Business Case: LoanTap Logistic Regression

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Introduction

Context:

LoanTap is an online platform committed to delivering customized loan products to millennials. They innovate in an otherwise dull loan segment, to deliver instant, flexible loans on consumer friendly terms to salaried professionals and businessmen.

The data science team at LoanTap is building an underwriting layer to determine the creditworthiness of MSMEs as well as individuals.

LoanTap deploys formal credit to salaried individuals and businesses 4 main financial instruments:

- Personal Loan
- EMI Free Loan
- Personal Overdraft
- Advance Salary Loan

This case study will focus on the underwriting process behind Personal Loan only

Problem_Statement

Given a set of attributes for an Individual, determine if a credit line should be extended to them. If so, what should the repayment terms be in business recommendations?

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import pylab

from scipy.stats import shapiro
import scipy.stats as stats
import scipy.stats as stats
import statsmodels.api as sm

import statsmodels.api as sm
import statsmodels.formula.api as smf


from scipy.stats import f_oneway, ttest_ind, kruskal
from scipy.stats import chi2_contingency
import statsmodels.stats.multicomp as multi
from statsmodels.formula.api import ols

import category_encoders as ce
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler


from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import precision_recall_curve, average_precision_score

from imblearn.over_sampling import SMOTE
```

In [2]:
```
df = pd.read_csv("../data/logistic_regression.csv")
df.head()
```

Out[2]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	...	open_acc	pub_rec	rev
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117000.0	...	16.0	0.0	3
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65000.0	...	17.0	0.0	2
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	RENT	43057.0	...	13.0	0.0	1
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54000.0	...	6.0	0.0	
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	9 years	MORTGAGE	55000.0	...	13.0	0.0	2

5 rows × 27 columns

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  object 
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  object 
 5   sub_grade             396030 non-null  object 
 6   emp_title             373103 non-null  object 
 7   emp_length            377729 non-null  object 
 8   home_ownership        396030 non-null  object 
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  object 
 11  issue_d               396030 non-null  object 
 12  loan_status           396030 non-null  object 
 13  purpose               396030 non-null  object 
 14  title                 394275 non-null  object 
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  object 
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  object 
 23  application_type      396030 non-null  object 
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object 
dtypes: float64(12), object(15)
memory usage: 81.6+ MB
```

DataDescription

- **loan_amnt** : The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.
- **term** : The number of payments on the loan. Values are in months and can be either 36 or 60.
- **int_rate** : Interest Rate on the loan
- **installment** : The monthly payment owed by the borrower if the loan originates.
- **grade** : LoanTap assigned loan grade
- **sub_grade** : LoanTap assigned loan subgrade
- **emp_title** :The job title supplied by the Borrower when applying for the loan.*
- **eemp_length** : Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.
- **home_ownership** : The home ownership status provided by the borrower during registration or obtained from the credit report.
- **annual_inc** : The self-reported annual income provided by the borrower during registration.
- **verification_status** : Indicates if income was verified by LoanTap, not verified, or if the income source was verified
- **issue_d** : The month which the loan was funded
- **purpose** : A category provided by the borrower for the loan request.
- **title** : The loan title provided by the borrower
- **dti** : A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested LoanTap loan, divided by the borrower’s self-reported monthly income.
- **earliest_cr_line** :The month the borrower's earliest reported credit line was opened
- **open_acc** : The number of open credit lines in the borrower's credit file.
- **pub_rec** : Number of derogatory public records
- **revol_bal** : Total credit revolving balance
- **revol_util** : Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.
- **total_acc** : The total number of credit lines currently in the borrower's credit file
- **initial_list_status** : The initial listing status of the loan. Possible values are – W, F
- **application_type** : Indicates whether the loan is an individual application or a joint application with two co-borrowers
- **mort_acc** : Number of mortgage accounts.
- **pub_rec_bankruptcies** : Number of public record bankruptcies
- **Address**: Address of the individual
- **loan_status**- : Current status of the loan - Target Variable

In [ ]:

In [ ]:

Records	Features
396030	27

Class Distribution	for loan_status
Fully Paid	80.38 %
Charged Off	19.61 %
highly imbalanced	

people have fully paid their Loan Amount

- 80.38 % of the people have fully paid their Loan Amount

Summary_Statistics

Descriptive_Statistics

In [4]:
```
df.describe().T
```

Out[4]:

	count	mean	std	min	25%	50%	75%	max
loan_amnt	396030.0	14113.888089	8357.441341	500.00	8000.00	12000.00	20000.00	40000.00
int_rate	396030.0	13.639400	4.472157	5.32	10.49	13.33	16.49	30.99
installment	396030.0	431.849698	250.727790	16.08	250.33	375.43	567.30	1533.81
annual_inc	396030.0	74203.175798	61637.621158	0.00	45000.00	64000.00	90000.00	8706582.00
dti	396030.0	17.379514	18.019092	0.00	11.28	16.91	22.98	9999.00
open_acc	396030.0	11.311153	5.137649	0.00	8.00	10.00	14.00	90.00
pub_rec	396030.0	0.178191	0.530671	0.00	0.00	0.00	0.00	86.00
revol_bal	396030.0	15844.539853	20591.836109	0.00	6025.00	11181.00	19620.00	1743266.00
revol_util	395754.0	53.791749	24.452193	0.00	35.80	54.80	72.90	892.30
total_acc	396030.0	25.414744	11.886991	2.00	17.00	24.00	32.00	151.00
mort_acc	358235.0	1.813991	2.147930	0.00	0.00	1.00	3.00	34.00
pub_rec_bankruptcies	395495.0	0.121648	0.356174	0.00	0.00	0.00	0.00	8.00

In [5]:
```
df.describe(include='object').T
```

Out[5]:

	count	unique	top	freq
term	396030	2	36 months	302005
grade	396030	7	B	116018
sub_grade	396030	35	B3	26655
emp_title	373103	173105	Teacher	4389
emp_length	377729	11	10+ years	126041
home_ownership	396030	6	MORTGAGE	198348
verification_status	396030	3	Verified	139563
issue_d	396030	115	Oct-2014	14846
loan_status	396030	2	Fully Paid	318357
purpose	396030	14	debt_consolidation	234507
title	394275	48817	Debt consolidation	152472
earliest_cr_line	396030	684	Oct-2000	3017
initial_list_status	396030	2	f	238066
application_type	396030	3	INDIVIDUAL	395319
address	396030	393700	USCGC Smith\r\nFPO AE 70466	8

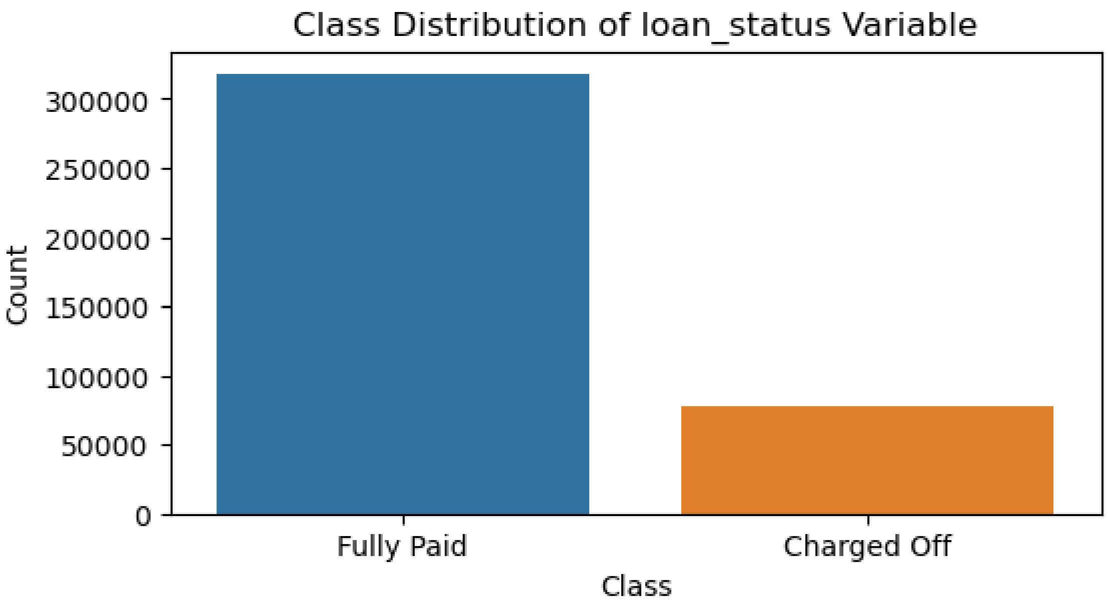
Class_Distribution

loan_status

In [6]:
```
class_counts = df['loan_status'].value_counts()
class_percentages = df['loan_status'].value_counts(normalize=True) * 100
# Combine counts and percentages into a DataFrame
class_distribution = pd.DataFrame({
    'Count': class_counts,
    'Percentage': class_percentages
})

print(f'Count and percentages of classes are: \n {class_distribution}')
```

```
Count and percentages of classes are: 
               Count  Percentage
Fully Paid   318357   80.387092
Charged Off   77673   19.612908
```

In [7]:
```
plt.figure(figsize=(6, 3))
sns.countplot(x='loan_status', data=df)
plt.title('Class Distribution of loan_status Variable')
plt.xlabel('Class')
plt.ylabel('Count')
plt.show()
```



Interpretation

- The target variable 'loan_status' is **imbalanced**, with :
  - 80.38% of the instances belonging to the **'Fully Paid'** class and
  - 19.61% to the **'Charged Off'** class.
- This significant class imbalance indicates that models trained on this data might be biased towards predicting the majority class ('Fully Paid').
- **Evaluation Metrics**: metrics that should be used for imbalanced datasets, such as **precision, recall, F1-score, and ROC-AUC, rather than accuracy**.

Duplicate_rows

In [8]:
```
df.duplicated().sum()
```

Out[8]:
```
0
```

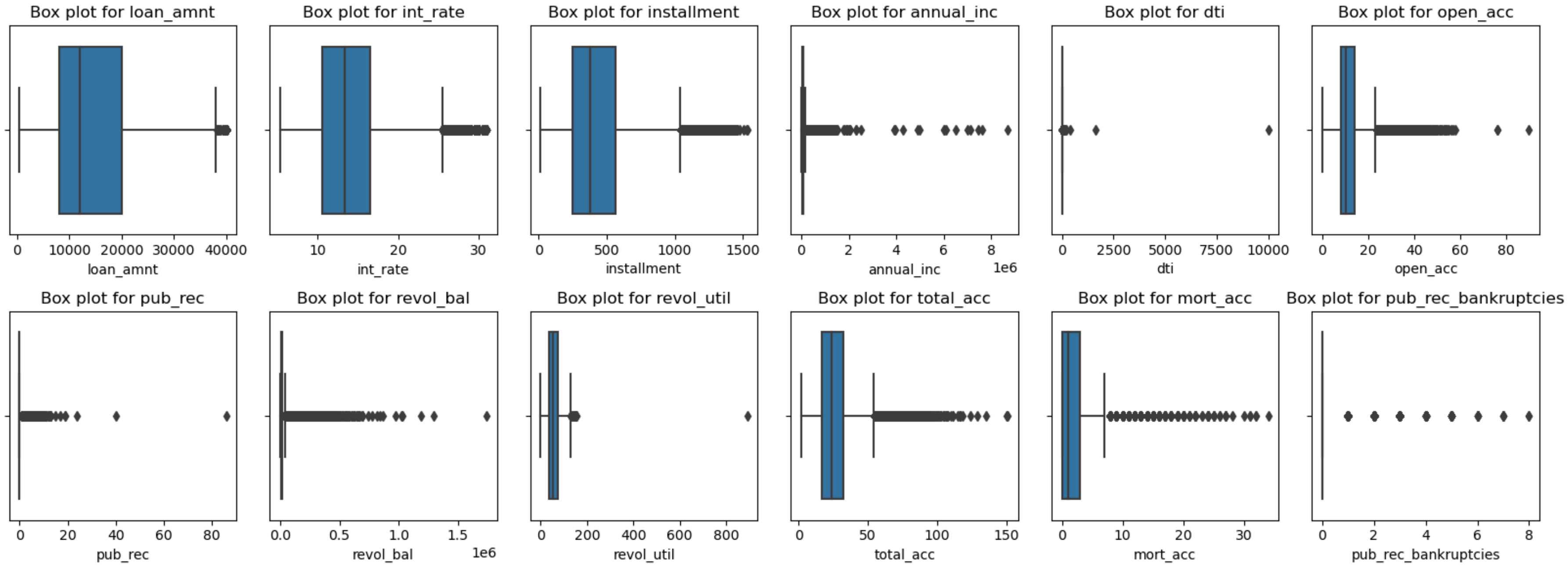
Interpretation

- There are no dublicate rows, no handling is required

Outliers

In [9]:
```
def detect_outliers_with_plots(data):
    """
    Detect outliers in each numerical feature of a dataset using the IQR method and plot box plots as subplots in four

    Parameters:
    data (pd.DataFrame): The dataset containing the features.

    Returns:
    pd.DataFrame: A DataFrame containing feature names, number of outliers, percentage of outliers, lower and upper bo
    """
    # Calculate the number of numerical features
    numerical_features = [col for col in data.columns if pd.api.types.is_numeric_dtype(data[col])]
    num_features = len(numerical_features)

    # Set up the figure and axes for subplots in four rows
    num_rows = 2
    num_cols = (num_features + num_rows - 1) // num_rows  # Calculate number of columns needed
    fig, axs = plt.subplots(num_rows, num_cols, figsize=(16, 3 * num_rows))  # Adjust figsize as needed

    # Initialize a list to store summary statistics
    summary_list = []

    # Iterate through numerical features
    for i, feature in enumerate(numerical_features):
        row = i // num_cols
        col = i % num_cols

        # Calculate Q1 (25th percentile) and Q3 (75th percentile)
        Q1 = data[feature].quantile(0.25)
        Q3 = data[feature].quantile(0.75)
        IQR = Q3 - Q1

        # Define bounds for outliers
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        # Identify outliers
        outliers = data[(data[feature] < lower_bound) | (data[feature] > upper_bound)]
        num_outliers = len(outliers)
        total_count = len(data)
        percentage_outliers = (num_outliers / total_count) * 100
```

```
        # Plot box plot on the corresponding subplot
        sns.boxplot(x=data[feature], ax=axs[row, col])
        axs[row, col].set_title(f'Box plot for {feature}')
        axs[row, col].set_xlabel(feature)

        # Append summary statistics to the list
        summary_list.append({
            'Feature': feature,
            'Num_Outliers': num_outliers,
            'Percentage_Outliers': percentage_outliers,
            'Lower_Boundary': lower_bound,
            'Upper_Boundary': upper_bound,
        })

    # Adjust layout and display the plot
    plt.tight_layout()
    plt.show()

    # Return summary statistics as a DataFrame
    return pd.DataFrame(summary_list)


# Detect outliers and generate plots
summary_df = detect_outliers_with_plots(df)
```


Box plot for loan_amnt
0 10000 20000 30000 40000
loan_amnt
Box plot for int_rate
10 20 30
int_rate
Box plot for installment
0 500 1000 1500
installment
Box plot for annual_inc
0 2 4 6 8
annual_inc
1e6
Box plot for dti
0 2500 5000 7500 10000
dti
Box plot for open_acc
0 20 40 60 80
open_acc
Box plot for pub_rec
0 20 40 60 80
pub_rec
Box plot for revol_bal
0.0 0.5 1.0 1.5
revol_bal
1e6
Box plot for revol_util
0 200 400 600 800
revol_util
Box plot for total_acc
0 50 100 150
total_acc
Box plot for mort_acc
0 10 20 30
mort_acc
Box plot for pub_rec_bankruptcies
0 2 4 6 8
pub_rec_bankruptcies

In [10]:
```
def calculate_summary_statistics(data):
    """
    Calculate and return summary statistics for a numerical feature.

    """
    summary_stats = {
        'Mean': np.round(np.mean(data), 2),
        'Median': np.round(np.median(data), 2),
        'Standard Deviation': np.round(np.std(data), 2),
        'Min': np.min(data),
        'Max': np.max(data),
        '25th Percentile': np.percentile(data, 25),
        '75th Percentile': np.percentile(data, 75),
    }

    return summary_stats


def skewness_based_on_mean_median(data):
    """
    Calculate skewness based on mean and median.

    """
    mean_val = np.mean(data)
    median_val = np.median(data)

    skewness = 3 * (mean_val - median_val) / np.std(data)
    print(f"Skewness based on mean and median: {np.round(skewness, 2)}")

    if skewness > 0:
        print("The distribution is right-skewed.")
    elif skewness < 0:
        print("The distribution is left-skewed.")
    else:
        print("The distribution is approximately symmetric.")

    return skewness
```

In [11]:
```
def plot_distributions(data , col):
    plt.figure(figsize=(10,2), tight_layout=True)
    plt.subplot(1, 3, 1)
    sns.kdeplot(x=col, data=data)
    plt.title(f'kdeplot for {col}')

    plt.subplot(1, 3, 2)
    sns.boxplot(x=col, data=data)

    plt.title(f'boxplot for {col}')

    ax3 = plt.subplot(1, 3, 3)
    #stats.probplot(data, dist="norm", plot=plt)
    sm.qqplot(data[col], line='s', ax=ax3)  # 's' indicates standardized line
    ax3.set_title(f'qqplot for {col}')
    plt.show()
```

In [12]:
```
def test_normality(dataframe, feature, alpha=0.05):

    H0 = f"{feature} is normally distributed"
    H1 = f"{feature} is not normally distributed"

    print(f"H0 : {H0}")
    print(f"H1 : {H1}")

    test_statistic, p_value = shapiro(dataframe[feature])
    print(f"Shapiro-Wilk Test Statistic: {test_statistic}")
    print(f"p-value: {p_value}")

    # Interpretation

    print(f"alpha = {alpha}")

    if p_value < alpha:
         print(f"Reject the null hypothesis as p_value '{p_value}' <  alpha '{alpha}' (data is not normally distribute
    else:
        print(f"Fail to reject the null hypothesis  as p_value '{p_value}' > alpha '{alpha}' (data is normally distrib




def perform_tests_numerical_vs_target(df, numerical_feature, categorical_feature, test_type):
    """
    Perform t-test, ANOVA, or Kruskal-Wallis test based on the number of groups specified in test_dict.

    """
    groups = df[categorical_feature].unique()
    num_groups = len(groups)

    if test_type == 'ttest' and num_groups == 2:
        group1 = df[df[categorical_feature] == groups[0]][numerical_feature]
        group2 = df[df[categorical_feature] == groups[1]][numerical_feature]
        testresult = ttest_ind(group1, group2)
        result = f"T-test - T-statistic: {testresult.statistic}, p-value: {testresult.pvalue}"


    elif test_type == 'anova':
```

```
        grouped_data = [df[df[categorical_feature] == group][numerical_feature] for group in groups]
        testresult = f_oneway(*grouped_data)
        result = f"ANOVA - F-statistic: {testresult.statistic}, p-value: {testresult.pvalue}"

    elif test_type == 'kruskal':
        grouped_data = [df[df[categorical_feature] == group][numerical_feature] for group in groups]
        testresult = kruskal(*grouped_data)
        result = f"Kruskal-Wallis - H-statistic: {testresult.statistic}, p-value: {testresult.pvalue}"

    else:
        result = "No valid test specified for the given number of groups."

    print(result)

    return testresult


def bivariate_analysis_numerical_vs_categorical(data, numeric_feature , cat_target_variable, test):

    plt.figure(figsize=(6,3))
    sns.boxplot(x=cat_target_variable, y =numeric_feature, data=data)
    plt.title(f'Distribution of {cat_target_variable} for {numeric_feature}')
    plt.show()

    print(20*'***')
    print(f'{test} : ')
    testresult = perform_tests_numerical_vs_target(df, numeric_feature, cat_target_variable, test)
    check_result(testresult.pvalue)
    print(20*'***')
```

In [13]:
```
def detect_outliers_iqr(data, feature):
    """
    Detect outliers using the Interquartile Range (IQR) method.
    """

    # Calculate Q1 (25th percentile) and Q3 (75th percentile)
    Q1 = np.percentile(data[feature], 25)
    Q3 = np.percentile(data[feature], 75)

    # Calculate IQR (Interquartile Range)
    IQR = Q3 - Q1

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

    # Identify outliers (indices where data is less than lower_bound or greater than upper_bound)
    outliers = data[(data[feature] < lower_bound) | (data[feature] > upper_bound)]

    num_outliers = len(outliers)
    total_count = len(data)
    percentage_outliers = (num_outliers / total_count) * 100

    return (num_outliers, np.round(percentage_outliers, 2))
```

In [14]:
```
def summary_statistics_and_distribution(data, feature_name):
    print(20*'***')
    print('summary_statistics:')
    print(20*'***')
    stats = calculate_summary_statistics(data[feature_name])
    for key, value in stats.items():
        print(f"{key}: {value}")

    print(20*'***')
    skewness_based_on_mean_median(data[feature_name])
    print(20*'***')

    outliers = detect_outliers_iqr(data, feature_name)
    print(f'outliers : numbers = {outliers[0]} and percentage = {outliers[1]} %')
    print(20*'***')

    plot_distributions(data,feature_name)
    print(20*'***')
    print("normality test: ")
    test_normality(data, feature_name)
    print(20*'***')

def check_result(pvalue):
    if pvalue < 0.05:
        print("Reject H0")
        print("Atleast one group has different mean")
    else:
        print("Fail to reject H0")
        print("All groups have same mean")
```

In [15]:
```
target_variable = 'loan_status'
```

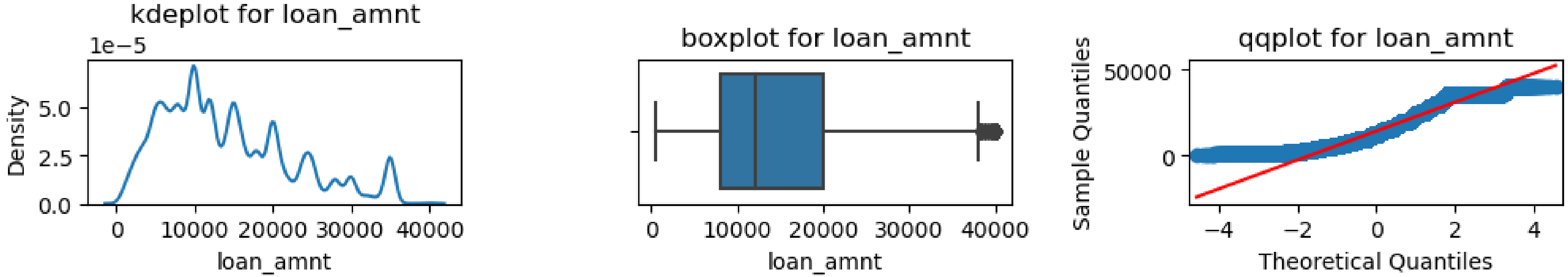
loan_amnt

- numberical feature
- right-skewed
- important to keep based on median difference against target variable

UnivariateAnalysis

In [16]:
```
feature_name = 'loan_amnt'
summary_statistics_and_distribution(df, feature_name)
```

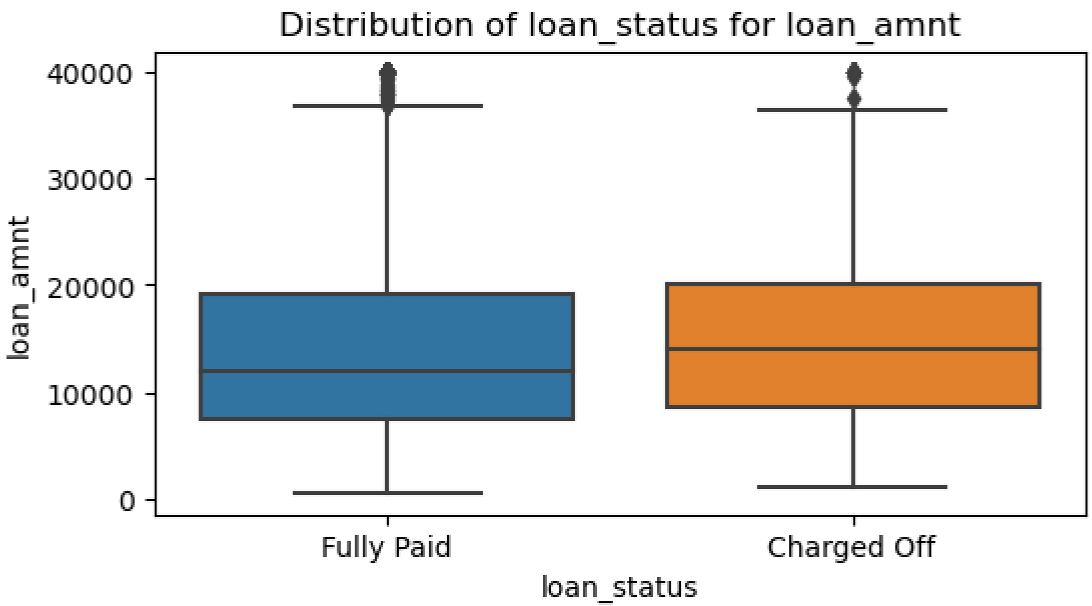
```
************************************************************
summary_statistics:
************************************************************
Mean: 14113.89
Median: 12000.0
Standard Deviation: 8357.43
Min: 500.0
Max: 40000.0
25th Percentile: 8000.0
75th Percentile: 20000.0
************************************************************
Skewness based on mean and median: 0.76
The distribution is right-skewed.
************************************************************
outliers : numbers = 191 and percentage = 0.05 %
************************************************************
```



```
************************************************************
normality test:
H0 : loan_amnt is normally distributed
H1 : loan_amnt is not normally distributed
Shapiro-Wilk Test Statistic: 0.9392586946487427
p-value: 0.0
alpha = 0.05
Reject the null hypothesis as p_value '0.0' <  alpha '0.05' (data is not normally distributed).
************************************************************

C:\Users\Upendra\anaconda3\Lib\site-packages\scipy\stats\_morestats.py:1882: UserWarning: p-value may not be accurat
e for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

BivariateAnalysis

In [17]:
```
bivariate_analysis_numerical_vs_categorical(df, feature_name, target_variable, 'kruskal')
```




```
************************************************************
kruskal :
Kruskal-Wallis - H-statistic: 1559.441461895931, p-value: 0.0
Reject H0
Atleast one group has different mean
************************************************************
```

Interpretation

- there are notacible difference between the medians for class variables 'fully paid' and 'charged off'
  - So this variable is important
- both class variable has outliers, needs to be checked if to keep these outliers or not ?

term

- categorical variable
- Mode : 36 months
- important for model building

In [18]:
```
def plot_distributions_categorical(data,feature_name):

    plt.figure(figsize=(6, 3), tight_layout=True)
    plt.subplot(1, 2, 1)
    df[feature_name].value_counts().plot(kind='bar')
    plt.title(f'"{feature_name}" Distribution')
    plt.xticks( rotation=90)

    plt.subplot(1, 2, 2)
    (df[feature_name].value_counts(normalize=True)*100).plot(kind='bar')
    plt.title(f'Frequency Dist for {feature_name} in %')
    plt.xticks( rotation=90)
    plt.show()
```

In [19]:
```
def statistics_and_freq_distribution(data, feature_name):

    print(20*'***')
    print(f"Unique Values: {data[feature].unique()}")
    mode_category = data[feature_name].mode()[0]
    print(f"Mode : {mode_category}")
    print(20*'***')

    plot_distributions_categorical(data, feature_name)

    print("Chi-Square test: ")
    chisqare_test(data, feature_name, target_variable)
    print(20*'***')
```

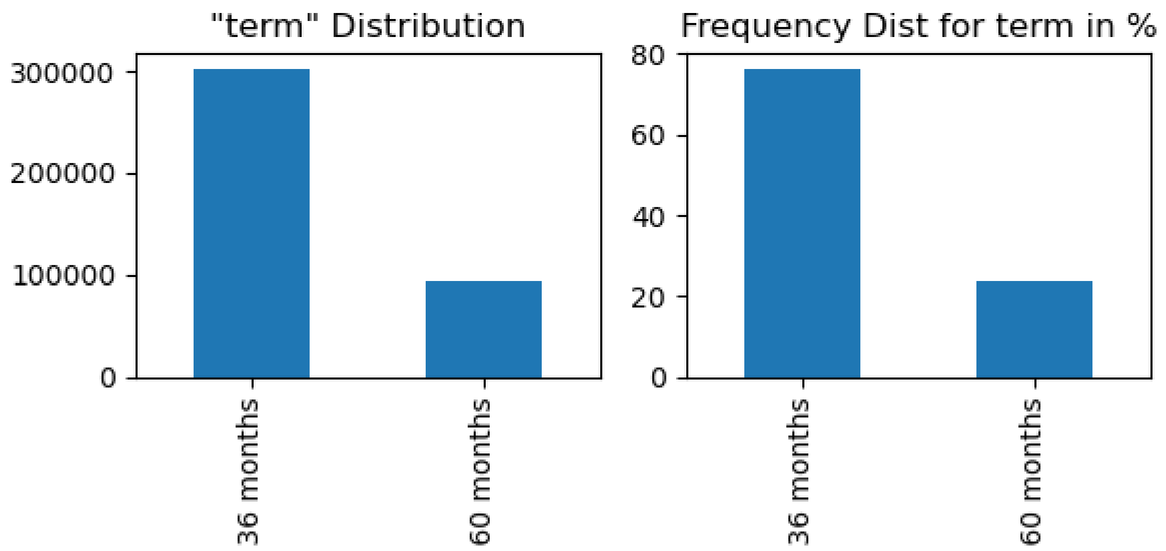
In [20]:
```
def chisqare_test(data, predictor, target):

    # Create contingency table
    contingency_table = pd.crosstab(data[predictor], data[target])

    # Perform Chi-Square test
    chi2, p, dof, expected = stats.chi2_contingency(contingency_table)

    H0 = f"(H0): There is no association between [{predictor} and {target}]."
    H1 = f"(H1): There is an association between [{predictor}' and {target}]."
    print (H0)
    print (H1)
    print('Chi-Square test statistic:', np.round(chi2, 2))
    print('p-value:', p)

    if p < 0.05:
        print(f'Reject the H0. There is significant association between "{predictor} and {target}" variables as p_valu
    else:
        print(f'Fail to Reject H0, There is no association between "{predictor} and {target}" variable as p_value {p}
```

In [21]:
```
def eda_highCardinality_categorical_vs_categorical(data, high_card_feature, target_variable):

    # Display unique value counts of the high cardinality feature
    unique_counts = data[high_card_feature].value_counts()
    print(20*'***')
    print("Unique value counts of the high cardinality feature:")
    print(unique_counts.head(10))

    # Get the top n unique values
    top_n_values = unique_counts.head(50).index
    df_top_n = data[data[high_card_feature].isin(top_n_values)]

    # Group by the high cardinality feature and target variable
    grouped = df_top_n.groupby([high_card_feature, target_variable]).size().unstack(fill_value=0)
    print(20*'***')
    print("\nGrouped data (first 10 rows):")
    print(grouped.head(10))

    # Chi-Square Test for Independence
    chi2, p, dof, ex = chi2_contingency(grouped)
    print(f"\nChi-Square Test: chi2 = {chi2}, p-value = {p}, degrees of freedom = {dof}")
    if p < 0.05:
        print("The high cardinality feature and target variable are dependent (reject H0).")
    else:
        print("The high cardinality feature and target variable are independent (fail to reject H0).")
```

BivariateAnalysis_term

In [22]:
```
feature= 'term'
statistics_and_freq_distribution(df, feature)
```

```
************************************************************
Unique Values: [' 36 months' ' 60 months']
Mode :  36 months
************************************************************
```




```
Chi-Square test:
(H0): There is no association between [term and loan_status].
(H1): There is an association between [term' and loan_status].
Chi-Square test statistic: 11885.54
p-value: 0.0
Reject the H0. There is significant association between "term and loan_status" variables as p_value 0.0 <  aplha =
0.05
************************************************************
```

Interpretation

- maximum loan is given for 36 months ~ 80%
- chisquare test suggest that this feature has a association with target_varible
    - so we keep this feature

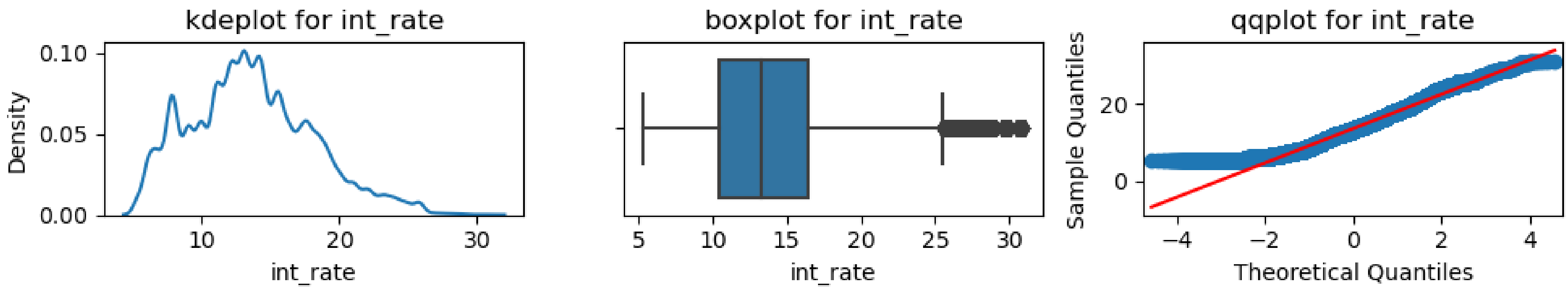
int_rate

- numberica data
- mean is not equal to median that mean skewed, its right skewed data

UnivariateAnalysis_int_rate

In [23]:
```
feature_name = 'int_rate'
summary_statistics_and_distribution(df, feature_name)
```

```
************************************************************
summary_statistics:
************************************************************
Mean: 13.64
Median: 13.33
Standard Deviation: 4.47
Min: 5.32
Max: 30.99
25th Percentile: 10.49
75th Percentile: 16.49
************************************************************
Skewness based on mean and median: 0.21
The distribution is right-skewed.
************************************************************
outliers : numbers = 3777 and percentage = 0.95 %
************************************************************
```

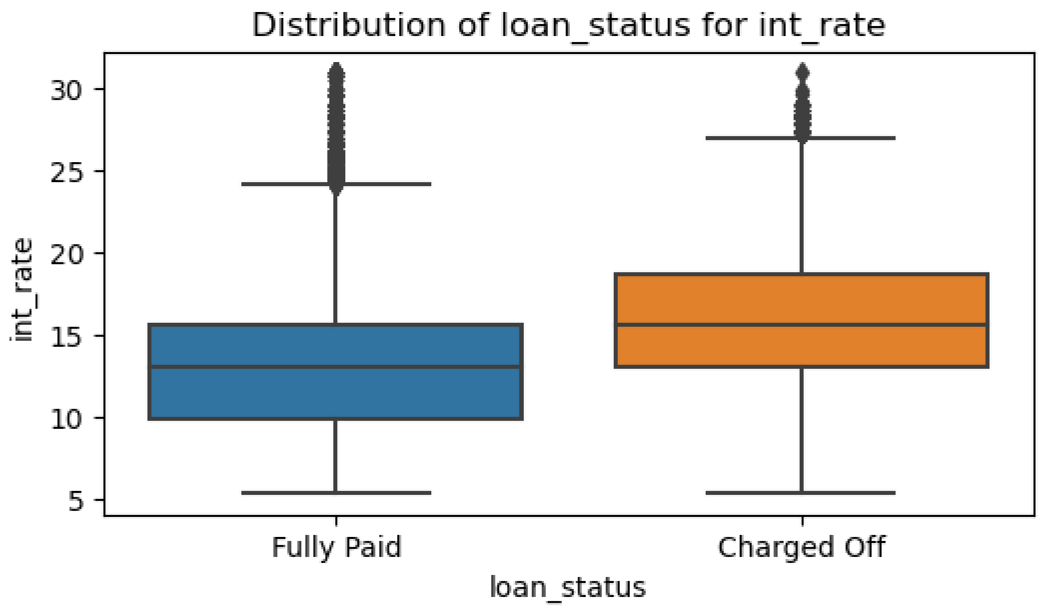



```
************************************************************
normality test:
H0 : int_rate is normally distributed
H1 : int_rate is not normally distributed
Shapiro-Wilk Test Statistic: 0.982596755027771
p-value: 0.0
alpha = 0.05
Reject the null hypothesis as p_value '0.0' <  alpha '0.05' (data is not normally distributed).
************************************************************
```

```
C:\Users\Upendra\anaconda3\Lib\site-packages\scipy\stats\_morestats.py:1882: UserWarning: p-value may not be accurat
e for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

BivariateAnalysis_int_rate

In [24]:
```
bivariate_analysis_numerical_vs_categorical(df, feature_name, target_variable, 'kruskal')
```




```
************************************************************
kruskal :
Kruskal-Wallis - H-statistic: 23684.80612332653, p-value: 0.0
Reject H0
Atleast one group has different mean
************************************************************
```

Interpretation

- there are notacible difference between the medians for class variables 'fully paid' and 'charged off' for int_rate
  - So this variable is important
- both class variable has outliers, needs to be checked if to keep these outliers or not ?

installment

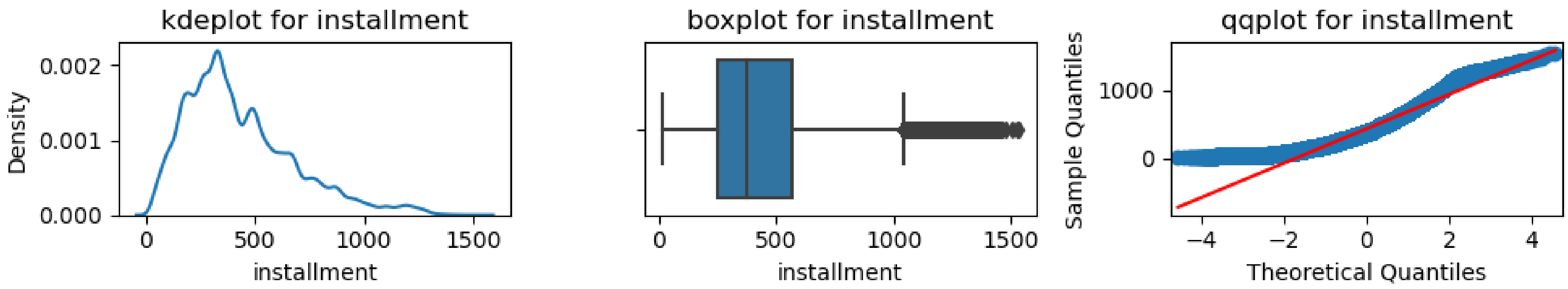
installment : The monthly payment owed by the borrower if the loan originates.

- numberical data

UnivariateAnalysis_installment

In [25]:
```
feature_name = 'installment'
summary_statistics_and_distribution(df, feature_name)
```

```
************************************************************
summary_statistics:
************************************************************
Mean: 431.85
Median: 375.43
Standard Deviation: 250.73
Min: 16.08
Max: 1533.81
25th Percentile: 250.33
75th Percentile: 567.3
************************************************************
Skewness based on mean and median: 0.68
The distribution is right-skewed.
************************************************************
outliers : numbers = 11250 and percentage = 2.84 %
************************************************************
```

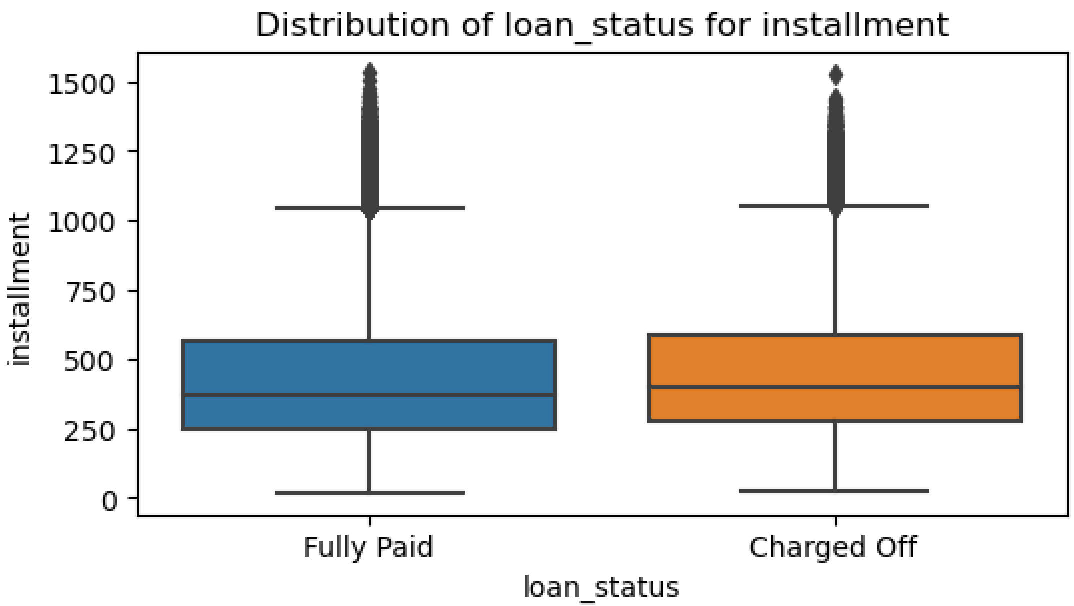



```
************************************************************
normality test:
H0 : installment is normally distributed
H1 : installment is not normally distributed
Shapiro-Wilk Test Statistic: 0.9357084631919861
p-value: 0.0
alpha = 0.05
Reject the null hypothesis as p_value '0.0' <  alpha '0.05' (data is not normally distributed).
************************************************************
```

```
C:\Users\Upendra\anaconda3\Lib\site-packages\scipy\stats\_morestats.py:1882: UserWarning: p-value may not be accurat
e for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

BivariateAnalysis_installment

In [26]:
```
bivariate_analysis_numerical_vs_categorical(df, feature_name, target_variable, 'kruskal')
```



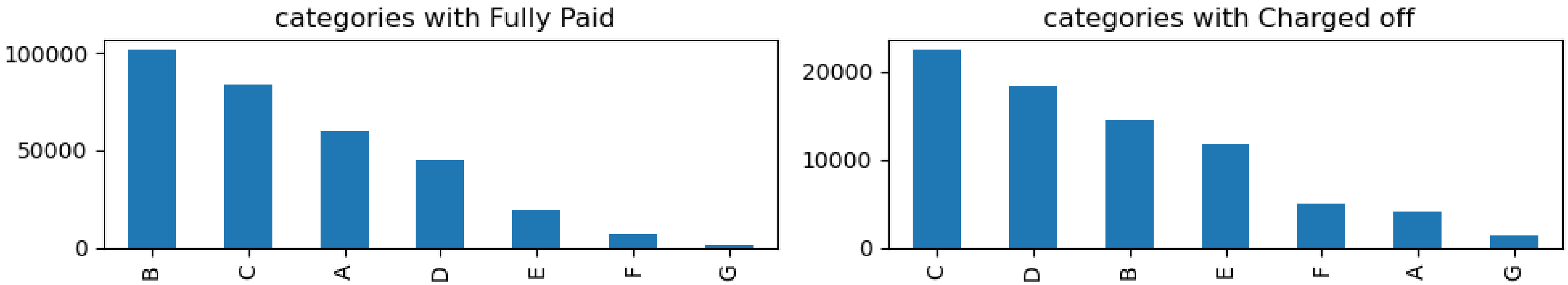

```
************************************************************
kruskal :
Kruskal-Wallis - H-statistic: 964.1975586238364, p-value: 1.0878479597631045e-211
Reject H0
Atleast one group has different mean
************************************************************
```

Interpretation

- test-statistic, p_values < 0.05. This indicates that the means of the two groups are significantly different.
    - This suggests that the categorical feature is important and should be considered in model building.
- both class variable has outliers

grade

In [27]:
```
plt.figure(figsize=(10, 2), tight_layout = True)
plt.subplot(121)
df[df['loan_status'] == 'Fully Paid']['grade'].value_counts().plot(kind='bar')
plt.title(' categories with Fully Paid')

plt.subplot(122)
df[df['loan_status'] == 'Charged Off']['grade'].value_counts().plot(kind='bar')
plt.title(' categories with Charged off')
plt.show()
```



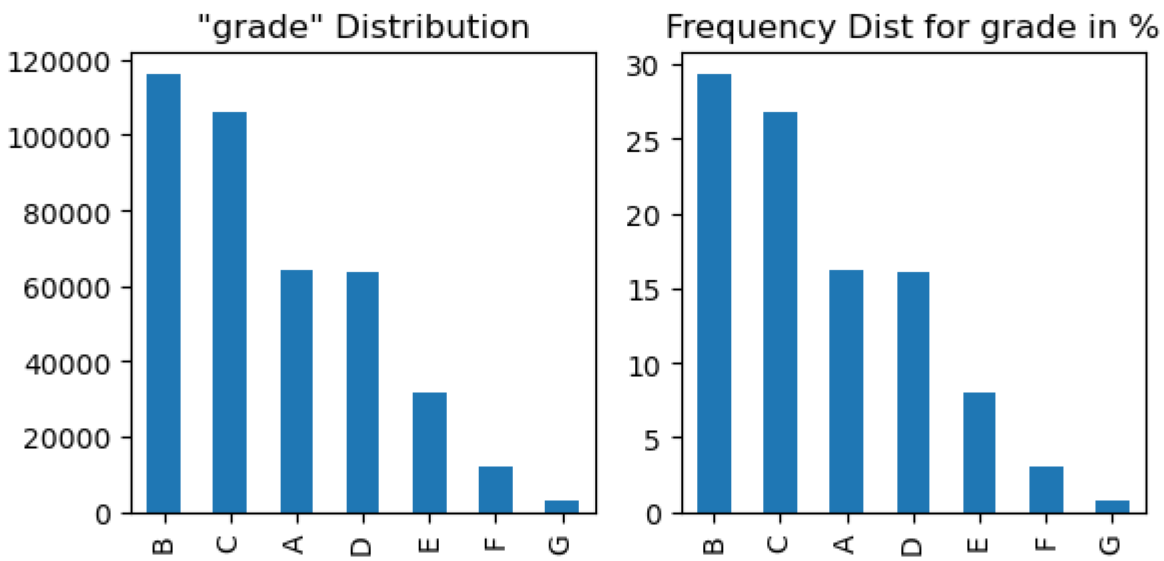
In [28]:
```
df[df['grade'] == 'A']['loan_status'].value_counts(normalize=True)*100
```

Out[28]:
```
Fully Paid     93.712122
Charged Off     6.287878
Name: loan_status, dtype: float64
```

- 93.7 % grade A has fully paid the loan amounts

In [29]:
```
feature= 'grade'
statistics_and_freq_distribution(df, feature)
```

```
************************************************************
Unique Values: ['B' 'A' 'C' 'E' 'D' 'F' 'G']
Mode : B
************************************************************
```

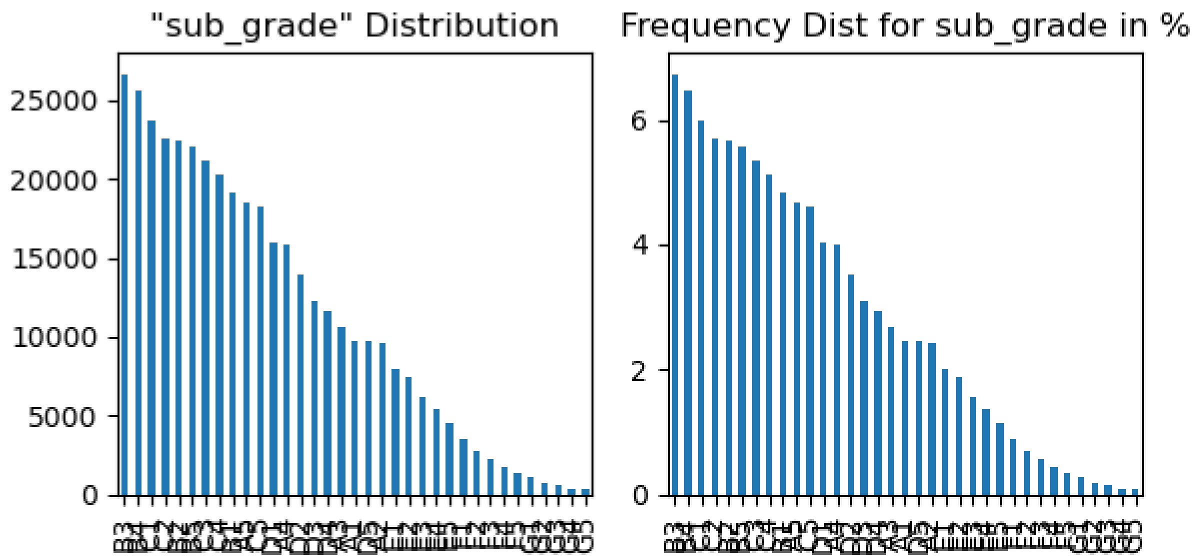



```
Chi-Square test:
(H0): There is no association between [grade and loan_status].
(H1): There is an association between [grade' and loan_status].
Chi-Square test statistic: 26338.06
p-value: 0.0
Reject the H0. There is significant association between "grade and loan_status" variables as p_value 0.0 <  aplha =
0.05
************************************************************
```

sub_grade

In [30]:
```
feature= 'sub_grade'
statistics_and_freq_distribution(df, feature)
```

```
**************************************************************
Unique Values: ['B4' 'B5' 'B3' 'A2' 'C5' 'C3' 'A1' 'B2' 'C1' 'A5' 'E4' 'A4' 'A3' 'D1'
 'C2' 'B1' 'D3' 'D5' 'D2' 'E1' 'E2' 'E5' 'F4' 'E3' 'D4' 'G1' 'F5' 'G2'
 'C4' 'F1' 'F3' 'G5' 'G4' 'F2' 'G3']
Mode : B3
**************************************************************
```




```
Chi-Square test:
(H0): There is no association between [sub_grade and loan_status].
(H1): There is an association between [sub_grade' and loan_status].
Chi-Square test statistic: 27560.2
p-value: 0.0
Reject the H0. There is significant association between "sub_grade and loan_status" variables as p_value 0.0 <  aplh
a = 0.05
**************************************************************
```

emp_title

In [31]:
```
print(df.emp_title.nunique())
eda_highCardinality_categorical_vs_categorical(df, 'emp_title', target_variable )
```

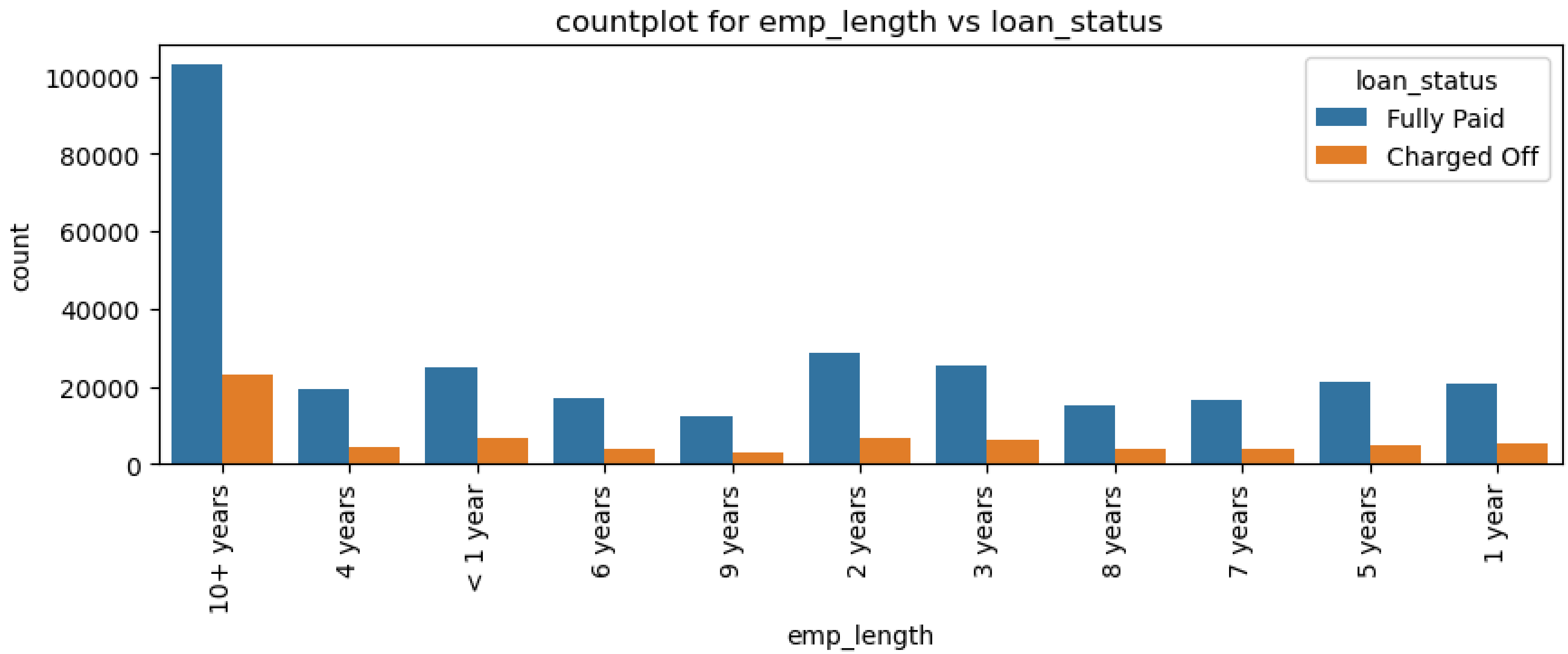
```
173105
************************************************************
Unique value counts of the high cardinality feature:
Teacher             4389
Manager             4250
Registered Nurse    1856
RN                  1846
Supervisor          1830
Sales               1638
Project Manager     1505
Owner               1410
Driver              1339
Office Manager      1218
Name: emp_title, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status                 Charged Off  Fully Paid
emp_title
Account Executive                    79         323
Account Manager                     139         553
Accountant                          122         626
Administrative Assistant            163         593
Administrator                        64         313
Analyst                             107         516
Assistant Manager                    98         333
Attorney                             77         590
Branch Manager                       70         412
Business Analyst                     60         349

Chi-Square Test: chi2 = 787.0106163033216, p-value = 1.0244371429862613e-133, degrees of freedom = 49
The high cardinality feature and target variable are dependent (reject H0).
```

In [ ]:

emp_length

In [32]:
```
print(df.emp_length.nunique())
eda_highCardinality_categorical_vs_categorical(df, 'emp_length', target_variable )
plt.figure(figsize=(10, 3))
sns.countplot(x='emp_length', data=df, hue='loan_status')
plt.title(f'countplot for emp_length vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

```
11
************************************************************
Unique value counts of the high cardinality feature:
10+ years    126041
2 years       35827
< 1 year      31725
3 years       31665
5 years       26495
1 year        25882
4 years       23952
6 years       20841
7 years       20819
8 years       19168
Name: emp_length, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status  Charged Off  Fully Paid
emp_length
1 year              5154       20728
10+ years          23215      102826
2 years             6924       28903
3 years             6182       25483
4 years             4608       19344
5 years             5092       21403
6 years             3943       16898
7 years             4055       16764
8 years             3829       15339
9 years             3070       12244

Chi-Square Test: chi2 = 122.11317384460878, p-value = 1.88404995201913e-21, degrees of freedom = 10
The high cardinality feature and target variable are dependent (reject H0).
```

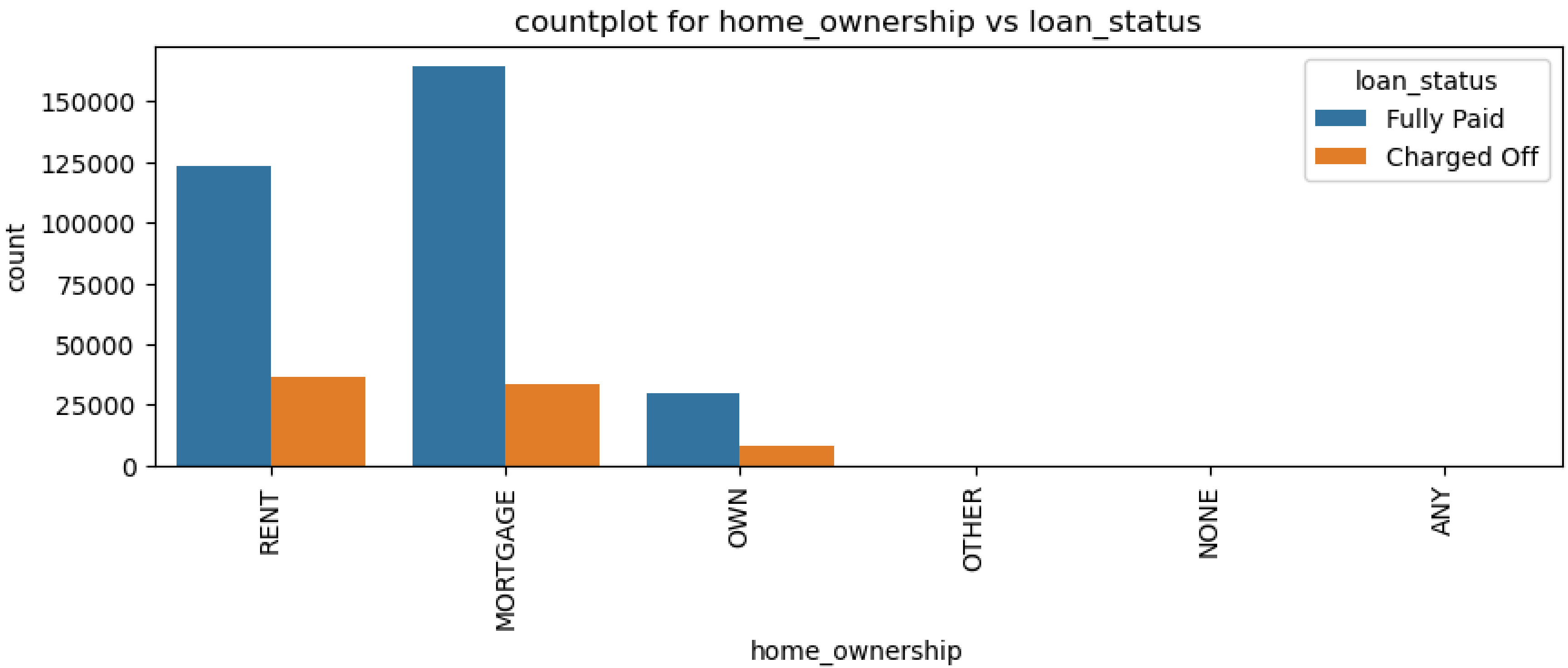

countplot for emp_length vs loan_status
loan_status
Fully Paid
Charged Off
count
100000
80000
60000
40000
20000
0
10+ years
4 years
< 1 year
6 years
9 years
2 years
3 years
8 years
7 years
5 years
1 year
emp_length

```
In [ ]:
```

home_ownership

In [33]:
```
feature = 'home_ownership'
print(f'unique counts : {df[feature].nunique()}')
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(10, 3))
sns.countplot(x=feature, data=df, hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

```
unique counts : 6
************************************************************
Unique value counts of the high cardinality feature:
MORTGAGE    198348
RENT        159790
OWN          37746
OTHER          112
NONE            31
ANY              3
Name: home_ownership, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status     Charged Off  Fully Paid
home_ownership
ANY                       0           3
MORTGAGE              33632      164716
NONE                      7          24
OTHER                    16          96
OWN                    7806       29940
RENT                  36212      123578

Chi-Square Test: chi2 = 1860.6350953584301, p-value = 0.0, degrees of freedom = 5
The high cardinality feature and target variable are dependent (reject H0).
```

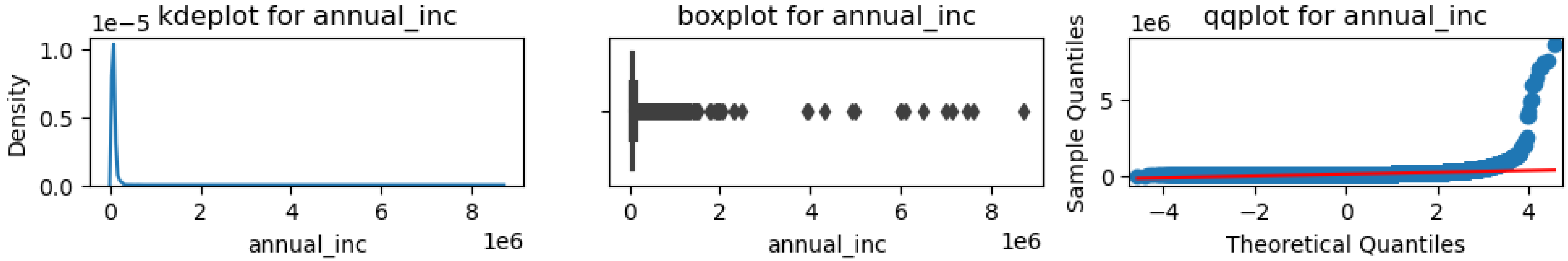


annual_inc

UnivariateAnalysis_annual_inc

In [34]:
```
feature = 'annual_inc'
summary_statistics_and_distribution(df, feature)
```

```
************************************************************
summary_statistics:
************************************************************
Mean: 74203.18
Median: 64000.0
Standard Deviation: 61637.54
Min: 0.0
Max: 8706582.0
25th Percentile: 45000.0
75th Percentile: 90000.0
************************************************************
Skewness based on mean and median: 0.5
The distribution is right-skewed.
************************************************************
outliers : numbers = 16700 and percentage = 4.22 %
************************************************************
```

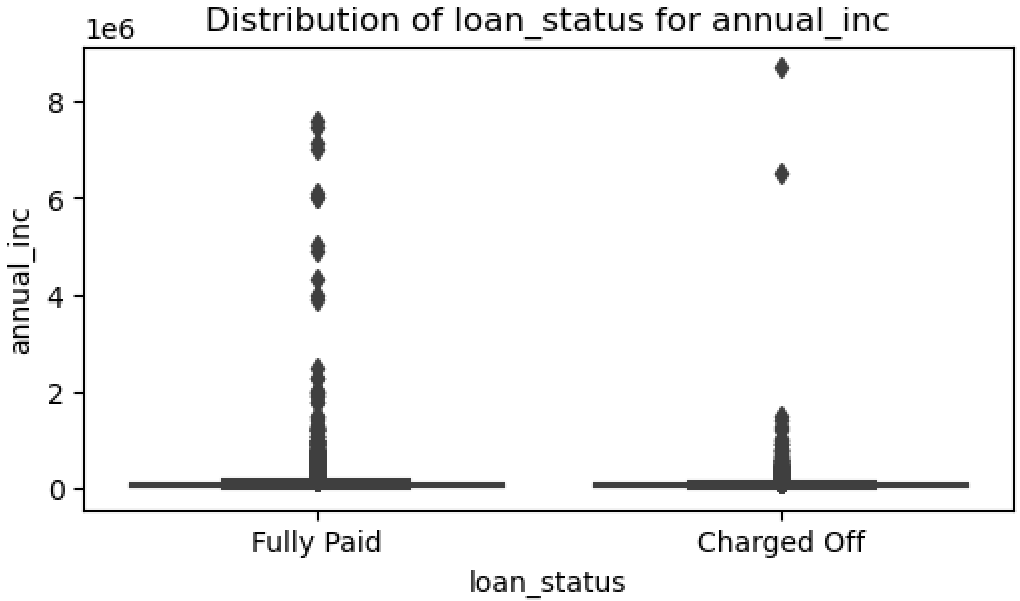



```
************************************************************
normality test:
H0 : annual_inc is normally distributed
H1 : annual_inc is not normally distributed
Shapiro-Wilk Test Statistic: 0.46121877431869507
p-value: 0.0
alpha = 0.05
Reject the null hypothesis as p_value '0.0' <  alpha '0.05' (data is not normally distributed).
************************************************************
```

```
C:\Users\Upendra\anaconda3\Lib\site-packages\scipy\stats\_morestats.py:1882: UserWarning: p-value may not be accurat
e for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

BivariateAnalysis_annual_inc

In [35]:
```
bivariate_analysis_numerical_vs_categorical(df, feature, target_variable, 'kruskal')
```




```
************************************************************
kruskal :
Kruskal-Wallis - H-statistic: 2945.6054924989753, p-value: 0.0
Reject H0
Atleast one group has different mean
************************************************************
```

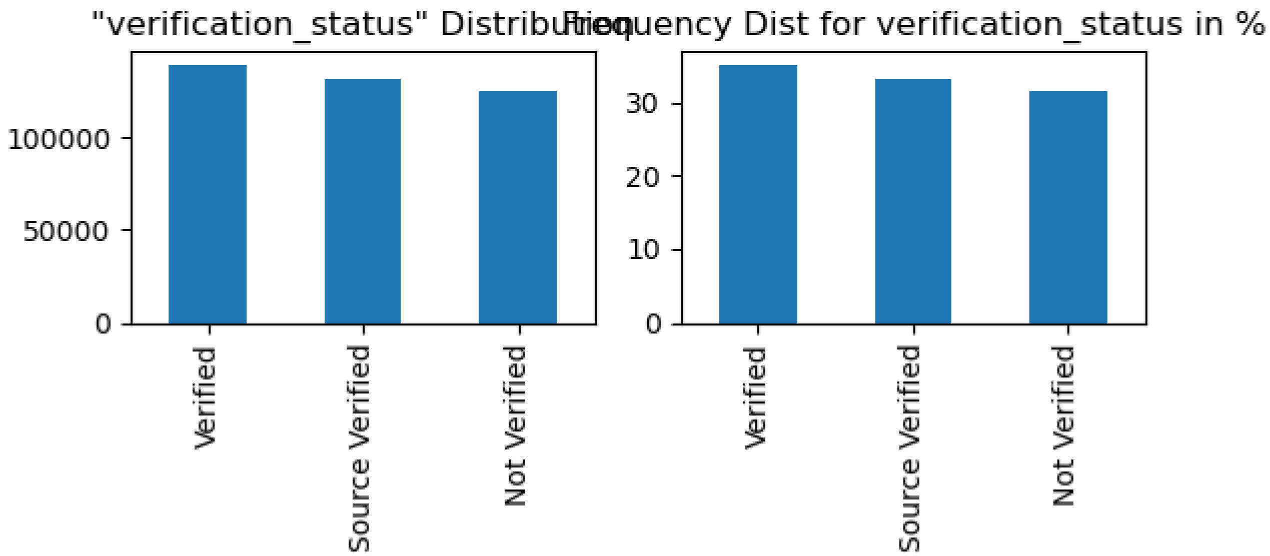
In [36]:
```
df.verification_status
```

Out[36]:
```
0            Not Verified
1            Not Verified
2         Source Verified
3            Not Verified
4                Verified
               ...       
396025    Source Verified
396026    Source Verified
396027           Verified
396028           Verified
396029           Verified
Name: verification_status, Length: 396030, dtype: object
```

verification_status

In [37]:
```
feature= 'verification_status'
statistics_and_freq_distribution(df, feature)
```

```
************************************************************
Unique Values: ['Not Verified' 'Source Verified' 'Verified']
Mode : Verified
************************************************************
```




```
Chi-Square test:
(H0): There is no association between [verification_status and loan_status].
(H1): There is an association between [verification_status' and loan_status].
Chi-Square test statistic: 2903.07
p-value: 0.0
Reject the H0. There is significant association between "verification_status and loan_status" variables as p_value
0.0 <  aplha = 0.05
************************************************************
```

issue_d

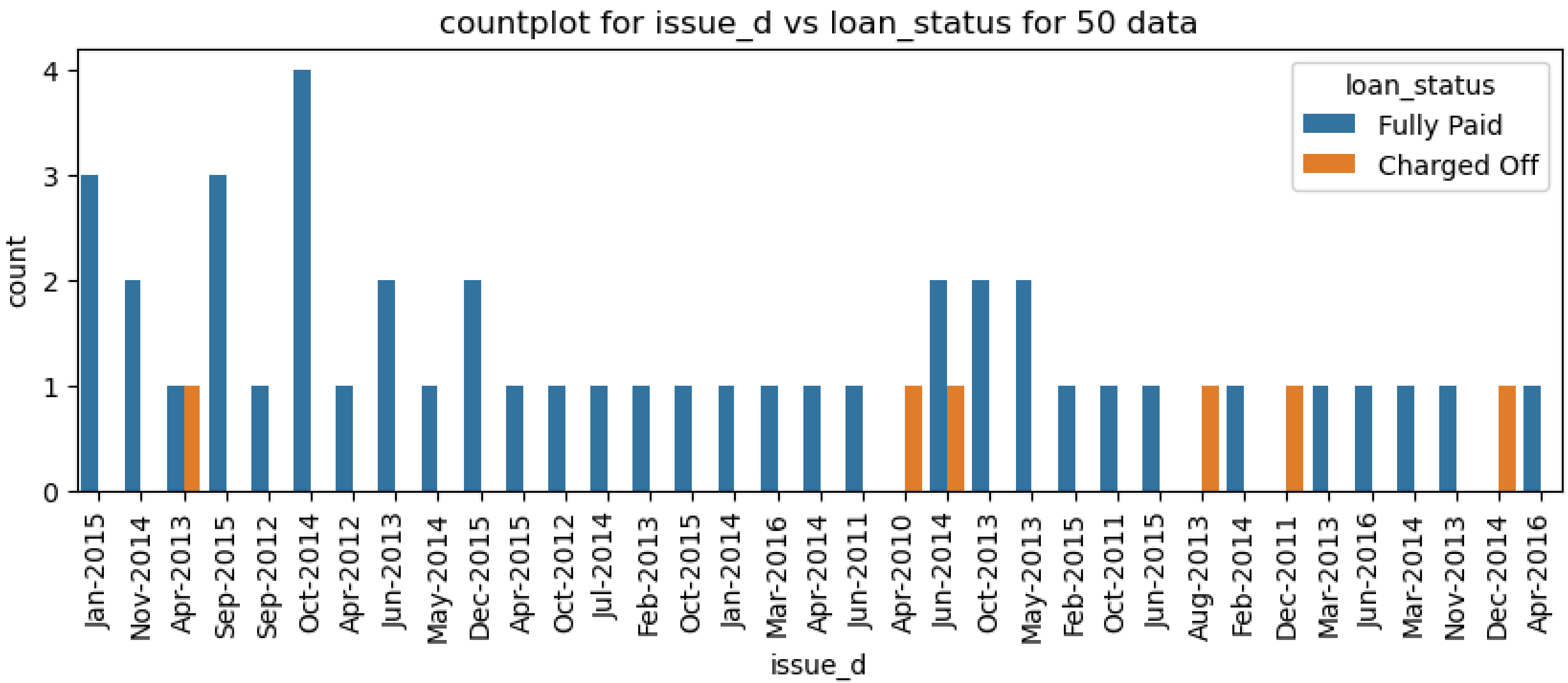
In [38]:
```
df.issue_d.nunique()
```

Out[38]:
```
115
```

In [39]:

```
feature = 'issue_d'
print(df[feature].nunique())
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(10, 3))
sns.countplot(x=feature, data=df[:50], hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status for 50 data')
plt.xticks(rotation=90)
plt.show()
```

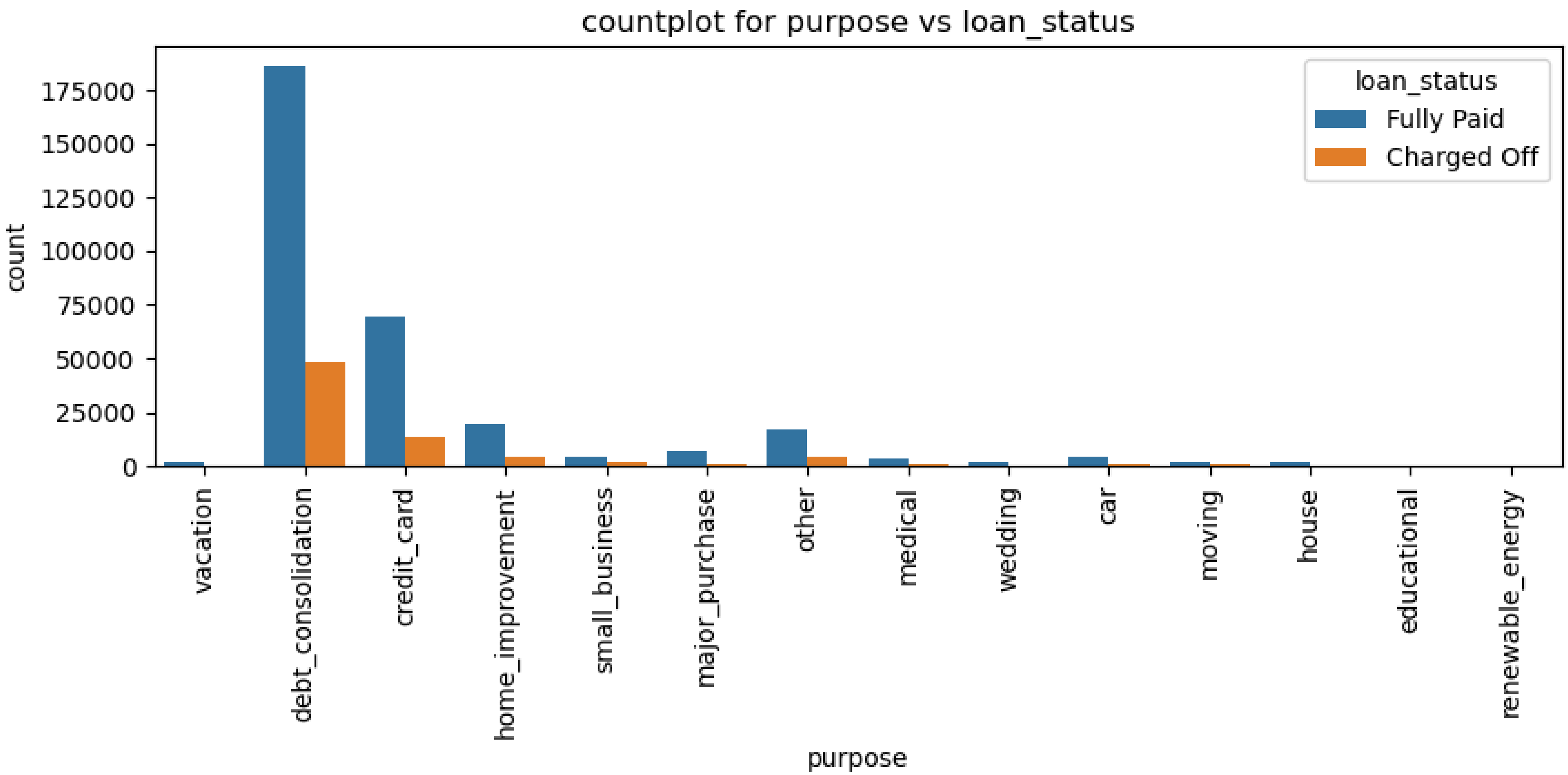
```
115
************************************************************
Unique value counts of the high cardinality feature:
Oct-2014    14846
Jul-2014    12609
Jan-2015    11705
Dec-2013    10618
Nov-2013    10496
Jul-2015    10270
Oct-2013    10047
Jan-2014     9705
Apr-2015     9470
Sep-2013     9179
Name: issue_d, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status  Charged Off  Fully Paid
issue_d
Apr-2012             396        2112
Apr-2013            1123        5847
Apr-2014            2050        6970
Apr-2015            2495        6975
Apr-2016             485        2542
Aug-2012             703        3517
Aug-2013            1417        7695
Aug-2014            1906        5954
Aug-2015            1746        5407
Dec-2012             688        3883

Chi-Square Test: chi2 = 3866.2413776298263, p-value = 0.0, degrees of freedom = 49
The high cardinality feature and target variable are dependent (reject H0).
```


countplot for issue_d vs loan_status for 50 data
loan_status
Fully Paid
Charged Off
count
0
1
2
3
4
issue_d
Jan-2015
Nov-2014
Apr-2013
Sep-2015
Sep-2012
Oct-2014
Apr-2012
Jun-2013
May-2014
Dec-2015
Apr-2015
Oct-2012
Jul-2014
Feb-2013
Oct-2015
Jan-2014
Mar-2016
Apr-2014
Jun-2011
Apr-2010
Jun-2014
Oct-2013
May-2013
Feb-2015
Oct-2011
Jun-2015
Aug-2013
Feb-2014
Dec-2011
Mar-2013
Jun-2016
Mar-2014
Nov-2013
Dec-2014
Apr-2016

purpose

In [40]:
```
feature = 'purpose'
print(df[feature].nunique())
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(10, 3))
sns.countplot(x=feature, data=df, hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

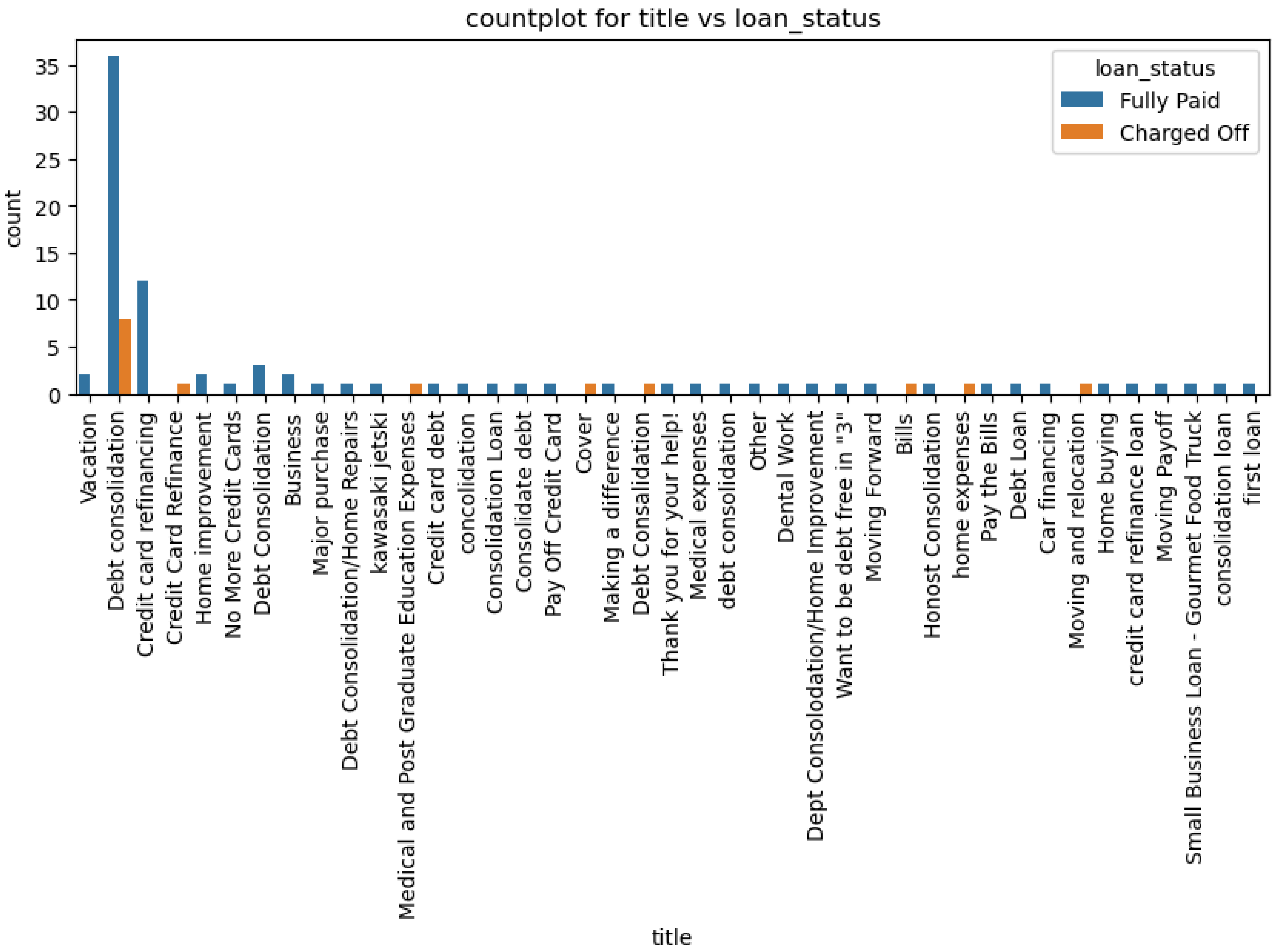
```
14
************************************************************
Unique value counts of the high cardinality feature:
debt_consolidation    234507
credit_card            83019
home_improvement       24030
other                  21185
major_purchase          8790
small_business          5701
car                     4697
medical                 4196
moving                  2854
vacation                2452
Name: purpose, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status         Charged Off  Fully Paid
purpose
car                         633        4064
credit_card               13874       69145
debt_consolidation        48640      185867
educational                  42         215
home_improvement           4087       19943
house                       434        1767
major_purchase             1448        7342
medical                     911        3285
moving                      670        2184
other                      4495       16690

Chi-Square Test: chi2 = 1397.0679601784623, p-value = 6.573354783158025e-291, degrees of freedom = 13
The high cardinality feature and target variable are dependent (reject H0).
```


countplot for purpose vs loan_status
count
175000
150000
125000
100000
75000
50000
25000
0
loan_status
Fully Paid
Charged Off
vacation
debt_consolidation
credit_card
home_improvement
small_business
major_purchase
other
medical
wedding
car
moving
house
educational
renewable_energy
purpose

title

In [41]:
```
feature = 'title'
print(df[feature].nunique())
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(10, 3))
sns.countplot(x=feature, data=df[:100], hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

```
48817
************************************************************
Unique value counts of the high cardinality feature:
Debt consolidation        152472
Credit card refinancing    51487
Home improvement           15264
Other                      12930
Debt Consolidation         11608
Major purchase              4769
Consolidation               3852
debt consolidation          3547
Business                    2949
Debt Consolidation Loan     2864
Name: title, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status              Charged Off  Fully Paid
title
Business                         959        1990
Car financing                    352        1787
Consolidate                      141         778
Consolidation                    550        3302
Consolidation Loan               163        1136
Credit Card                       54         393
Credit Card Consolidation        193        1582
Credit Card Loan                  77         550
Credit Card Payoff               103         949
Credit Card Refinance             98         996

Chi-Square Test: chi2 = 2037.4981184535297, p-value = 0.0, degrees of freedom = 49
The high cardinality feature and target variable are dependent (reject H0).
```



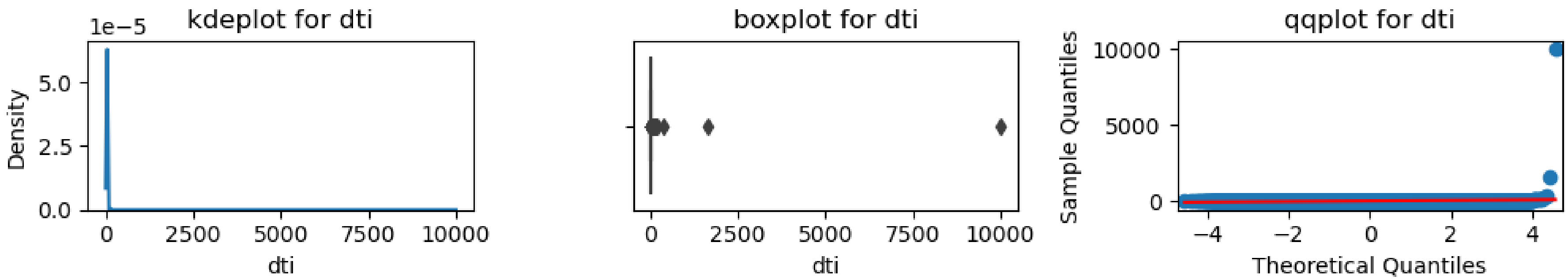
countplot for title vs loan_status
count
title
loan_status
Fully Paid
Charged Off
0
5
10
15
20
25
30
35
Vacation
Debt consolidation
Credit card refinancing
Credit Card Refinance
Home improvement
No More Credit Cards
Debt Consolidation
Business
Major purchase
Debt Consolidation/Home Repairs
kawasaki jetski
Medical and Post Graduate Education Expenses
Credit card debt
concolidation
Consolidation Loan
Consolidate debt
Pay Off Credit Card
Cover
Making a difference
Debt Consalidation
Thank you for your help!
Medical expenses
debt consolidation
Other
Dental Work
Dept Consolodation/Home Improvement
Want to be debt free in "3"
Moving Forward
Bills
Honost Consolidation
home expenses
Pay the Bills
Debt Loan
Car financing
Moving and relocation
Home buying
credit card refinance loan
Moving Payoff
Small Business Loan - Gourmet Food Truck
consolidation loan
first loan

dti

A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested LoanTap loan, divided by the borrower’s self-reported monthly income.

In [42]:
```
feature = 'dti'
summary_statistics_and_distribution(df, feature)
```

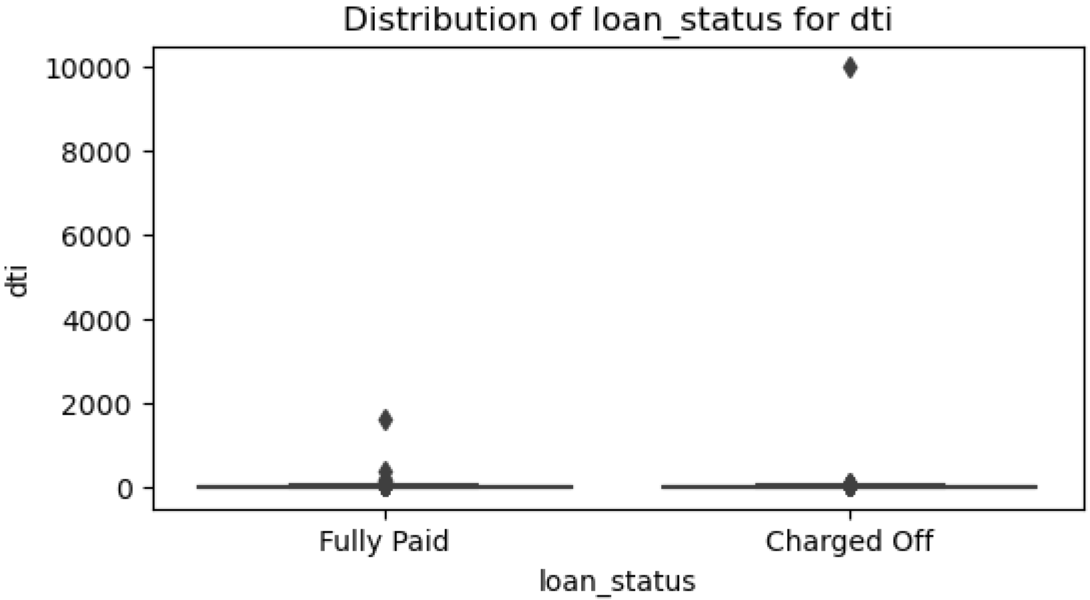
```
************************************************************
summary_statistics:
************************************************************
Mean: 17.38
Median: 16.91
Standard Deviation: 18.02
Min: 0.0
Max: 9999.0
25th Percentile: 11.28
75th Percentile: 22.98
************************************************************
Skewness based on mean and median: 0.08
The distribution is right-skewed.
************************************************************
outliers : numbers = 275 and percentage = 0.07 %
************************************************************
```




```
************************************************************
normality test:
H0 : dti is normally distributed
H1 : dti is not normally distributed
Shapiro-Wilk Test Statistic: 0.20904600620269775
p-value: 0.0
alpha = 0.05
Reject the null hypothesis as p_value '0.0' <  alpha '0.05' (data is not normally distributed).
************************************************************
```

```
C:\Users\Upendra\anaconda3\Lib\site-packages\scipy\stats\_morestats.py:1882: UserWarning: p-value may not be accurat
e for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [43]:
```
bivariate_analysis_numerical_vs_categorical(df, feature, target_variable, 'kruskal')
```



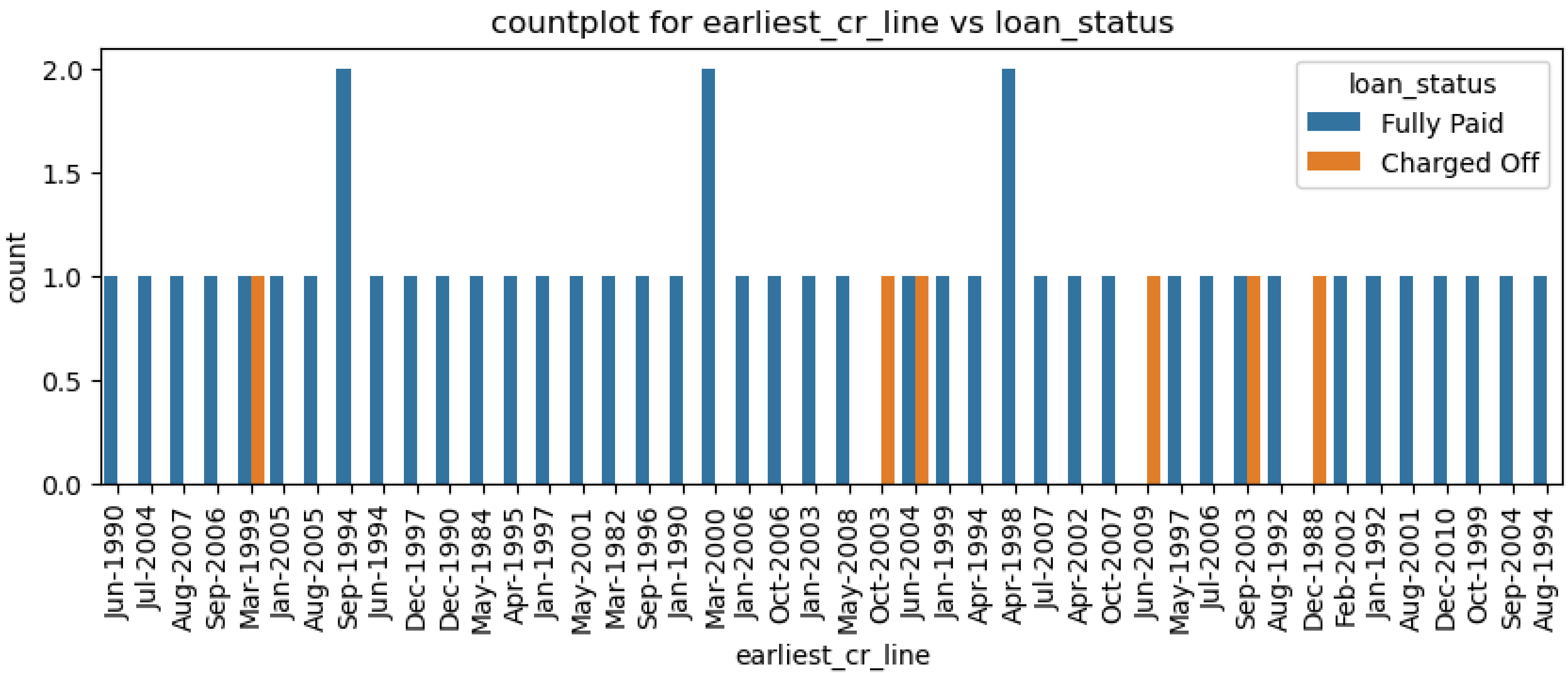

```
************************************************************
kruskal :
Kruskal-Wallis - H-statistic: 6467.646643302864, p-value: 0.0
Reject H0
Atleast one group has different mean
************************************************************
```

earliest_cr_line

earliest_cr_line :The month the borrower's earliest reported credit line was opened

In [44]:
```
feature = 'earliest_cr_line'
print(df[feature].nunique())
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(10, 3))
sns.countplot(x=feature, data=df[:50], hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

```
684
************************************************************
Unique value counts of the high cardinality feature:
Oct-2000    3017
Aug-2000    2935
Oct-2001    2896
Aug-2001    2884
Nov-2000    2736
Oct-1999    2726
Nov-1999    2700
Sep-2000    2691
Oct-2002    2640
Aug-2002    2599
Name: earliest_cr_line, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status       Charged Off  Fully Paid
earliest_cr_line
Apr-2000                  391        1622
Apr-2001                  473        1634
Aug-1998                  408        1741
Aug-1999                  506        2042
Aug-2000                  569        2366
Aug-2001                  573        2311
Aug-2002                  513        2086
Aug-2003                  440        1829
Dec-1998                  425        1904
Dec-1999                  475        2004

Chi-Square Test: chi2 = 81.67282766728353, p-value = 0.002341293953584884, degrees of freedom = 49
The high cardinality feature and target variable are dependent (reject H0).
```

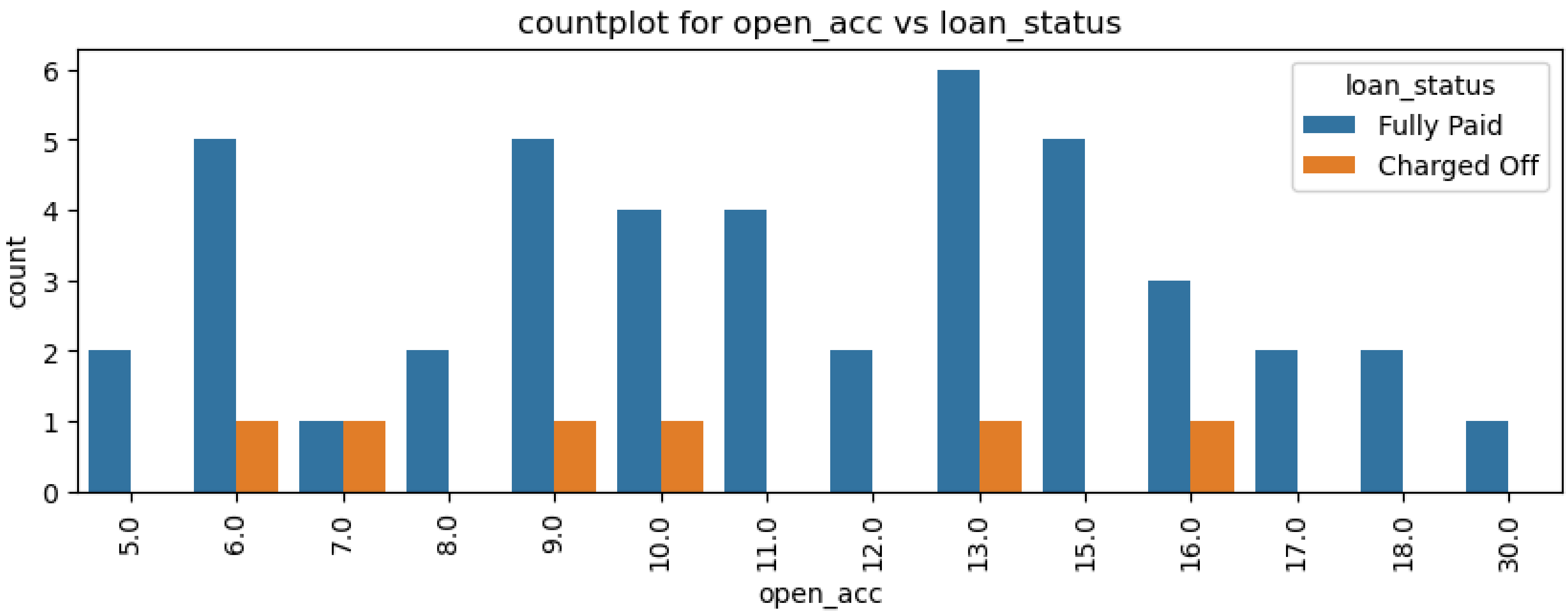


open_acc

open_acc : The number of open credit lines in the borrower's credit file.

In [45]:
```
feature = 'open_acc'
print(df[feature].nunique())
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(10, 3))
sns.countplot(x=feature, data=df[:50], hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

```
61
************************************************************
Unique value counts of the high cardinality feature:
9.0     36779
10.0    35441
8.0     35137
11.0    32695
7.0     31328
12.0    29157
6.0     25927
13.0    24983
14.0    21173
5.0     18308
Name: open_acc, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status  Charged Off  Fully Paid
open_acc
1.0                   15          70
2.0                  277        1182
3.0                  850        3933
4.0                 1921        8788
5.0                 3290       15018
6.0                 4725       21202
7.0                 5757       25571
8.0                 6544       28593
9.0                 7034       29745
10.0                6994       28447

Chi-Square Test: chi2 = 360.25946417312923, p-value = 5.455962628243132e-49, degrees of freedom = 49
The high cardinality feature and target variable are dependent (reject H0).
```

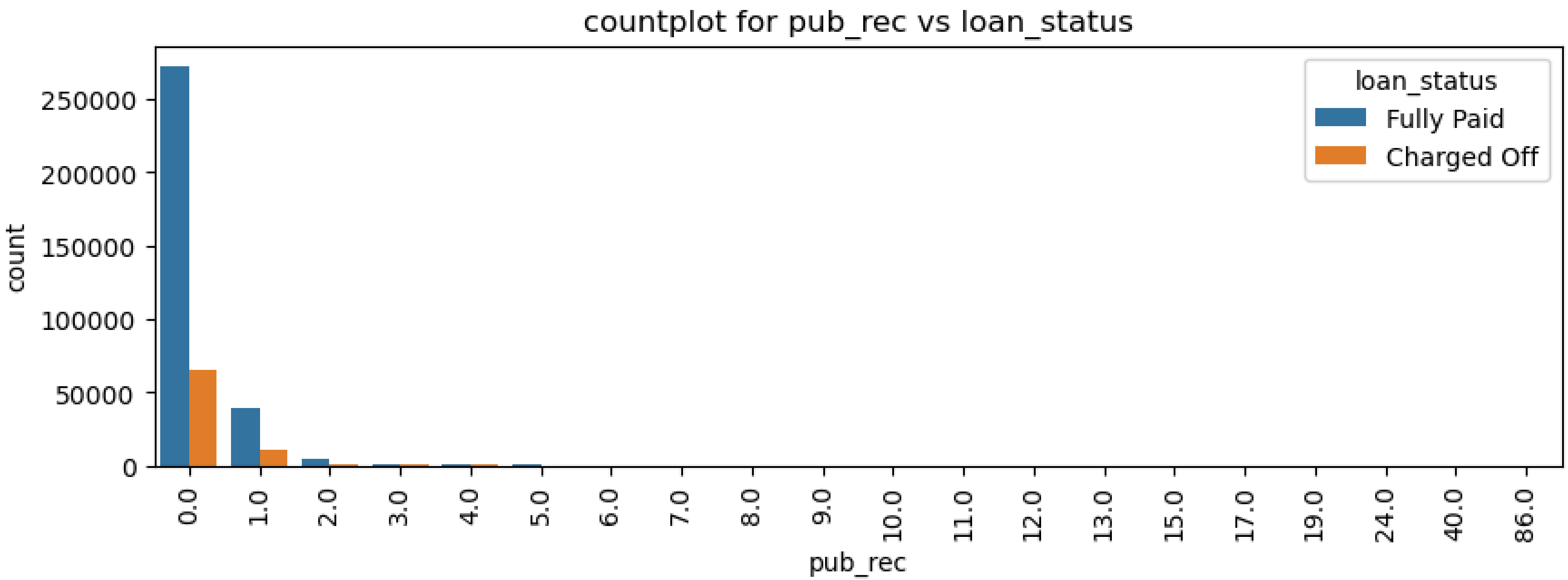


pub_rec

pub_rec : Number of derogatory public records

In [46]:
```
feature = 'pub_rec'
print(df[feature].nunique())
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(10, 3))
sns.countplot(x=feature, data=df, hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

```
20
************************************************************
Unique value counts of the high cardinality feature:
0.0    338272
1.0     49739
2.0      5476
3.0      1521
4.0       527
5.0       237
6.0       122
7.0        56
8.0        34
9.0        12
Name: pub_rec, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status  Charged Off  Fully Paid
pub_rec
0.0                65339      272933
1.0                10469       39270
2.0                 1254        4222
3.0                  340        1181
4.0                  145         382
5.0                   56         181
6.0                   31          91
7.0                   16          40
8.0                    6          28
9.0                    5           7

Chi-Square Test: chi2 = 195.1034353105139, p-value = 3.1977870014319198e-31, degrees of freedom = 19
The high cardinality feature and target variable are dependent (reject H0).
```



Observations :

- This feature is is important target variable is dependent on this.

revol_bal

revol_bal : Total credit revolving balance

In [ ]:

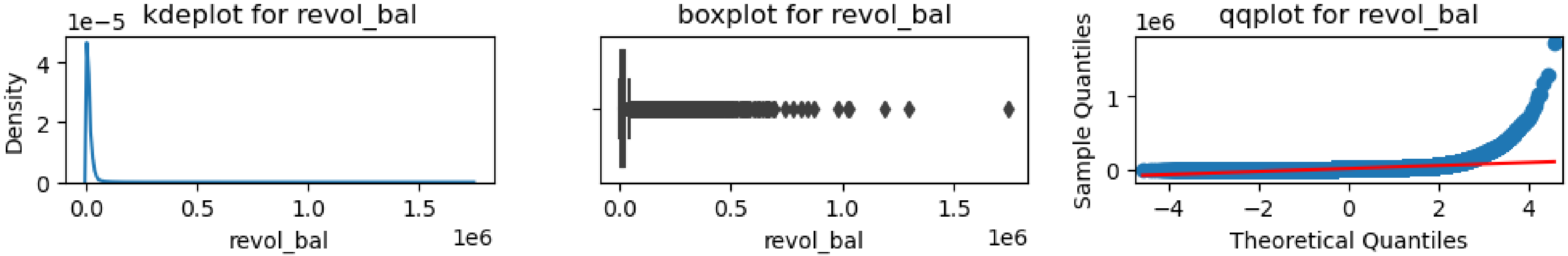
In [47]:
```
df['revol_bal'].nlargest(5)
```

Out[47]:
```
118582    1743266.0
244156    1298783.0
53563     1190046.0
119450    1030826.0
255310    1023940.0
Name: revol_bal, dtype: float64
```

UnivariateAnalysis_revol_bal

In [48]:
```
feature = 'revol_bal'
summary_statistics_and_distribution(df, feature )
```

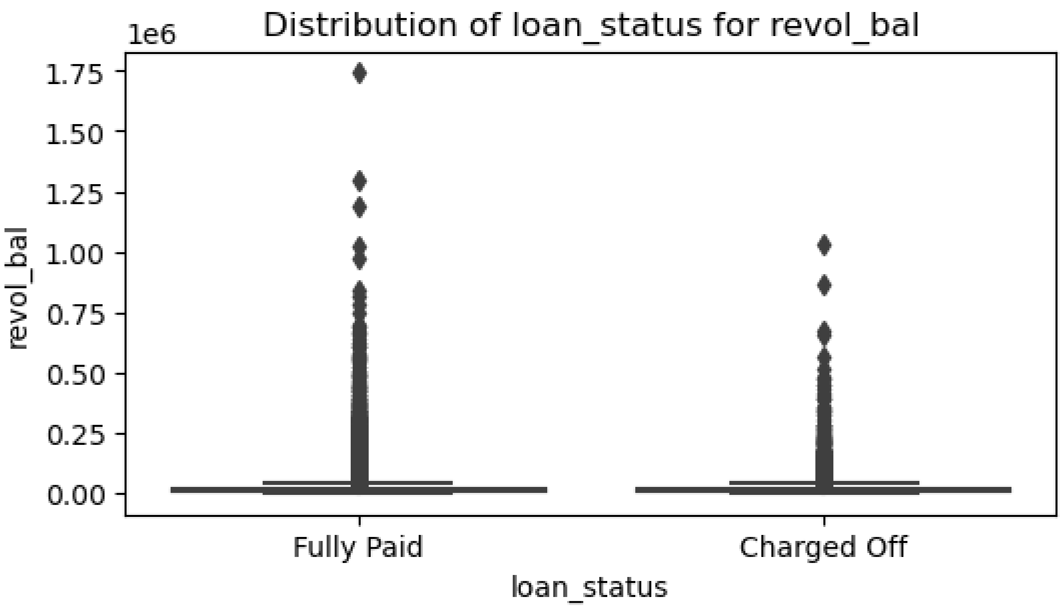
```
************************************************************
summary_statistics:
************************************************************
Mean: 15844.54
Median: 11181.0
Standard Deviation: 20591.81
Min: 0.0
Max: 1743266.0
25th Percentile: 6025.0
75th Percentile: 19620.0
************************************************************
Skewness based on mean and median: 0.68
The distribution is right-skewed.
************************************************************
outliers : numbers = 21259 and percentage = 5.37 %
************************************************************
```



```
************************************************************
normality test:
H0 : revol_bal is normally distributed
H1 : revol_bal is not normally distributed
Shapiro-Wilk Test Statistic: 0.4984705448150635
p-value: 0.0
alpha = 0.05
Reject the null hypothesis as p_value '0.0' <  alpha '0.05' (data is not normally distributed).
************************************************************

C:\Users\Upendra\anaconda3\Lib\site-packages\scipy\stats\_morestats.py:1882: UserWarning: p-value may not be accurat
e for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

BivariateAnalysis_revol_bal

In [49]:
```
bivariate_analysis_numerical_vs_categorical(df, feature, target_variable,'kruskal')
```




```
************************************************************
kruskal :
Kruskal-Wallis - H-statistic: 2.8250079804767285, p-value: 0.09280643097612803
Fail to reject H0
All groups have same mean
************************************************************
```

Observations :

- This feature is not important as groups has same mean

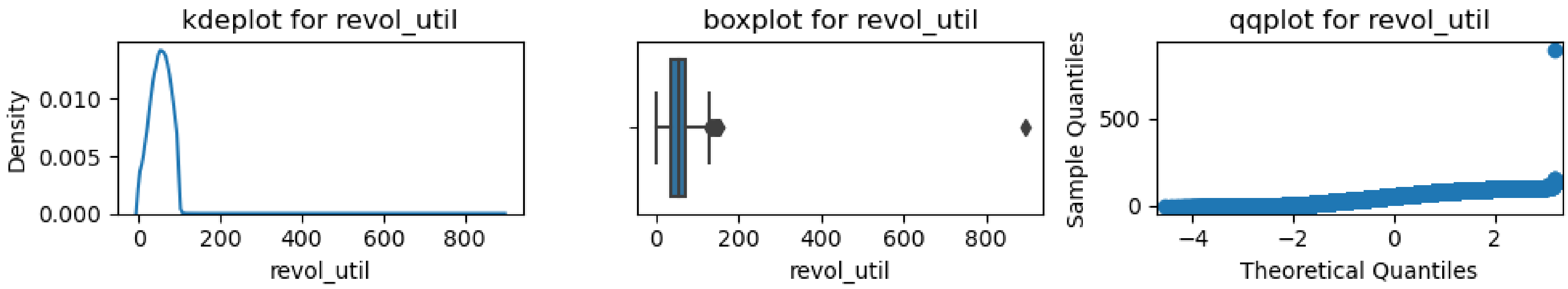
revol_util

revol_util : Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.

UnivariateAnalysis_revol_util

In [50]:
```
feature = 'revol_util'
summary_statistics_and_distribution(df, feature )
```

```
************************************************************
summary_statistics:
************************************************************
Mean: 53.79
Median: nan
Standard Deviation: 24.45
Min: 0.0
Max: 892.3
25th Percentile: nan
75th Percentile: nan
************************************************************
Skewness based on mean and median: nan
The distribution is approximately symmetric.
************************************************************
outliers : numbers = 0 and percentage = 0.0 %
************************************************************
```

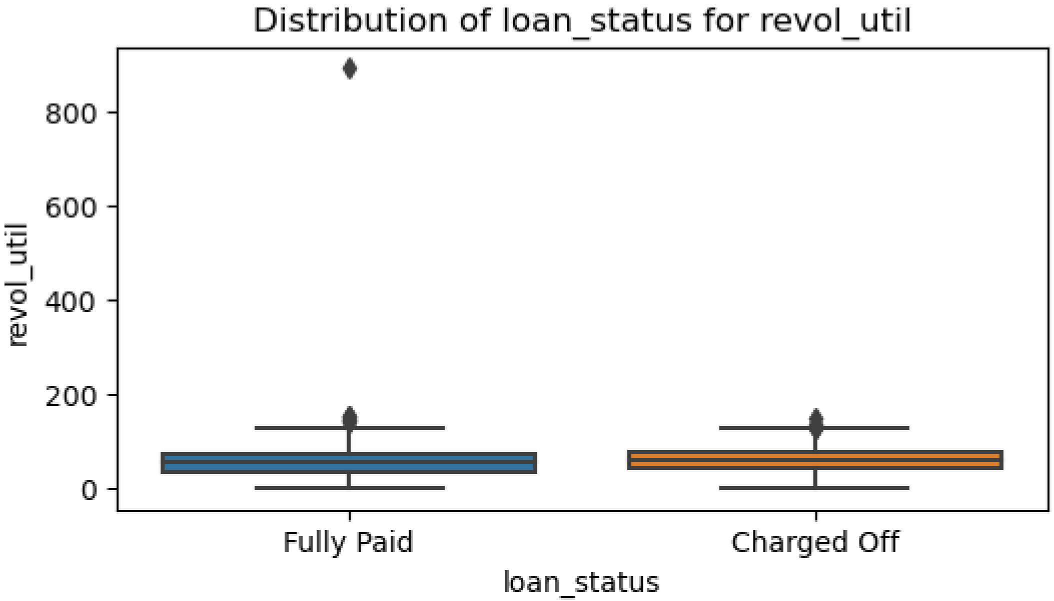



```
************************************************************
normality test:
H0 : revol_util is normally distributed
H1 : revol_util is not normally distributed
Shapiro-Wilk Test Statistic: nan
p-value: 1.0
alpha = 0.05
Fail to reject the null hypothesis  as p_value '1.0' > alpha '0.05' (data is normally distributed).
************************************************************
```

```
C:\Users\Upendra\anaconda3\Lib\site-packages\scipy\stats\_morestats.py:1882: UserWarning: p-value may not be accurat
e for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

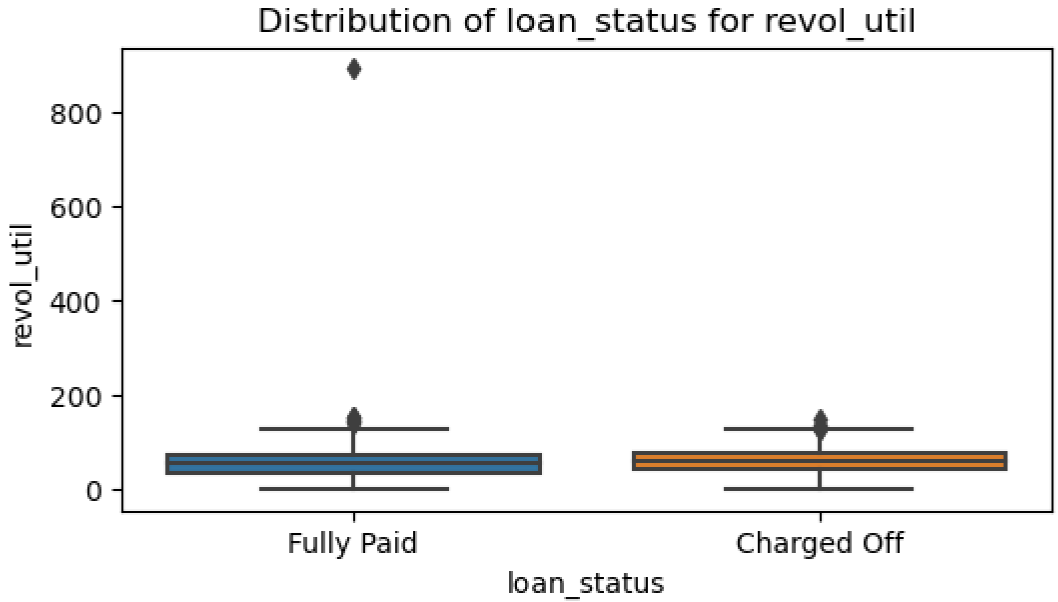
BivariateAnalysis_revol_util

In [51]:
```
bivariate_analysis_numerical_vs_categorical(df, feature, target_variable,'anova')
```




```
************************************************************
anova :
ANOVA - F-statistic: nan, p-value: nan
Fail to reject H0
All groups have same mean
************************************************************
```

In [52]:
```
bivariate_analysis_numerical_vs_categorical(df, feature, target_variable,'kruskal')
```




```
************************************************************
kruskal :
Kruskal-Wallis - H-statistic: nan, p-value: nan
Fail to reject H0
All groups have same mean
************************************************************
```

Observations :

- This feature is not important as groups has same mean

total_acc

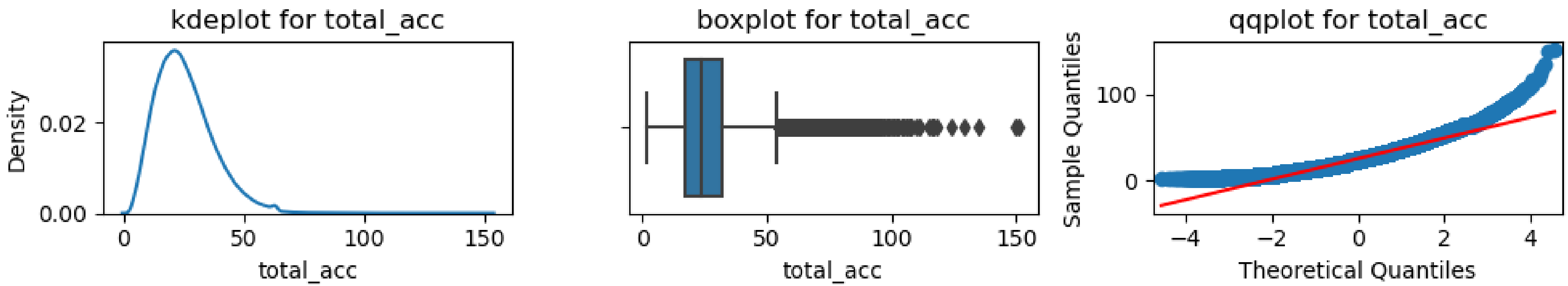
In [53]:
```
df.total_acc
```

Out[53]:
```
0         25.0
1         27.0
2         26.0
3         13.0
4         43.0
          ...
396025    23.0
396026     8.0
396027    23.0
396028    20.0
396029    19.0
Name: total_acc, Length: 396030, dtype: float64
```

UnivariateAnalysis_total_acc

In [54]:
```
feature = 'total_acc'
summary_statistics_and_distribution(df, feature )
```

```
************************************************************
summary_statistics:
************************************************************
Mean: 25.41
Median: 24.0
Standard Deviation: 11.89
Min: 2.0
Max: 151.0
25th Percentile: 17.0
75th Percentile: 32.0
************************************************************
Skewness based on mean and median: 0.36
The distribution is right-skewed.
************************************************************
outliers : numbers = 8499 and percentage = 2.15 %
************************************************************
```

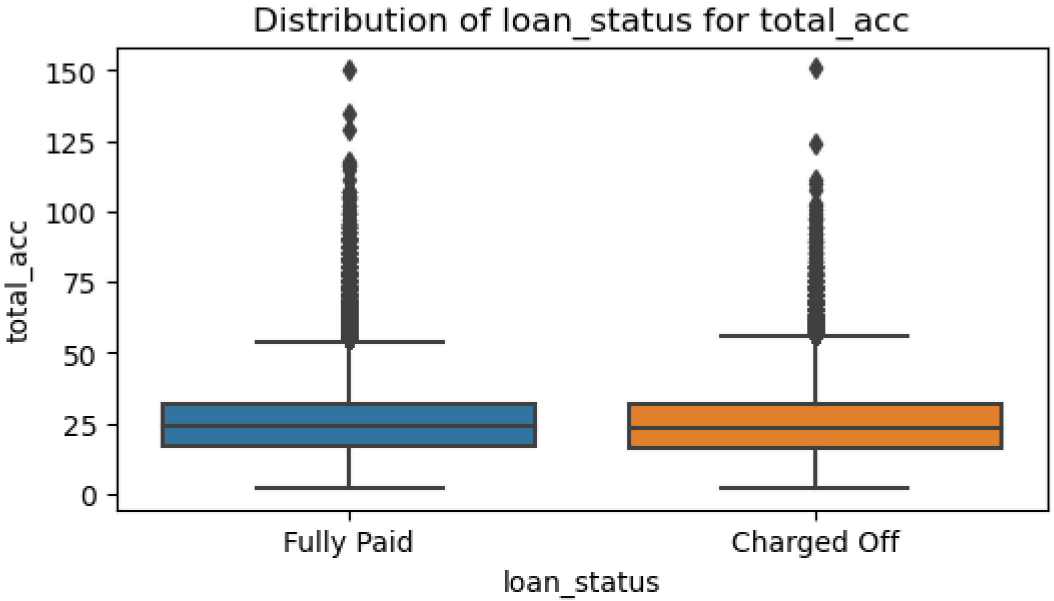



```
************************************************************
normality test:
H0 : total_acc is normally distributed
H1 : total_acc is not normally distributed
Shapiro-Wilk Test Statistic: 0.9599084854125977
p-value: 0.0
alpha = 0.05
Reject the null hypothesis as p_value '0.0' <  alpha '0.05' (data is not normally distributed).
************************************************************
```

```
C:\Users\Upendra\anaconda3\Lib\site-packages\scipy\stats\_morestats.py:1882: UserWarning: p-value may not be accurat
e for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

BivariateAnalysis_total_acc

In [55]:
```
bivariate_analysis_numerical_vs_categorical(df, feature, target_variable,'kruskal')
```




```
************************************************************
kruskal :
Kruskal-Wallis - H-statistic: 169.26173993580815, p-value: 1.0725359453336761e-38
Reject H0
Atleast one group has different mean
************************************************************
```

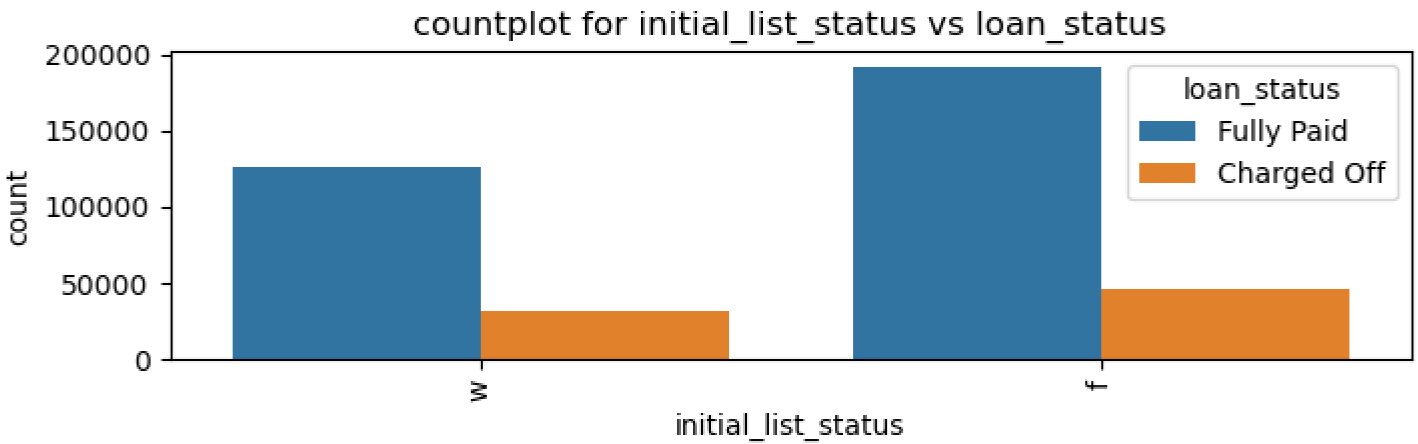
Observations :

- This feature is is important as groups has different mean.

initial_list_status

In [56]:
```
feature = 'initial_list_status'
print(df[feature].nunique())
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(8, 2))
sns.countplot(x=feature, data=df, hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

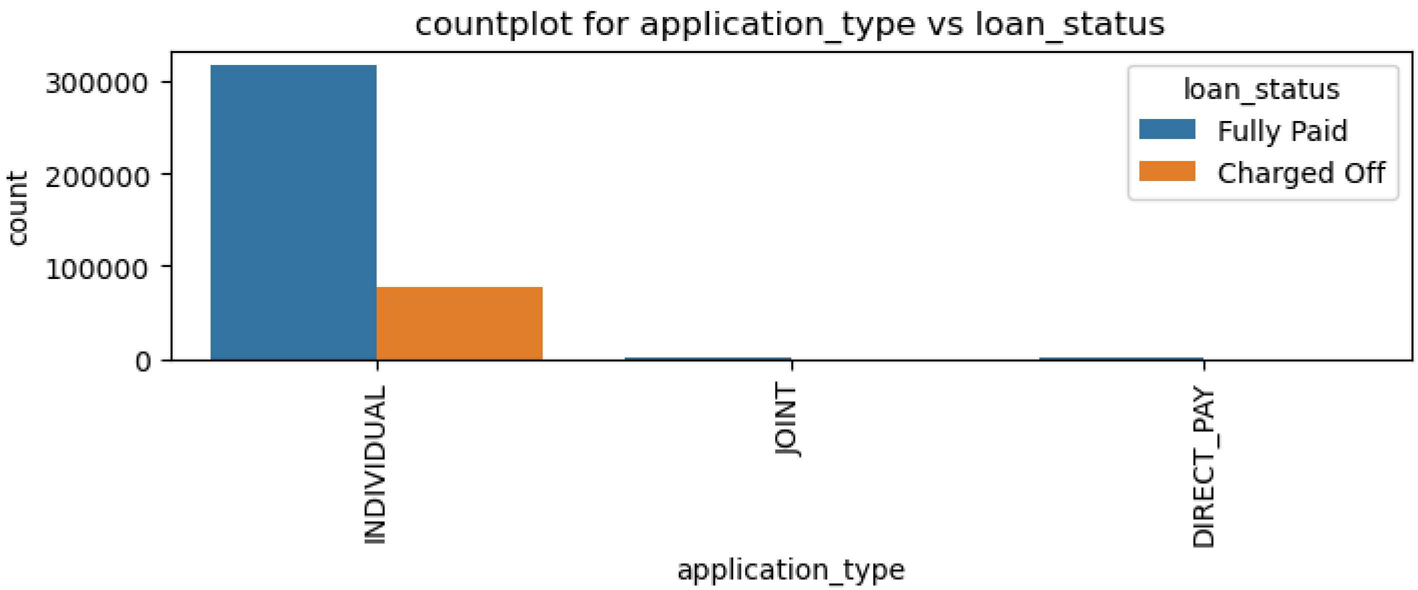
```
2
************************************************************
Unique value counts of the high cardinality feature:
f    238066
w    157964
Name: initial_list_status, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status          Charged Off  Fully Paid
initial_list_status                         
f                          45961      192105
w                          31712      126252

Chi-Square Test: chi2 = 35.61125549485254, p-value = 2.408916483118551e-09, degrees of freedom = 1
The high cardinality feature and target variable are dependent (reject H0).
```


countplot for initial_list_status vs loan_status
200000
150000
100000
50000
0
count
w
f
initial_list_status
loan_status
Fully Paid
Charged Off

application_type

In [57]:
```
feature = 'application_type'
print(df[feature].nunique())
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(8, 2))
sns.countplot(x=feature, data=df, hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

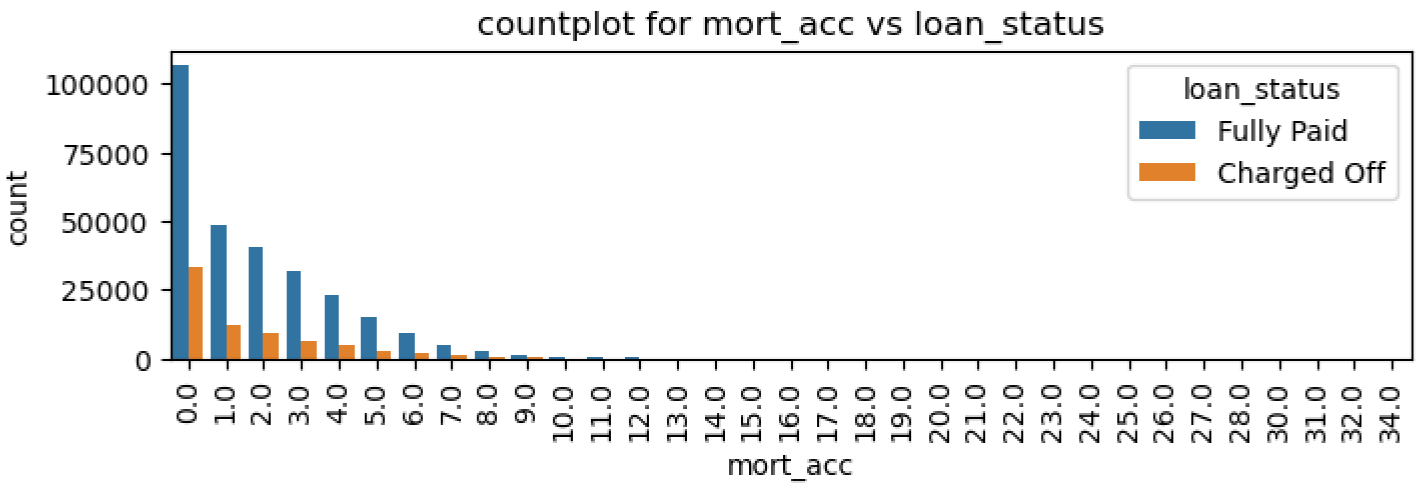
```
3
************************************************************
Unique value counts of the high cardinality feature:
INDIVIDUAL    395319
JOINT            425
DIRECT_PAY       286
Name: application_type, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status       Charged Off  Fully Paid
application_type
DIRECT_PAY                102         184
INDIVIDUAL              77517      317802
JOINT                      54         371

Chi-Square Test: chi2 = 59.601902791548355, p-value = 1.1418557766942247e-13, degrees of freedom = 2
The high cardinality feature and target variable are dependent (reject H0).
```


countplot for application_type vs loan_status
count
300000
200000
100000
0
loan_status
Fully Paid
Charged Off
INDIVIDUAL
JOINT
DIRECT_PAY
application_type

mort_acc

In [58]:
```
feature = 'mort_acc'
print(df[feature].nunique())
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(8, 2))
sns.countplot(x=feature, data=df, hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

```
33
************************************************************
Unique value counts of the high cardinality feature:
0.0    139777
1.0     60416
2.0     49948
3.0     38049
4.0     27887
5.0     18194
6.0     11069
7.0      6052
8.0      3121
9.0      1656
Name: mort_acc, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status  Charged Off  Fully Paid
mort_acc
0.0                33157      106620
1.0                12122       48294
2.0                 9297       40651
3.0                 6535       31514
4.0                 4615       23272
5.0                 2858       15336
6.0                 1721        9348
7.0                  897        5155
8.0                  443        2678
9.0                  209        1447

Chi-Square Test: chi2 = 2302.124710409491, p-value = 0.0, degrees of freedom = 32
The high cardinality feature and target variable are dependent (reject H0).
```



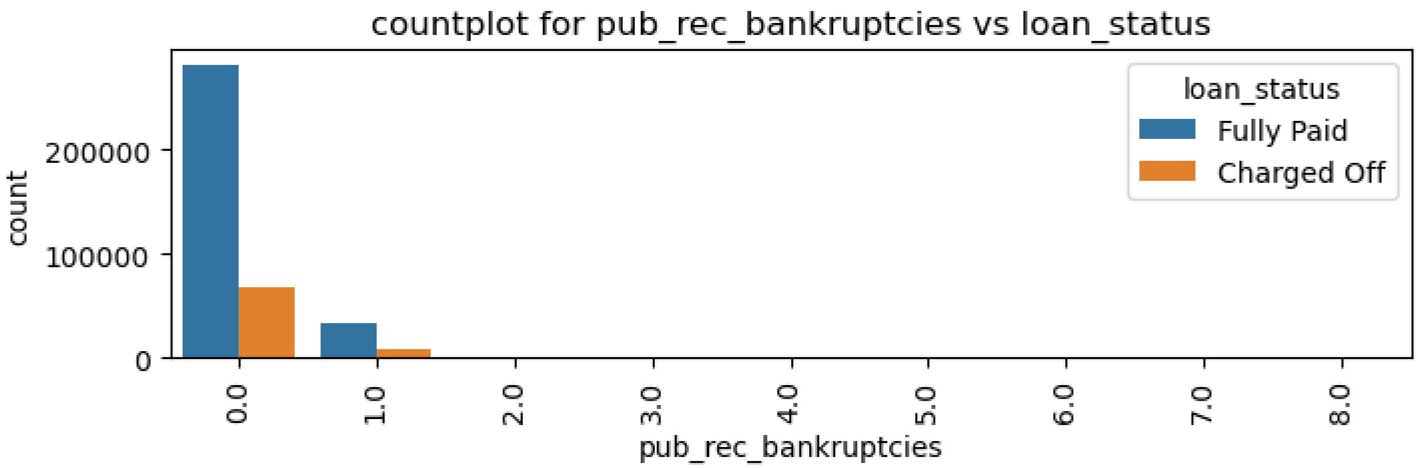
In [ ]:

pub_rec_bankruptcies

pub_rec_bankruptcies : Number of public record bankruptcies

In [59]:
```
feature = 'pub_rec_bankruptcies'
print(df[feature].nunique())
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(8, 2))
sns.countplot(x=feature, data=df, hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

```
9
************************************************************
Unique value counts of the high cardinality feature:
0.0    350380
1.0     42790
2.0      1847
3.0       351
4.0        82
5.0        32
6.0         7
7.0         4
8.0         2
Name: pub_rec_bankruptcies, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status           Charged Off  Fully Paid
pub_rec_bankruptcies
0.0                         68321      282059
1.0                          8727       34063
2.0                           429        1418
3.0                            74         277
4.0                            26          56
5.0                             5          27
6.0                             2           5
7.0                             1           3
8.0                             1           1

Chi-Square Test: chi2 = 44.77652714609038, p-value = 4.056824231550618e-07, degrees of freedom = 8
The high cardinality feature and target variable are dependent (reject H0).
```



address

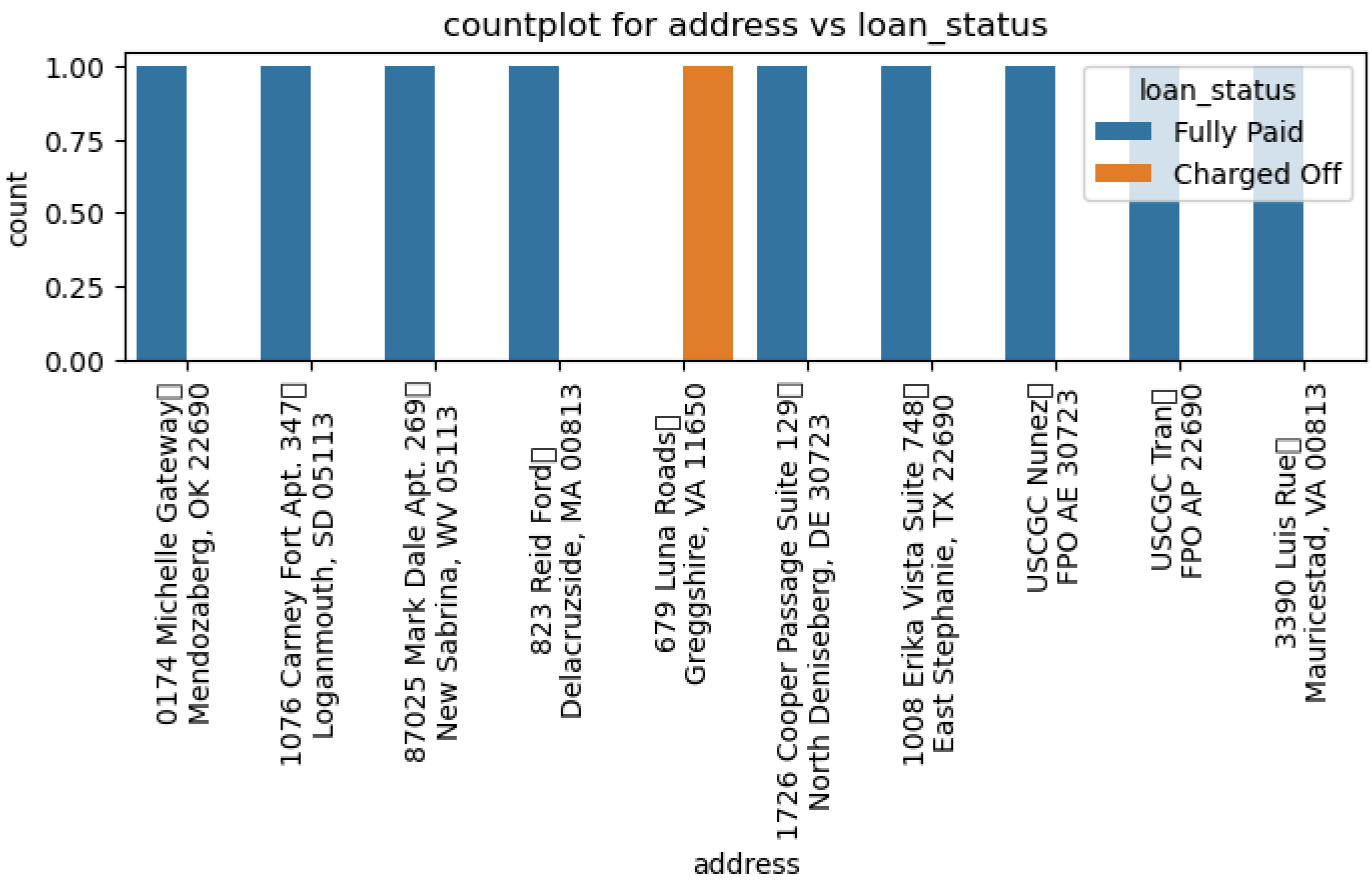
In [60]:
```
df.address
```

Out[60]:
```
0              0174 Michelle Gateway\r\nMendozaberg, OK 22690
1           1076 Carney Fort Apt. 347\r\nLoganmouth, SD 05113
2           87025 Mark Dale Apt. 269\r\nNew Sabrina, WV 05113
3                     823 Reid Ford\r\nDelacruzside, MA 00813
4                      679 Luna Roads\r\nGreggshire, VA 11650
                                 ...
396025     12951 Williams Crossing\r\nJohnnyville, DC 30723
396026    0114 Fowler Field Suite 028\r\nRachelborough, ...
396027    953 Matthew Points Suite 414\r\nReedfort, NY 7...
396028    7843 Blake Freeway Apt. 229\r\nNew Michael, FL...
396029       787 Michelle Causeway\r\nBriannaton, AR 48052
Name: address, Length: 396030, dtype: object
```

In [61]:
```
feature = 'address'
print(df[feature].nunique())
eda_highCardinality_categorical_vs_categorical(df, feature, target_variable )
plt.figure(figsize=(8, 2))
sns.countplot(x=feature, data=df[:10], hue='loan_status')
plt.title(f'countplot for {feature} vs loan_status')
plt.xticks(rotation=90)
plt.show()
```

```
393700
************************************************************
Unique value counts of the high cardinality feature:
USCGC Smith\r\nFPO AE 70466     8
USS Johnson\r\nFPO AE 48052     8
USNS Johnson\r\nFPO AE 05113    8
USS Smith\r\nFPO AP 70466       8
USNS Johnson\r\nFPO AP 48052    7
USNV Smith\r\nFPO AA 00813      6
USCGC Smith\r\nFPO AA 70466     6
USCGC Jones\r\nFPO AE 22690     6
USNS Johnson\r\nFPO AA 70466    6
USNV Smith\r\nFPO AE 30723      6
Name: address, dtype: int64
************************************************************

Grouped data (first 10 rows):
loan_status                   Charged Off  Fully Paid
address
USCGC Brown\r\nFPO AA 30723             0           5
USCGC Jones\r\nFPO AE 22690             3           3
USCGC Jones\r\nFPO AE 30723             1           4
USCGC Lee\r\nFPO AA 22690               1           4
USCGC Miller\r\nFPO AA 22690            0           6
USCGC Smith\r\nFPO AA 29597             0           5
USCGC Smith\r\nFPO AA 70466             1           5
USCGC Smith\r\nFPO AE 00813             0           5
USCGC Smith\r\nFPO AE 05113             0           5
USCGC Smith\r\nFPO AE 22690             3           2

Chi-Square Test: chi2 = 70.40149540517963, p-value = 0.024178457266521285, degrees of freedom = 49
The high cardinality feature and target variable are dependent (reject H0).
```

```
) missing from current font.ib\site-packages\IPython\core\pylabtools.py:152: UserWarning: Glyph 13 (
  fig.canvas.print_figure(bytes_io, **kw)
```

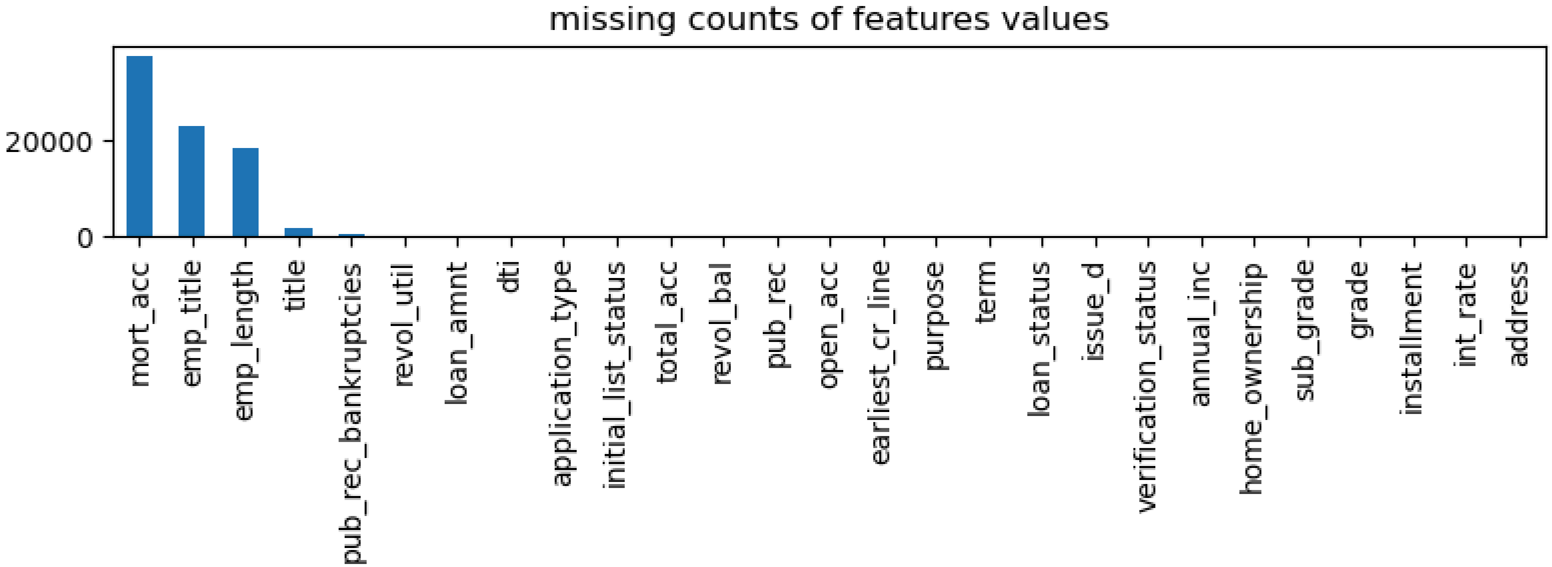


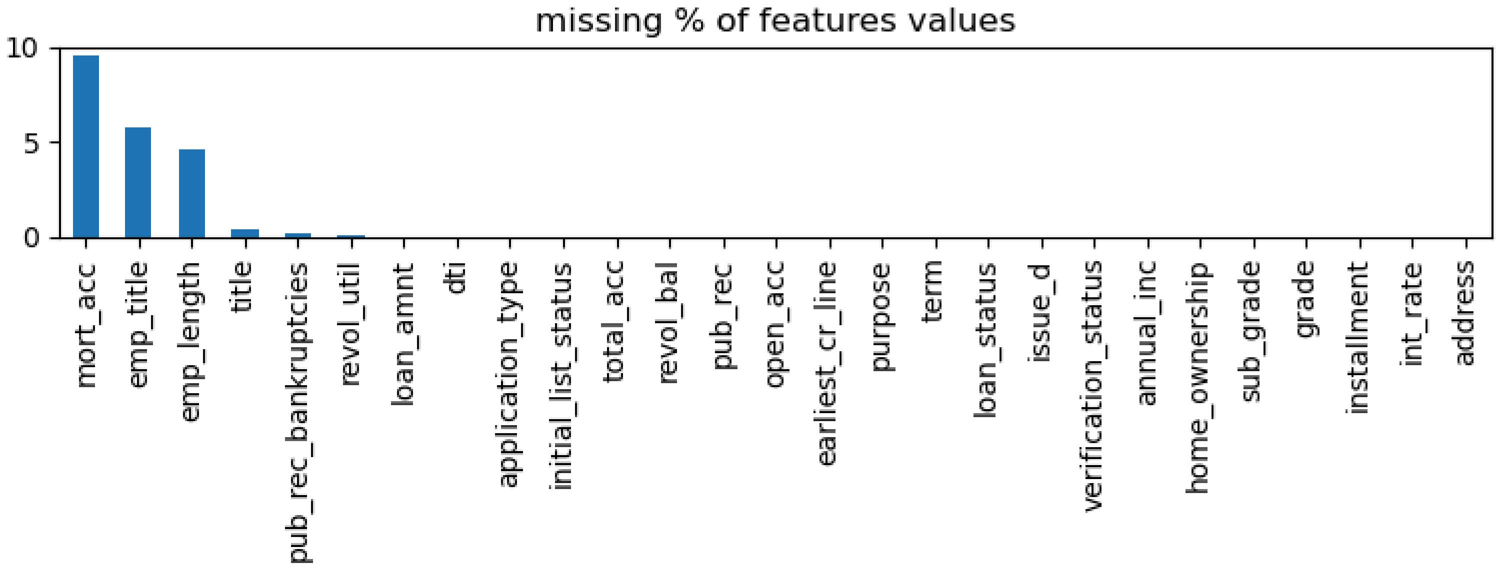
Data_Preprocessing

Missing_value_treatment

In [62]:
```
count_missing_values = df.isnull().sum()
per_missing_values = np.round(df.isnull().sum()/len(df) * 100, 2)

df_missing = pd.DataFrame({
    'missingCounts': count_missing_values,
    'missingPercentage': per_missing_values
})
df_missing.sort_values(by = 'missingCounts', ascending=False).head(10)

plt.figure(figsize=(8,6), tight_layout=True)
ax1 = plt.subplot(2, 1, 1)
df_missing.sort_values(by='missingCounts', ascending=False)['missingCounts'].plot(kind='bar')
ax1.set_title('missing counts of features values')

ax2 = plt.subplot(2, 1, 2)
df_missing.sort_values(by='missingPercentage', ascending=False)['missingPercentage'].plot(kind='bar')
ax2.set_title('missing % of features values')
```

Out[62]:
```
Text(0.5, 1.0, 'missing % of features values')
```





Interpretation

- Follwing features has % of missing values:
  - mort_acc = 9.54
  - emp_title = 5.79

  - emp_length = 4.62
  - title 1756 = 0.44
  - pub_rec_bankruptcies = 0.14
  - revol_util = 0.07
- Above features needs to be handled during features Engineering using methods like **Mean/Median/Mode Imputation**

emp_title_handle_missing

In [ ]:

```

```

In [63]:

```
df.emp_title.isna().sum()
```

Out[63]:

```
22927
```

In [64]:

```
# get the unique values of another feature 'home_ownership' when emp_title is null
df[df.emp_title.isna()]['home_ownership'].value_counts()
```

Out[64]:

```
MORTGAGE    10958
RENT         8049
OWN          3911
OTHER           5
NONE            2
ANY             2
Name: home_ownership, dtype: int64
```

In [65]:

```
# find the mode value 'emp_title' corresponding to  'home_ownership'
dict_h_ownshp_4Nulls = {}
for h_ownshp in df[df.emp_title.isna()]['home_ownership'].unique():
    dict_h_ownshp_4Nulls[h_ownshp] = df[df['home_ownership'] ==h_ownshp]['emp_title'].mode()[0]
```

In [66]:
```
dict_h_ownshp_4Nulls
```

Out[66]:
```
{'RENT': 'Manager',
 'MORTGAGE': 'Teacher',
 'OWN': 'Teacher',
 'NONE': 'Advanced Biotech',
 'OTHER': 'AAR',
 'ANY': 'General Manager'}
```

In [67]:
```
df[df.emp_title.isna() & (df.home_ownership == 'RENT')]['emp_title'].head(3)
```

Out[67]:
```
35    NaN
36    NaN
99    NaN
Name: emp_title, dtype: object
```

In [68]:
```
 # replace null with 'Manager'
df.loc[df.emp_title.isna() & (df.home_ownership == 'RENT'), 'emp_title'] = dict_h_ownshp_4Nulls['RENT']
```

In [69]:
```
# like wise null with 'Teacher' if home_ownership is MORTGAGE
for key in dict_h_ownshp_4Nulls.keys():
    df.loc[df.emp_title.isna() & (df.home_ownership == key), 'emp_title'] = dict_h_ownshp_4Nulls[key]
```

mort_acc_handle_missing

In [70]:
```
df['mort_acc'].isna().sum()
```

Out[70]:
```
37795
```

In [71]:
```
df[df['mort_acc'].isna()]['home_ownership'].value_counts()
```

Out[71]:
```
RENT        18106
MORTGAGE    16642
OWN          2967
OTHER          78
NONE            2
Name: home_ownership, dtype: int64
```

In [72]:
```
mapdict = {}
for h_ownshp in df[df['mort_acc'].isna()]['home_ownership'].unique():
    mapdict[h_ownshp] = (df[df['home_ownership'] == h_ownshp]['mort_acc'].mode()[0])

print(mapdict)

for key in mapdict.keys():
    df.loc[df['mort_acc'].isna() & (df['home_ownership'] == key), 'mort_acc'] = mapdict[key]
```

```
{'OWN': 0.0, 'RENT': 0.0, 'MORTGAGE': 1.0, 'NONE': 0.0, 'OTHER': 0.0}
```

In [73]:
```
df['mort_acc'].isna().sum()
```

Out[73]:
```
0
```

emp_length_handle_missing

In [74]:
```
featurewithnulls = 'emp_length'
print(f'before impute null values {df[featurewithnulls].isna().sum()}')
df[df[featurewithnulls].isna()]['home_ownership'].value_counts()

mapdict = {}
for h_ownshp in df[df[featurewithnulls].isna()]['home_ownership'].unique():
    mapdict[h_ownshp] = (df[df['home_ownership'] == h_ownshp][featurewithnulls].mode()[0])

print(mapdict)

for key in mapdict.keys():
    df.loc[df[featurewithnulls].isna() & (df['home_ownership'] == key), featurewithnulls] = mapdict[key]

print(f'after impute null values {df[featurewithnulls].isna().sum()}')
```

```
before impute null values 18301
{'RENT': '10+ years', 'MORTGAGE': '10+ years', 'OWN': '10+ years', 'OTHER': '10+ years', 'NONE': '10+ years'}
after impute null values 0
```

title_handle_missing

In [75]:
```
featurewithnulls = 'title'
print(f'{featurewithnulls} : before impute null values {df[featurewithnulls].isna().sum()}')
df[df[featurewithnulls].isna()]['home_ownership'].value_counts()

mapdict = {}
for h_ownshp in df[df[featurewithnulls].isna()]['home_ownership'].unique():
    mapdict[h_ownshp] = (df[df['home_ownership'] == h_ownshp][featurewithnulls].mode()[0])

print(mapdict)

for key in mapdict.keys():
    df.loc[df[featurewithnulls].isna() & (df['home_ownership'] == key), featurewithnulls] = mapdict[key]

print(f'{featurewithnulls} : after impute null values {df[featurewithnulls].isna().sum()}')
```

```
title : before impute null values 1755
{'RENT': 'Debt consolidation', 'MORTGAGE': 'Debt consolidation', 'OWN': 'Debt consolidation'}
title : after impute null values 0
```

pub_rec_bankruptcies_handle_missing

In [76]:
```
featurewithnulls = 'pub_rec_bankruptcies'
print(f'{featurewithnulls} : before impute null values {df[featurewithnulls].isna().sum()}')
df[df[featurewithnulls].isna()]['home_ownership'].value_counts()

mapdict = {}
for h_ownshp in df[df[featurewithnulls].isna()]['home_ownership'].unique():
    mapdict[h_ownshp] = (df[df['home_ownership'] == h_ownshp][featurewithnulls].mode()[0])

print(mapdict)

for key in mapdict.keys():
    df.loc[df[featurewithnulls].isna() & (df['home_ownership'] == key), featurewithnulls] = mapdict[key]

print(f'{featurewithnulls} : after impute null values {df[featurewithnulls].isna().sum()}')
```

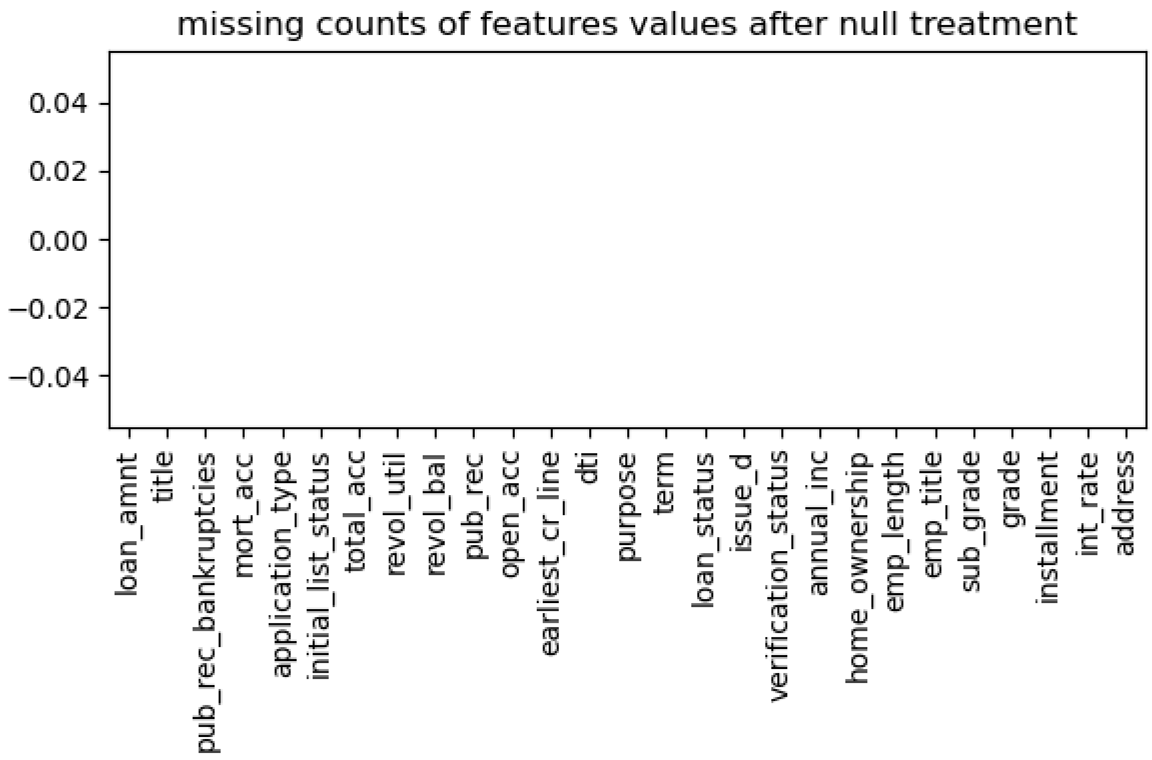
```
pub_rec_bankruptcies : before impute null values 535
{'RENT': 0.0, 'OWN': 0.0, 'MORTGAGE': 0.0, 'NONE': 0.0}
pub_rec_bankruptcies : after impute null values 0
```

revol_util_handle_missing

In [77]:
```
featurewithnulls = 'revol_util'
print(f'{featurewithnulls} : before impute null values {df[featurewithnulls].isna().sum()}')
df[df[featurewithnulls].isna()]['home_ownership'].value_counts()

mapdict = {}
for h_ownshp in df[df[featurewithnulls].isna()]['home_ownership'].unique():
    mapdict[h_ownshp] = (df[df['home_ownership'] == h_ownshp][featurewithnulls].mode()[0])

print(mapdict)

for key in mapdict.keys():
    df.loc[df[featurewithnulls].isna() & (df['home_ownership'] == key), featurewithnulls] = mapdict[key]

print(f'{featurewithnulls} : after impute null values {df[featurewithnulls].isna().sum()}')
```

```
revol_util : before impute null values 276
{'MORTGAGE': 0.0, 'RENT': 0.0, 'OWN': 0.0, 'OTHER': 0.0}
revol_util : after impute null values 0
```

In [78]:
```
count_missing_values = df.isnull().sum()
per_missing_values = np.round(df.isnull().sum()/len(df) * 100, 2)

df_missing = pd.DataFrame({
    'missingCounts': count_missing_values,
    'missingPercentage': per_missing_values
})
df_missing.sort_values(by = 'missingCounts', ascending=False).head(10)

plt.figure(figsize=(6,4), tight_layout=True)
df_missing.sort_values(by='missingCounts', ascending=False)['missingCounts'].plot(kind='bar')
plt.title('missing counts of features values after null treatment')
plt.show()
```



Outlier_treatment

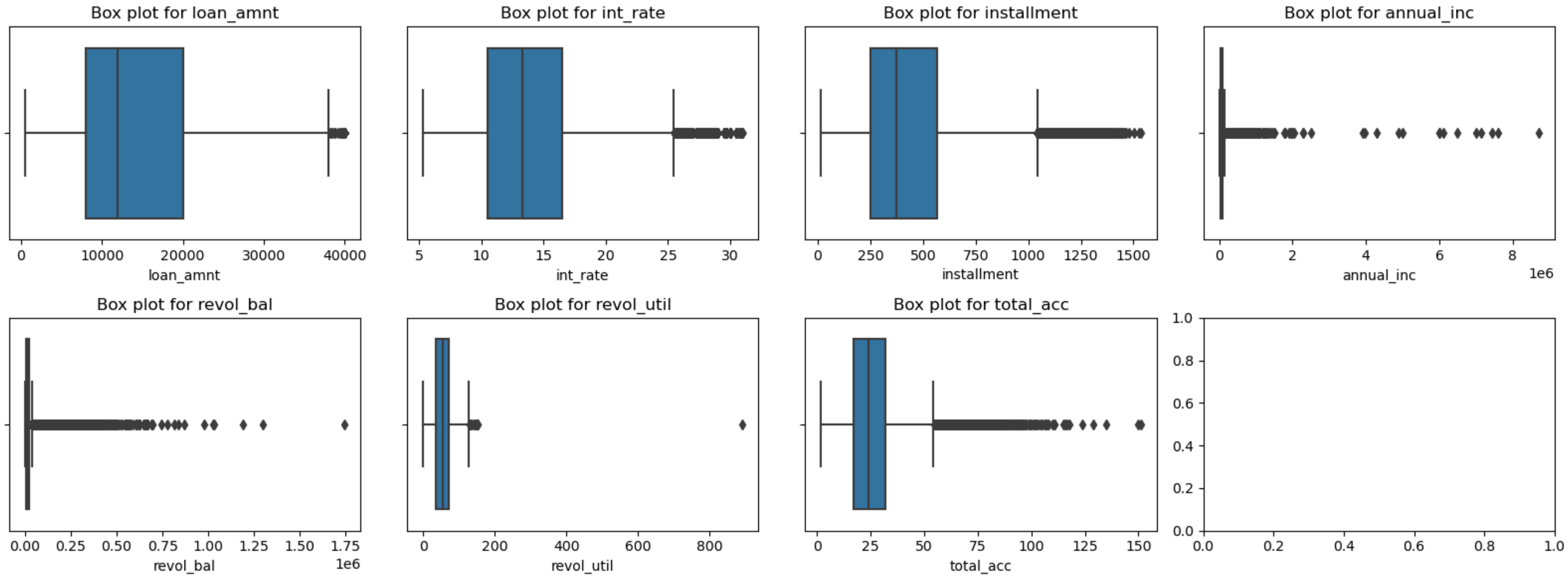
In [79]:
```
df.isna().sum().sum()
```

Out[79]:
```
0
```

In [80]:
```
def remove_outliers_iqr(df, feature):
    Q1 = df[feature].quantile(0.25)
    Q3 = df[feature].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    df_out = df[(df[feature] >= lower_bound) & (df[feature] <= upper_bound)]
    return df_out

def cap_outliers_iqr(df, feature):
    Q1 = df[feature].quantile(0.25)
    Q3 = df[feature].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    df[feature] = df[feature].apply(lambda x: lower_bound if x < lower_bound else upper_bound if x > upper_bound else
    return df
```

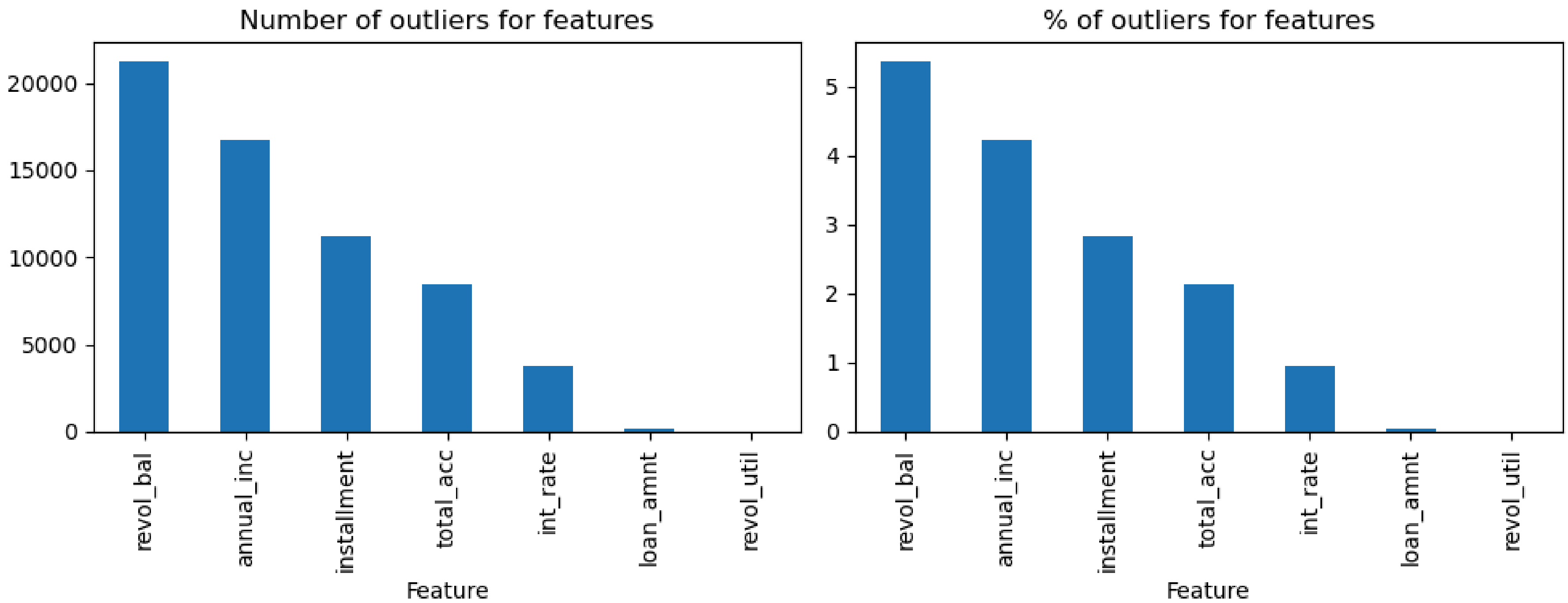
In [81]:
```
numeric_features = ['loan_amnt', 'int_rate', 'installment', 'annual_inc', 'revol_bal',  'revol_util',   'total_acc']
```

In [82]:
```
summary_df = detect_outliers_with_plots(df[numeric_features])
# Print the summary DataFrame
df_outliers = summary_df.sort_values(by='Num_Outliers', ascending=False).set_index('Feature')
print(df_outliers)

plt.figure(figsize=(10,4), tight_layout=True)
ax1 = plt.subplot(1, 2, 1)
df_outliers['Num_Outliers'].plot(kind='bar')
ax1.set_title('Number of outliers for features')

ax2 = plt.subplot(1, 2, 2)
df_outliers['Percentage_Outliers'].plot(kind='bar')
ax2.set_title('% of outliers for features')
```



Feature	Num_Outliers	Percentage_Outliers	Lower_Boundary	Upper_Boundary
revol_bal	21259	5.368028	-14367.500	40012.500
annual_inc	16700	4.216852	-22500.000	157500.000
installment	11250	2.840694	-225.125	1042.755
total_acc	8499	2.146050	-5.500	54.500
int_rate	3777	0.953716	1.490	25.490
loan_amnt	191	0.048229	-10000.000	38000.000
revol_util	12	0.003030	-19.850	128.550

Out[82]:
```
Text(0.5, 1.0, '% of outliers for features')
```



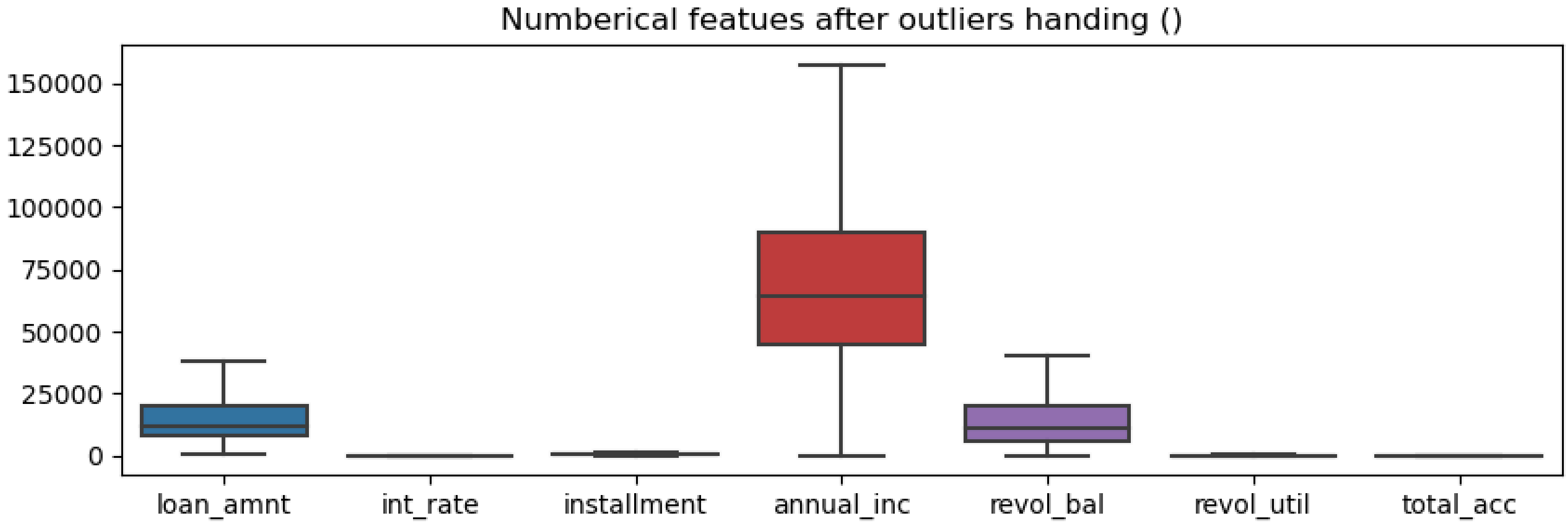
CAPPING

In [83]:
```
for feature in numeric_features : cap_outliers_iqr(df, feature)
```

After_Outliers_handling

In [84]:
```
plt.figure(figsize=(10, 3))
sns.boxplot(df[numeric_features])
plt.title('Numberical featues after outliers handing ()')
```

Out[84]: `Text(0.5, 1.0, 'Numberical featues after outliers handing ()')`



Label_Encoding

In [85]:
```
# categorical features

columns_to_encode = [
    'term',
    'grade',
    'sub_grade',
    'emp_title',
    'emp_length',
    'home_ownership',
    'verification_status',
    'issue_d',
    'purpose',
    'title',
    'open_acc',
    'pub_rec',
    'initial_list_status',
    'application_type',
    'mort_acc',
    'pub_rec_bankruptcies',
    'address',
    'earliest_cr_line'
]

target_encoder = ce.TargetEncoder(cols=columns_to_encode)
```

In [86]:
```
# Instantiate the label encoder
label_encoder = LabelEncoder()

# Fit and transform the target variable
df['target_encoded'] = label_encoder.fit_transform(df[target_variable])
df['target_encoded'].head()
```

Out[86]:
```
0    1
1    1
2    1
3    1
4    0
Name: target_encoded, dtype: int32
```

In [87]:
```
df_encoded = target_encoder.fit_transform(df[columns_to_encode],df['target_encoded'] )
```

In [88]:
```
df_encoded
```

Out[88]:

	term	grade	sub_grade	emp_title	emp_length	home_ownership	verification_status	issue_d	purpose	title	open_acc	pub
0	0.842254	0.874270	0.861607	0.752860	0.804263	0.773378	0.853640	0.747971	0.810767	0.794991	0.796745	0.80
1	0.842254	0.874270	0.844963	0.782678	0.807615	0.830439	0.853640	0.747971	0.792586	0.770358	0.794801	0.80
2	0.842254	0.874270	0.876646	0.808007	0.793128	0.773378	0.785257	0.747971	0.832882	0.807194	0.798543	0.80
3	0.842254	0.937121	0.951814	0.829389	0.810806	0.773378	0.853640	0.753443	0.832882	0.807194	0.817758	0.80
4	0.680585	0.788191	0.754933	0.699281	0.799530	0.830439	0.776789	0.838881	0.832882	0.910420	0.798543	0.80
...	...	...	...	...	...	...	...	...	...	...	...	
396025	0.680585	0.874270	0.861607	0.829389	0.806738	0.773378	0.785257	0.782169	0.792586	0.770358	0.817758	0.80
396026	0.842254	0.788191	0.826304	0.779570	0.807813	0.830439	0.785257	0.744803	0.792586	0.770358	0.817758	0.80
396027	0.842254	0.874270	0.901418	0.731997	0.804263	0.773378	0.776789	0.844730	0.792586	0.793103	0.798467	0.80
396028	0.680585	0.788191	0.802480	0.829389	0.804263	0.830439	0.776789	0.833412	0.792586	0.829389	0.808750	0.80
396029	0.842254	0.788191	0.802480	0.782766	0.804263	0.773378	0.776789	0.834135	0.792586	0.829389	0.822287	0.80

396030 rows × 18 columns

In [89]:
```
# now all data is numberical type
df[columns_to_encode] = df_encoded[columns_to_encode]
```

In [90]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 28 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  float64
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  float64
 5   sub_grade             396030 non-null  float64
 6   emp_title             396030 non-null  float64
 7   emp_length            396030 non-null  float64
 8   home_ownership        396030 non-null  float64
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  float64
 11  issue_d               396030 non-null  float64
 12  loan_status           396030 non-null  object 
 13  purpose               396030 non-null  float64
 14  title                 396030 non-null  float64
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  float64
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            396030 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  float64
 23  application_type      396030 non-null  float64
 24  mort_acc              396030 non-null  float64
 25  pub_rec_bankruptcies  396030 non-null  float64
 26  address               396030 non-null  float64
 27  target_encoded        396030 non-null  int32  
dtypes: float64(26), int32(1), object(1)
memory usage: 83.1+ MB
```

In [91]:
```
X = df.drop(columns=['loan_status', 'target_encoded'])
y = df['target_encoded']
```

In [92]:
```
X_tr_cv, X_test, y_train_cv, y_test = train_test_split(X, y, test_size=0.2, random_state=4)
X_train, X_val, y_train, y_val = train_test_split(X_tr_cv, y_train_cv, test_size=0.25, random_state=4)
```

In [93]:
```
print(X.shape, y.shape)
print(X_tr_cv.shape, y_train_cv.shape, X_test.shape, y_test.shape)
print(X_train.shape, y_train.shape, X_val.shape, y_val.shape)
```

```
(396030, 26) (396030,)
(316824, 26) (316824,) (79206, 26) (79206,)
(237618, 26) (237618,) (79206, 26) (79206,)
```

Scaling

In [94]:
```
scalar = StandardScaler()
X_train_scaled = pd.DataFrame(scalar.fit_transform(X_train), columns=X_train.columns)
X_val_scaled = pd.DataFrame(scalar.transform(X_val), columns=X_val.columns)
X_test_scaled = pd.DataFrame(scalar.transform(X_test), columns=X_test.columns)
```

In [95]:
```
X_train_scaled.head()
```

Out[95]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	...	open_acc	pub_re
0	-1.289694	0.558960	0.441719	-1.295744	-0.900584	-0.642909	-0.280082	-2.642136	-0.390452	-1.121114	...	1.054165	0.3723
1	0.705094	0.558960	-0.675597	0.929082	0.690188	0.839014	0.570661	-1.068188	0.978314	2.160770	...	-0.464499	0.3723
2	1.486836	-1.789035	2.550457	1.458062	-2.259532	-2.477717	-0.679144	0.095701	-1.118852	0.033963	...	1.054165	0.3723
3	-0.492976	0.558960	1.089178	-0.267726	-0.900584	-0.800705	0.570661	1.704255	0.978314	-0.610598	...	-0.464499	0.3723
4	0.764998	0.558960	0.574359	1.226347	-0.150150	-0.371432	-2.985145	-0.739790	0.978314	-0.698115	...	-0.312523	0.3723

5 rows × 26 columns

Model_building

In [96]:
```
def plot_auroc(fpr, tpr, typedata):
    roc_auc = auc(fpr, tpr)

    # Plot ROC curve
    plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'Receiver Operating Characteristic for {typedata}')
    plt.legend(loc="lower right")
```

In [97]:
```
logreg = LogisticRegression(random_state=42)
logreg.fit(X_train_scaled, y_train)
```

Out[97]:
```
▾ LogisticRegression
LogisticRegression(random_state=42)
```

In [ ]:
```
```

In [98]:
```
# Calculate accuracy validations
y_pred  = logreg.predict(X_val_scaled)
val_accuracy = accuracy_score(y_val, y_pred)

print("Validation Accuracy: {:.2f}%".format(val_accuracy * 100))
print("\nClassification Report (Validation Set):\n", classification_report(y_val, y_pred))
print("\nConfusion Matrix (Validation Set):\n", confusion_matrix(y_val, y_pred))
```

```
Validation Accuracy: 99.95%

Classification Report (Validation Set):
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     15534
           1       1.00      1.00      1.00     63672

    accuracy                           1.00     79206
   macro avg       1.00      1.00      1.00     79206
weighted avg       1.00      1.00      1.00     79206


Confusion Matrix (Validation Set):
 [[15508    26]
 [   15 63657]]
```

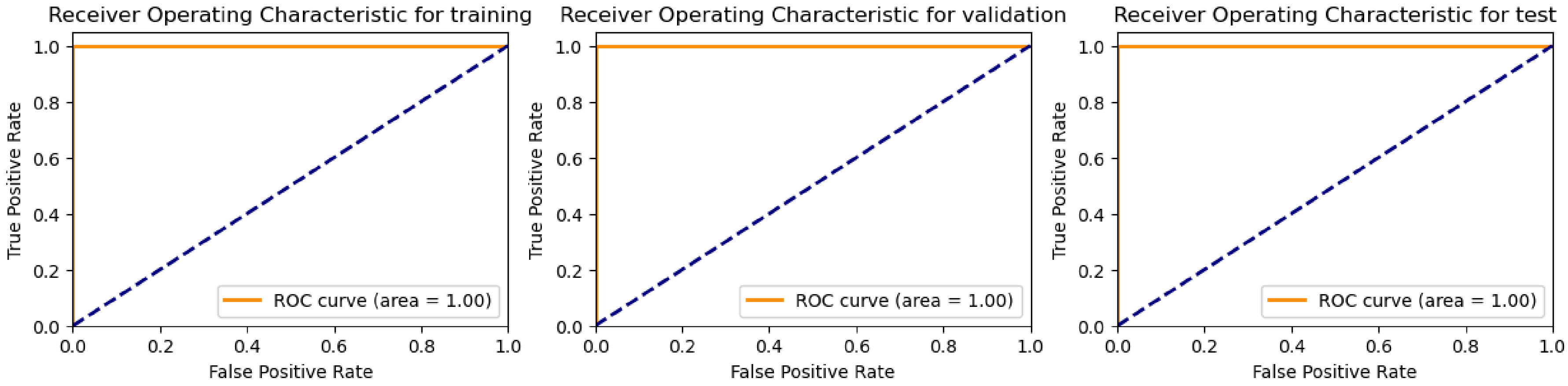
In [99]:
```
y_pred  = logreg.predict(X_train_scaled)
train_accuracy = accuracy_score(y_train, y_pred)


print("training  Accuracy: {:.2f}%".format(train_accuracy * 100))
print("\nClassification Report (training Set):\n", classification_report(y_train, y_pred))
print("\nConfusion Matrix (training Set):\n", confusion_matrix(y_train, y_pred))
```

```
training  Accuracy: 99.94%

Classification Report (training Set):
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     46795
           1       1.00      1.00      1.00    190823

    accuracy                           1.00    237618
   macro avg       1.00      1.00      1.00    237618
weighted avg       1.00      1.00      1.00    237618


Confusion Matrix (training Set):
 [[ 46716     79]
 [    60 190763]]
```

In [100]:
```
y_pred  = logreg.predict(X_test_scaled)
test_accuracy = accuracy_score(y_test, y_pred)


print("test  Accuracy: {:.2f}%".format(test_accuracy * 100))
print("\nClassification Report (test Set):\n", classification_report(y_test, y_pred))
print("\nConfusion Matrix (test Set):\n", confusion_matrix(y_test, y_pred))
```

```
test  Accuracy: 99.93%

Classification Report (test Set):
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     15344
           1       1.00      1.00      1.00     63862

    accuracy                           1.00     79206
   macro avg       1.00      1.00      1.00     79206
weighted avg       1.00      1.00      1.00     79206


Confusion Matrix (test Set):
 [[15308    36]
 [   18 63844]]
```

In [101]:
```
plt.figure(figsize=(15, 3))
plt.subplot(131)
y_prob = logreg.predict_proba(X_train_scaled)[:, 1]
fpr, tpr, _ = roc_curve(y_train, y_prob)
plot_auroc(fpr, tpr, 'training')

plt.subplot(132)
y_val_prob = logreg.predict_proba(X_val_scaled)[:, 1]
fpr, tpr, _ = roc_curve(y_val, y_val_prob)
plot_auroc(fpr, tpr, 'validation')

plt.subplot(133)
y_prob = logreg.predict_proba(X_test_scaled)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_prob)
plot_auroc(fpr, tpr, 'test')
```

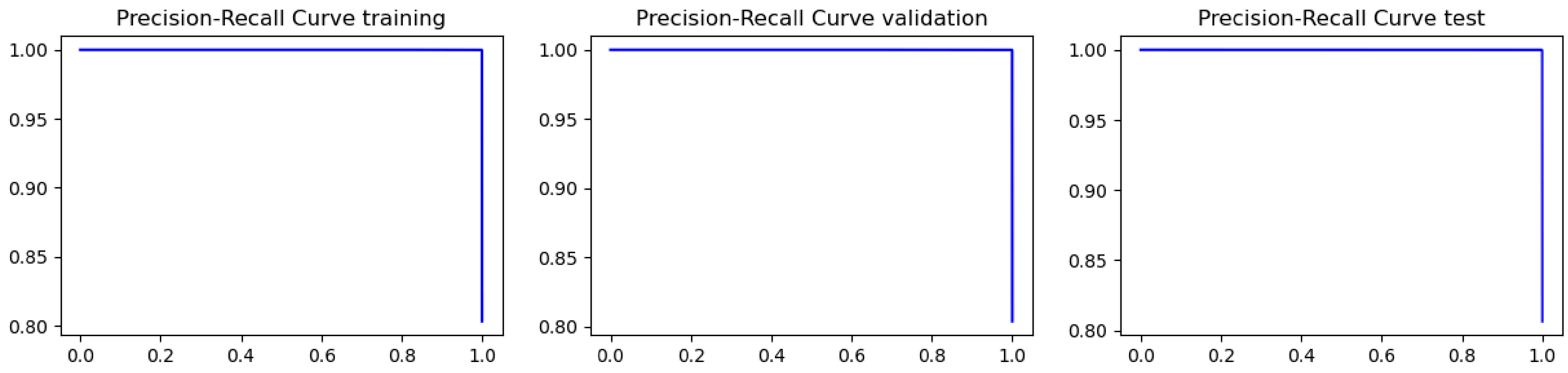


In [104]:

```
plt.figure(figsize=(15, 3))

plt.subplot(131)
y_train_prob = logreg.predict_proba(X_train_scaled)[:, 1]  # Probabilities for the positive class
precision, recall, _ = precision_recall_curve(y_train, y_train_prob)
pr_auc = auc(recall, precision)
plt.plot(recall, precision, color='b', label=f'Precision-Recall curve (AUC = {pr_auc:.2f})')
plt.title('Precision-Recall Curve training')

plt.subplot(132)
y_val_prob = logreg.predict_proba(X_val_scaled)[:, 1]  # Probabilities for the positive class
precision, recall, _ = precision_recall_curve(y_val, y_val_prob)
pr_auc = auc(recall, precision)
plt.plot(recall, precision, color='b', label=f'Precision-Recall curve (AUC = {pr_auc:.2f})')
plt.title('Precision-Recall Curve validation')


plt.subplot(133)
y_test_prob = logreg.predict_proba(X_test_scaled)[:, 1]  # Probabilities for the positive class
precision, recall, _ = precision_recall_curve(y_test, y_test_prob)
pr_auc = auc(recall, precision)
plt.plot(recall, precision, color='b', label=f'Precision-Recall curve (AUC = {pr_auc:.2f})')
plt.title('Precision-Recall Curve test')
```

Out[104]:

```
Text(0.5, 1.0, 'Precision-Recall Curve test')
```



In [ ]:

SMOTE

In [105]:

```
X_tr_cv, X_test, y_train_cv, y_test = train_test_split(X, y, test_size=0.2, random_state=4)
X_train, X_val, y_train, y_val = train_test_split(X_tr_cv, y_train_cv, test_size=0.25, random_state=4)

scalar = StandardScaler()
X_train_scaled = pd.DataFrame(scalar.fit_transform(X_train), columns=X_train.columns)
X_val_scaled = pd.DataFrame(scalar.transform(X_val), columns=X_val.columns)
X_test_scaled = pd.DataFrame(scalar.transform(X_test), columns=X_test.columns)

# Step  Apply SMOTE to the training data
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train_scaled, y_train)
```

In [106]:
```
# Training accuracty
y_pred  = logreg.predict(X_train_smote)
train_accuracy = accuracy_score(y_train_smote, y_pred)
print("training  Accuracy: {:.2f}%".format(train_accuracy * 100))
print("\nClassification Report (training Set):\n", classification_report(y_train_smote, y_pred))
print("\nConfusion Matrix (training Set):\n", confusion_matrix(y_train_smote, y_pred))
```

```
training  Accuracy: 99.95%

Classification Report (training Set):
               precision    recall  f1-score   support

           0       1.00      1.00      1.00    190823
           1       1.00      1.00      1.00    190823

    accuracy                           1.00    381646
   macro avg       1.00      1.00      1.00    381646
weighted avg       1.00      1.00      1.00    381646


Confusion Matrix (training Set):
 [[190693    130]
 [    60 190763]]
```

In [107]:
```
# validation  accuracty
y_pred  = logreg.predict(X_val_scaled)
val_accuracy = accuracy_score(y_val, y_pred)
print("validation  Accuracy: {:.2f}%".format(val_accuracy * 100))
print("\nClassification Report (validation Set):\n", classification_report(y_val, y_pred))
print("\nConfusion Matrix (validation Set):\n", confusion_matrix(y_val, y_pred))
```

```
validation  Accuracy: 99.95%

Classification Report (validation Set):
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     15534
           1       1.00      1.00      1.00     63672

    accuracy                           1.00     79206
   macro avg       1.00      1.00      1.00     79206
weighted avg       1.00      1.00      1.00     79206


Confusion Matrix (validation Set):
 [[15508    26]
 [   15 63657]]
```

In [108]:
```
# test  accuracty
y_pred  = logreg.predict(X_test_scaled)
accuracy = accuracy_score(y_test, y_pred)
print("test  Accuracy: {:.2f}%".format(accuracy * 100))
print("\nClassification Report (test Set):\n", classification_report(y_test, y_pred))
print("\nConfusion Matrix (test Set):\n", confusion_matrix(y_test, y_pred))
```

```
test  Accuracy: 99.93%

Classification Report (test Set):
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     15344
           1       1.00      1.00      1.00     63862

    accuracy                           1.00     79206
   macro avg       1.00      1.00      1.00     79206
weighted avg       1.00      1.00      1.00     79206


Confusion Matrix (test Set):
 [[15308    36]
 [   18 63844]]
```

percentage of customers have fully paid their Loan Amount

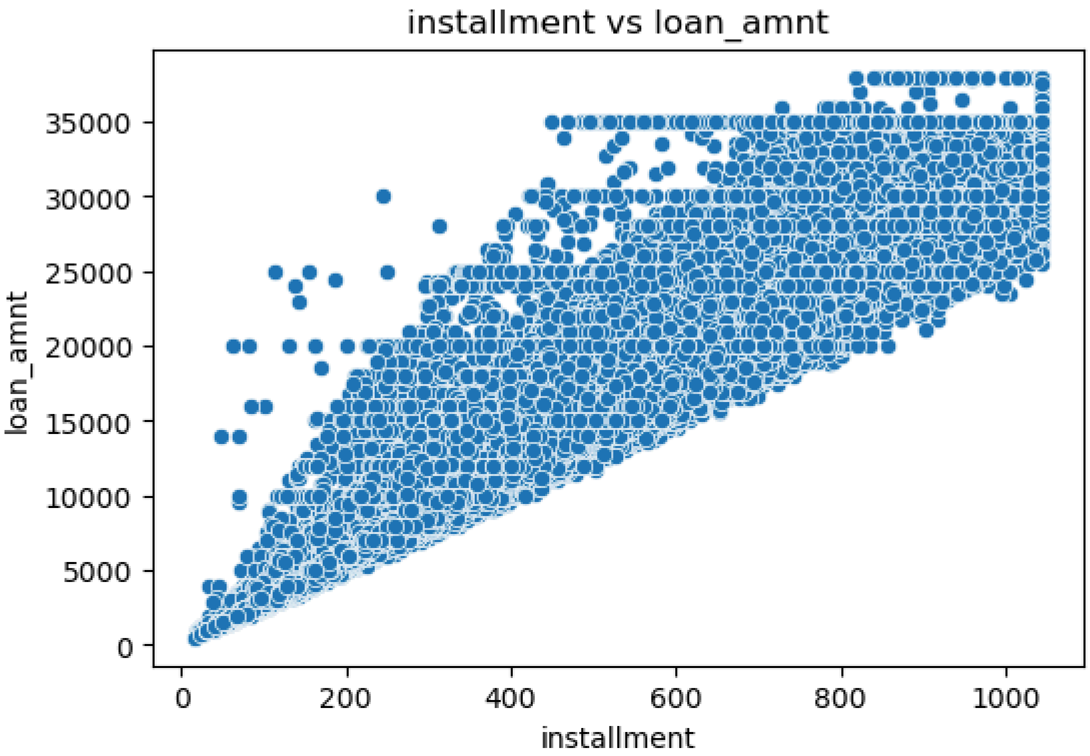
In [109]:
```
df.loan_status.value_counts(normalize=True)*100
```

Out[109]:
```
Fully Paid     80.387092
Charged Off    19.612908
Name: loan_status, dtype: float64
```

- 80.38 % of the people have fully paid their Loan Amount

correlation between Loan Amount and Installment features.

In [110]:
```
plt.figure(figsize=(6, 4))
sns.scatterplot(x='installment', y='loan_amnt', data=df)
plt.title('installment vs loan_amnt')
plt.show()
```



In [111]:
```
df[['installment', 'loan_amnt']].corr()
```

Out[111]:

	installment	loan_amnt
installment	1.000000	0.958065
loan_amnt	0.958065	1.000000

- 'installment', 'loan_amnt' features are posiviely correlated

majority of people who have home ownership

- majority is MORTGAGE for home ownership

People with grades ‘A’ are more likely to fully pay their loan.

- 93.7 % times grade 'A' has fully paid the loan

Name the top 2 afforded job titles.

- Teacher and Manager are two afforded job titles

bank's perspective, which metric should our primary focus be on

- looking for high "F1 Score" score where :
  - he wants to reduce false positive aiming for high precision values (do not loose bussiness who can pay loan)
  - and also reducing false negative to get high recall (do not give loan to defaulters)

Which were the features that heavily affected the outcome?

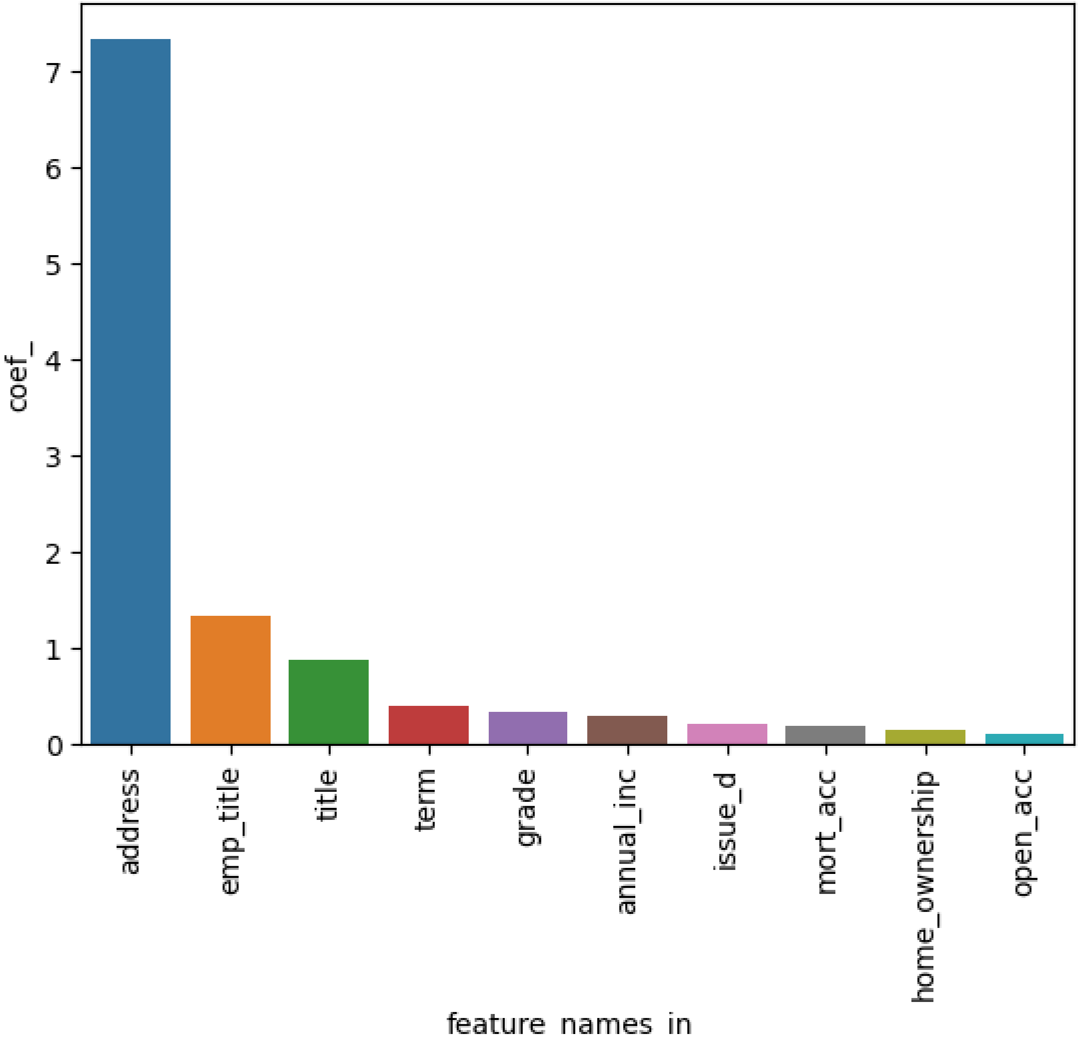
In [113]:
```
feature_imp = pd.DataFrame()
feature_imp['feature_names_in_'] = logreg.feature_names_in_
feature_imp['coef_'] = logreg.coef_[0]
```

In [114]:
```
feature_imp.sort_values('coef_', ascending=False)[:10]
```

Out[114]:

	feature_names_in_	coef_
25	address	7.327846
6	emp_title	1.329222
13	title	0.866776
1	term	0.386623
4	grade	0.325958
9	annual_inc	0.287636
11	issue_d	0.209507
23	mort_acc	0.186704
8	home_ownership	0.151400
16	open_acc	0.106233

In [115]:
```
sns.barplot(x='feature_names_in_', y = 'coef_', data = feature_imp.sort_values('coef_', ascending=False)[:10])
plt.xticks(rotation=90)
plt.show()
```



- Featues like 'address', emp_title, title, grade, annual_inc, isse_d are very important

Will the results be affected by geographical location? (Yes/No)

- Yes as address is important feature to predict the model