotNull()).count() > 0:
            Q1_list = df.approxQuantile(column, [0.25], relativeError=0)
            Q3_list = df.approxQuantile(column, [0.75], relativeError=0)

            # Check if the quantile lists are not empty
            if Q1_list and Q3_list:
                Q1 = Q1_list[0]
                Q3 = Q3_list[0]

                # IQR : Inter Quantile Range
                IQR = Q3 - Q1

                #selecting the data, with -1.5*IQR to + 1.5*IQR., where param = 1.5 default value
                less_Q1 =  Q1 - 1.5*IQR
                more_Q3 =  Q3 + 1.5*IQR

                isOutlierCol = 'is_outlier_{}'.format(column)

                df = df.withColumn(isOutlierCol,when((col(column) > more_Q3) | (col(column) < less_Q1), 1).otherwise(0))
            else:
                 # If quantiles cannot be calculated, mark all rows as not outliers for this column
                 isOutlierCol = 'is_outlier_{}'.format(column)
                 df = df.withColumn(isOutlierCol, lit(0))
        else:
            # If column has no non-null values, mark all rows as not outliers for this column
            isOutlierCol = 'is_outlier_{}'.format(column)
            df = df.withColumn(isOutlierCol, lit(0))


    # Selecting the specific columns which we have added above, to check if there are any outliers
    selected_columns = [column for column in df.columns if column.startswith("is_outlier")]

    # Adding all the outlier columns into a new colum "total_outliers", to see the total number of outliers
    if selected_columns: # Check if there are any outlier columns to sum
        # Need to sum the columns using a list comprehension with col
        df = df.withColumn('total_outliers', sum(col(c) for c in selected_columns))
    else:
        df = df.withColumn('total_outliers', lit(0))


    # Dropping the extra columns created above, just to create nice dataframe., without extra columns
    df = df.drop(*[column for column in df.columns if column.startswith("is_outlier")])
```

```
    return df


new_df = find_outliers(df)
new_df.show()
```

```
Processing column: int_rate
Processing column: installment
Processing column: annual_inc
Processing column: pub_rec
Processing column: revol_bal
Processing column: revol_util
Processing column: total_acc
Processing column: pub_rec_bankruptcies
+---------+----------+--------+-----------+-----+---------+--------------------+----------+--------------+----------+------------------
|loan_amnt|      term|int_rate|installment|grade|sub_grade|           emp_title|emp_length|home_ownership|annual_inc|verification_statu
+---------+----------+--------+-----------+-----+---------+--------------------+----------+--------------+----------+------------------
|  10000.0| 36 months|   11.44|     329.48|    B|       B4|           Marketing| 10+ years|          RENT|  117000.0|      Not Verifie
|   8000.0| 36 months|   11.99|     265.68|    B|       B5|     Credit analyst |   4 years|      MORTGAGE|   65000.0|      Not Verifie
|  15600.0| 36 months|   10.49|     506.97|    B|       B3|        Statistician|  < 1 year|          RENT|   43057.0|   Source Verifie
|   7200.0| 36 months|    6.49|     220.65|    A|       A2|     Client Advocate|   6 years|          RENT|   54000.0|      Not Verifie
|  24375.0| 60 months|   17.27|     609.33|    C|       C5|Destiny Managemen...|   9 years|      MORTGAGE|   55000.0|          Verifie
|  20000.0| 36 months|   13.33|     677.07|    C|       C3|       HR Specialist| 10+ years|      MORTGAGE|   86788.0|          Verifie
|  18000.0| 36 months|    5.32|     542.07|    A|       A1|Software Developm...|   2 years|      MORTGAGE|  125000.0|   Source Verifie
|  13000.0| 36 months|   11.14|     426.47|    B|       B2|        Office Depot| 10+ years|          RENT|   46000.0|      Not Verifie
|  18900.0| 60 months|   10.99|     410.84|    B|       B3|Application Archi...| 10+ years|          RENT|  103000.0|          Verifie
|  26300.0| 36 months|   16.29|      928.4|    C|       C5|  Regado Biosciences|   3 years|      MORTGAGE|  115000.0|          Verifie
|  10000.0| 36 months|   13.11|     337.47|    B|       B4|              Sodexo|   2 years|          RENT|   95000.0|          Verifie
|  35000.0| 36 months|   14.64|    1207.13|    C|       C3|Director Bureau o...|   8 years|      MORTGAGE|  130000.0|          Verifie
|   7500.0| 36 months|    9.17|      239.1|    B|       B2|Social Work/Care ...|   7 years|           OWN|   55000.0|      Not Verifie
|  35000.0| 60 months|   12.29|      783.7|    C|       C1|    Regional Counsel| 10+ years|      MORTGAGE|  157000.0|          Verifie
|  25975.0| 36 months|    6.62|     797.53|    A|       A2|Pullman Regional ...|   9 years|      MORTGAGE|   65000.0|          Verifie
|  18000.0| 36 months|    8.39|      567.3|    A|       A5|         firefighter|   8 years|      MORTGAGE|   45000.0|      Not Verifie
|  32350.0| 60 months|   21.98|     893.11|    E|       E4|Comcast Corporate...| 10+ years|      MORTGAGE|   72000.0|          Verifie
|  11200.0| 60 months|   12.29|     250.79|    C|       C1|           principal| 10+ years|      MORTGAGE|   81000.0|      Not Verifie
|  34000.0| 36 months|     7.9|    1063.87|    A|       A4|               Pilot| 10+ years|          RENT|  130580.0|          Verifie
|  20000.0| 36 months|    6.97|     617.27|    A|       A3|     Registered Nurse|   7 years|      MORTGAGE|   85000.0|      Not Verifie
+---------+----------+--------+-----------+-----+---------+--------------------+----------+--------------+----------+------------------
only showing top 20 rows
```

```
new_df_with_no_outliers = new_df.filter(new_df['total_Outliers']<=1)
new_df_with_no_outliers = new_df_with_no_outliers.select(*df.columns)

new_df_with_no_outliers.show()
```

```
+---------+----------+--------+-----------+-----+---------+--------------------+----------+--------------+----------+------------------
|loan_amnt|      term|int_rate|installment|grade|sub_grade|           emp_title|emp_length|home_ownership|annual_inc|verification_statu
+---------+----------+--------+-----------+-----+---------+--------------------+----------+--------------+----------+------------------
|  10000.0| 36 months|   11.44|     329.48|    B|       B4|           Marketing| 10+ years|          RENT|  117000.0|      Not Verifie
|   8000.0| 36 months|   11.99|     265.68|    B|       B5|     Credit analyst |   4 years|      MORTGAGE|   65000.0|      Not Verifie
|  15600.0| 36 months|   10.49|     506.97|    B|       B3|        Statistician|  < 1 year|          RENT|   43057.0|   Source Verifie
|   7200.0| 36 months|    6.49|     220.65|    A|       A2|     Client Advocate|   6 years|          RENT|   54000.0|      Not Verifie
|  24375.0| 60 months|   17.27|     609.33|    C|       C5|Destiny Managemen...|   9 years|      MORTGAGE|   55000.0|          Verifie
|  20000.0| 36 months|   13.33|     677.07|    C|       C3|       HR Specialist| 10+ years|      MORTGAGE|   86788.0|          Verifie
|  18000.0| 36 months|    5.32|     542.07|    A|       A1|Software Developm...|   2 years|      MORTGAGE|  125000.0|   Source Verifie
|  13000.0| 36 months|   11.14|     426.47|    B|       B2|        Office Depot| 10+ years|          RENT|   46000.0|      Not Verifie
|  18900.0| 60 months|   10.99|     410.84|    B|       B3|Application Archi...| 10+ years|          RENT|  103000.0|          Verifie
|  26300.0| 36 months|   16.29|      928.4|    C|       C5|  Regado Biosciences|   3 years|      MORTGAGE|  115000.0|          Verifie
|   7500.0| 36 months|    9.17|      239.1|    B|       B2|Social Work/Care ...|   7 years|           OWN|   55000.0|      Not Verifie
|  25975.0| 36 months|    6.62|     797.53|    A|       A2|Pullman Regional ...|   9 years|      MORTGAGE|   65000.0|          Verifie
|  18000.0| 36 months|    8.39|      567.3|    A|       A5|         firefighter|   8 years|      MORTGAGE|   45000.0|      Not Verifie
|  32350.0| 60 months|   21.98|     893.11|    E|       E4|Comcast Corporate...| 10+ years|      MORTGAGE|   72000.0|          Verifie
|  34000.0| 36 months|     7.9|    1063.87|    A|       A4|               Pilot| 10+ years|          RENT|  130580.0|          Verifie
|  20000.0| 36 months|    6.97|     617.27|    A|       A3|     Registered Nurse|   7 years|      MORTGAGE|   85000.0|      Not Verifie
|   9200.0| 36 months|    6.62|     282.48|    A|       A2|     Personal Trainer|  < 1 year|          RENT|   65000.0|   Source Verifie
|   7350.0| 36 months|   13.11|     248.05|    B|       B4|Francis Howell Sc...| 10+ years|      MORTGAGE|   54800.0|      Not Verifie
|  20000.0| 36 months|    8.39|     630.34|    A|       A5|      Office Manager| 10+ years|           OWN|   55000.0|   Source Verifie
|   5000.0| 36 months|   15.61|     174.83|    D|       D1|  Operations Manager|   5 years|          RENT|   75000.0|          Verifie
+---------+----------+--------+-----------+-----+---------+--------------------+----------+--------------+----------+------------------
only showing top 20 rows
```

```
print(f"Number of rows: {new_df_with_no_outliers.count()}")
print(f"Number of columns: {len(new_df_with_no_outliers.columns)}")
```

```
Number of rows: 290078
Number of columns: 28
```

```
# Plotting the box for the dataset after removing the outliers

dataset_after_removing_outliers = new_df_with_no_outliers.toPandas()
dataset_after_removing_outliers.head(10)
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	...	pub_rec	revol_b
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117000.0	...	0.0	3636
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65000.0	...	0.0	2013
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	RENT	43057.0	...	0.0	1198
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54000.0	...	0.0	547
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	9 years	MORTGAGE	55000.0	...	0.0	2458
5	20000.0	36 months	13.33	677.07	C	C3	HR Specialist	10+ years	MORTGAGE	86788.0	...	0.0	2575
6	18000.0	36 months	5.32	542.07	A	A1	Software Development Engineer	2 years	MORTGAGE	125000.0	...	0.0	417
7	13000.0	36 months	11.14	426.47	B	B2	Office Depot	10+ years	RENT	46000.0	...	0.0	1342
8	18900.0	60 months	10.99	410.84	B	B3	Application Architect	10+ years	RENT	103000.0	...	0.0	1863
9	26300.0	36 months	16.29	928.40	C	C5	Regado Biosciences	3 years	MORTGAGE	115000.0	...	0.0	2217

10 rows × 28 columns

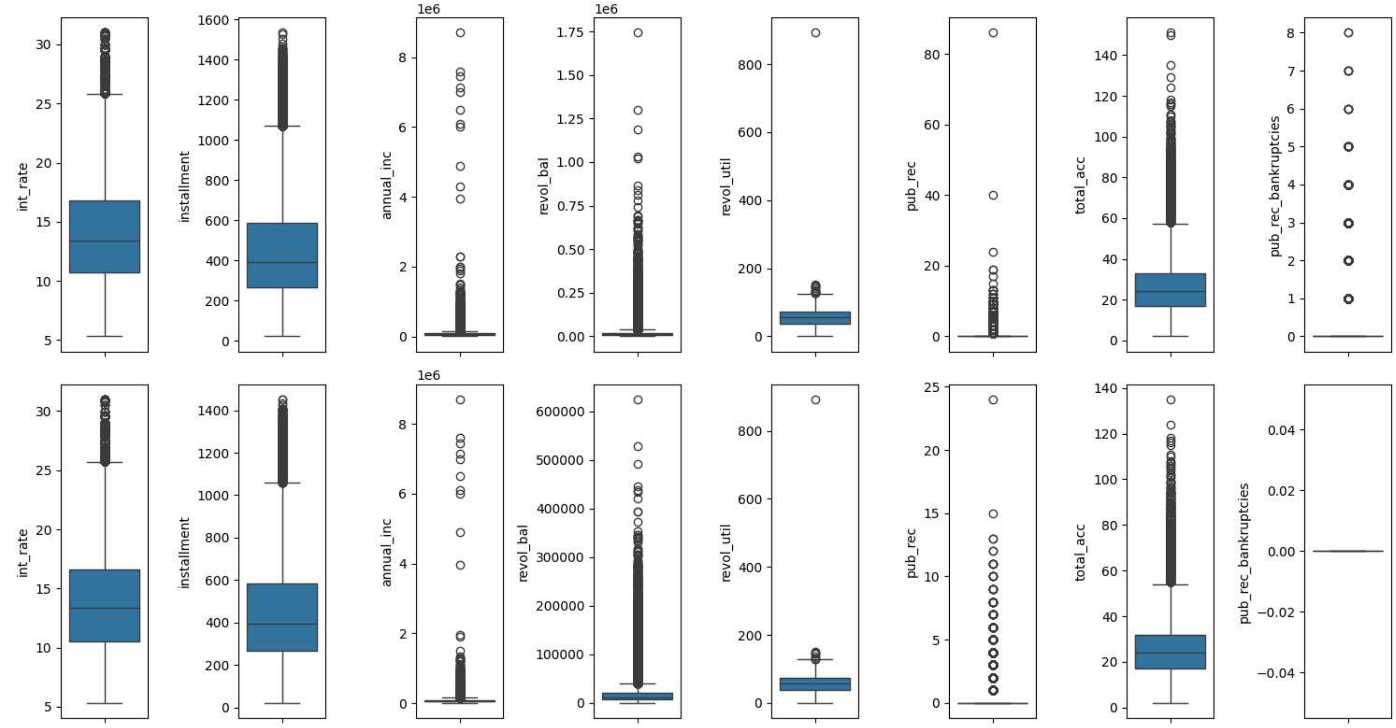
```
import matplotlib.pyplot as plt
import seaborn as sns

# Use the correct list of numeric columns
# true_numeric_cols is defined in cell TBpeMXrtcnr6
numeric_columns_for_plotting = true_numeric_cols

fig,ax = plt.subplots(2, len(numeric_columns_for_plotting),figsize=(15,8)) # Adjust the number of columns in subplots
for i,df in enumerate([original_numerical_df,dataset_after_removing_outliers]):

    for j, col in enumerate(numeric_columns_for_plotting): # Iterate through the correct list of columns
        sns.boxplot(data = df, y=col,ax=ax[i][j])

plt.tight_layout() # Add tight_layout to prevent overlapping titles/labels
plt.show() # Display the plots
```




```
print(f"Number of rows: {dataset_after_removing_outliers.count()}")
print(f"Number of columns: {len(dataset_after_removing_outliers.columns)}")
```

```
Number of rows: loan_amnt               290078
term                    290078
int_rate                290078
installment             290078
grade                   290078
sub_grade               290078
emp_title               287316
emp_length              290078
home_ownership          290078
annual_inc              290078
verification_status     290078
issue_d                 290078
loan_status             290078
purpose                 290078
title                   288823
dti                     290078
earliest_cr_line        290078
open_acc                290078
pub_rec                 290078
revol_bal               290078
revol_util              290078
total_acc               290078
initial_list_status     290078
application_type        290078
mort_acc                290078
pub_rec_bankruptcies    290078
address                 290078
zip_code                290078
dtype: int64
Number of columns: 28
```

```
#Undersampling of data
```

```
!pip install -U imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in /usr/local/lib/python3.11/dist-packages (0.13.0)
Requirement already satisfied: numpy<3,>=1.24.3 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (2.0.2)
Requirement already satisfied: scipy<2,>=1.10.1 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (1.16.0)
Requirement already satisfied: scikit-learn<2,>=1.3.2 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (1.6.1)
Requirement already satisfied: sklearn-compat<1,>=0.1 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (0.1.3
Requirement already satisfied: joblib<2,>=1.1.1 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (1.5.1)
Requirement already satisfied: threadpoolctl<4,>=2.0.0 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn) (3.6.0
```

```
# Undersampling of data using PySpark

# The 'new_df_with_no_outliers' is the PySpark DataFrame after outlier removal.
# Undersampling in PySpark requires a different approach than using libraries like imbalanced-learn,
# which are designed for Pandas DataFrames.
# A common approach in PySpark is to sample the majority class to match the minority class size.

# First, let's check the class distribution of the target variable 'loan_status'
class_counts = new_df_with_no_outliers.groupBy("loan_status").count()
class_counts.show()

# Assuming 'Fully Paid' is the majority class and 'Charged Off' is the minority class
# (You should verify this from the class_counts output)
majority_class_name = "Fully Paid" # Replace with the actual majority class name if different
minority_class_name = "Charged Off" # Replace with the actual minority class name if different

# Get the count of the minority class
minority_count = class_counts.filter(f.col("loan_status") == minority_class_name).select("count").collect()[0][0]

# Filter the DataFrame into majority and minority classes
majority_df = new_df_with_no_outliers.filter(f.col("loan_status") == majority_class_name)
minority_df = new_df_with_no_outliers.filter(f.col("loan_status") == minority_class_name)

# Undersample the majority class
# The fraction is calculated based on the ratio of minority count to majority count
majority_count_val = class_counts.filter(f.col("loan_status") == majority_class_name).select("count").collect()[0][0]
sampling_fraction = minority_count / majority_count_val

undersampled_majority_df = majority_df.sample(False, sampling_fraction, seed=42)

# Combine the undersampled majority class with the minority class
undersampled_df = undersampled_majority_df.unionAll(minority_df)

# Show the class distribution after undersampling
print("Class distribution after undersampling:")
undersampled_df.groupBy("loan_status").count().show()

# Now 'undersampled_df' is your PySpark DataFrame with balanced classes.
# You can proceed with model training using this DataFrame.
```

```
+-----------+------+
|loan_status| count|
+-----------+------+
| Fully Paid|232518|
|Charged Off| 57560|
+-----------+------+

Class distribution after undersampling:
+-----------+-----+
|loan_status|count|
+-----------+-----+
| Fully Paid|57919|
|Charged Off|57560|
+-----------+-----+
```

Model Training and building

```
from pyspark.ml.feature import StringIndexer, OneHotEncoder, VectorAssembler
from pyspark.ml.classification import LogisticRegression, RandomForestClassifier
from pyspark.ml import Pipeline
from pyspark.ml.evaluation import MulticlassClassificationEvaluator


# Step : Index target label
label_indexer = StringIndexer(inputCol="loan_status", outputCol="label", handleInvalid="keep")

# Step 2: Identify categorical and numerical columns using the PySpark DataFrame
categorical_cols = [field for (field, dtype) in undersampled_df.dtypes if dtype == "string" and field != "loan_status"]
numerical_cols = [field for (field, dtype) in undersampled_df.dtypes if dtype in ["int", "double", "float"]]


# Step : Split Data using the PySpark DataFrame
train_df, test_df = undersampled_df.randomSplit([0.8, 0.2], seed=42)
```

One Hot Encoding

```
# Step : Index and encode categorical features
# Filter out categorical columns with less than 2 distinct values in the training data
categorical_cols_filtered = [col for col in categorical_cols if train_df.select(col).distinct().count() >= 2]

indexers = [StringIndexer(inputCol=column, outputCol=column + "_indexed", handleInvalid="keep") for column in categorical_cols_filtered]
encoders = [OneHotEncoder(inputCol=col + "_indexed", outputCol=col + "_ohe") for col in categorical_cols_filtered]

# Step 4: Combine all features
assembler_inputs = [col + "_ohe" for col in categorical_cols_filtered] + numerical_cols
assembler = VectorAssembler(inputCols=assembler_inputs, outputCol="features")
```

Logistic Regression Model

```
# Step : Model Definitions
lr = LogisticRegression(featuresCol="features", labelCol="label")


# Step : Build Pipelines
lr_pipeline = Pipeline(stages=[label_indexer] + indexers + encoders + [assembler, lr])


lr_model = lr_pipeline.fit(train_df)


# Step : Predict on Test Data
lr_predictions = lr_model.transform(test_df)


# Step : Evaluate
evaluator = MulticlassClassificationEvaluator(labelCol="label", predictionCol="prediction", metricName="accuracy")

lr_accuracy = evaluator.evaluate(lr_predictions)


print(f"Logistic Regression Accuracy: {lr_accuracy:.4f}")
```

```
Logistic Regression Accuracy: 0.6367
```

```
# Stop the existing Spark session if it's running
spark.stop()

# Start Spark session with increased memory allocation
```