Landing Page Case Study

In [169]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Import Data

In [2]:

```
data = pd.read_csv("loan.csv")
data.head()
```

```
C:\Users\Admin\AppData\Roaming\MobaXterm\slash\var\log\xwin\ipykernel_16312\1485934119.py:1: DtypeWarning: Columns (47) hav
e mixed types. Specify dtype option on import or set low_memory=False.
  data = pd.read_csv("loan.csv")
```

Out[2]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	...	num_tl_90g_dpd_24m	num_tl_op_
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87	B	B2	...	NaN	
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83	C	C4	...	NaN	
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33	C	C5	...	NaN	
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31	C	C1	...	NaN	
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.79	B	B5	...	NaN	

5 rows × 111 columns

In [3]:

```
print(data.dtypes)
```

```
id                          int64
member_id                   int64
loan_amnt                   int64
funded_amnt                 int64
funded_amnt_inv           float64
                           ...
tax_liens                 float64
tot_hi_cred_lim           float64
total_bal_ex_mort         float64
total_bc_limit            float64
total_il_high_credit_limit    float64
Length: 111, dtype: object
```

In [4]:

```
data.info(verbose=True)
```

```
 77   bc_util                        float64
 78   chargeoff_within_12_mths       float64
 79   delinq_amnt                    int64
 80   mo_sin_old_il_acct             float64
 81   mo_sin_old_rev_tl_op           float64
 82   mo_sin_rcnt_rev_tl_op          float64
 83   mo_sin_rcnt_tl                 float64
 84   mort_acc                       float64
 85   mths_since_recent_bc           float64
 86   mths_since_recent_bc_dlq       float64
 87   mths_since_recent_inq          float64
 88   mths_since_recent_revol_delinq float64
 89   num_accts_ever_120_pd          float64
 90   num_actv_bc_tl                 float64
 91   num_actv_rev_tl                float64
 92   num_bc_sats                    float64
 93   num_bc_tl                      float64
 94   num_il_tl                      float64
 95   num_op_rev_tl                  float64
 96   num_rev_accts                  float64
```

In [5]:

```
data.nunique()
```

Out[5]:

```
id                            39717
member_id                     39717
loan_amnt                       885
funded_amnt                    1041
funded_amnt_inv                8205
                              ...
tax_liens                         1
tot_hi_cred_lim                   0
total_bal_ex_mort                 0
total_bc_limit                    0
total_il_high_credit_limit        0
Length: 111, dtype: int64
```

In [6]:

```
data.isnull().mean()*100
```

Out[6]:

```
id                              0.000000
member_id                       0.000000
loan_amnt                       0.000000
funded_amnt                     0.000000
funded_amnt_inv                 0.000000
                                 ...
tax_liens                       0.098195
tot_hi_cred_lim               100.000000
total_bal_ex_mort             100.000000
total_bc_limit                100.000000
total_il_high_credit_limit    100.000000
Length: 111, dtype: float64
```

In [7]:

```
data.loan_status.unique()
```

Out[7]:

```
array(['Fully Paid', 'Charged Off', 'Current'], dtype=object)
```

Data Cleaning

- **Dropping unnecessary Columns**
- **Dropping / Filling NULL values**
- **Seprate Year and Month from data columns**
- **Detecting Outliers**
- **Remove Outliers**

In [8]:

```
# Here we are dropping data whose loan is currently going on because we can not consider this data because people whose loan is going

data = data[data["loan_status"] != "Current"]
```

In [9]:

```
# Dropping Columns that contains all blank data

data = data.dropna(axis=1, how='all')
```

In [10]:

```
# Dropping Columns that contains only one unique data

data.drop(columns=data.columns[data.nunique()==1], inplace=True)
```

In [11]:

```
# Dropping Columns that contains null values more than 50%

data = data.dropna(thresh=len(data) - len(data)/2, axis=1)
```

In [12]:

```
# Dropping Columns that doen not have any effect on analysis

data = data.drop(['emp_title','desc',"delinq_2yrs","inq_last_6mths","open_acc","pub_rec","revol_bal","revol_util","total_acc","total_
```

In [13]:

```
data.isnull().mean()*100
```

Out[13]:

```
loan_amnt               0.000000
funded_amnt             0.000000
funded_amnt_inv         0.000000
term                    0.000000
int_rate                0.000000
installment             0.000000
grade                   0.000000
sub_grade               0.000000
emp_length              2.677761
home_ownership          0.000000
annual_inc              0.000000
verification_status     0.000000
issue_d                 0.000000
loan_status             0.000000
purpose                 0.000000
dti                     0.000000
earliest_cr_line        0.000000
last_pymnt_d            0.184047
pub_rec_bankruptcies    1.806776
dtype: float64
```

In [14]:

```
# Dropping Rows that contains NULL values
# Here Null values ration is very low so it's good to drops rows which contains NULL values

data.dropna(subset = ['pub_rec_bankruptcies','last_pymnt_d','emp_length'], inplace = True)
```

In [15]:

```
data.shape
```

Out[15]:

```
(36781, 19)
```

In [16]:

```
#Converting date data into proper datatime format

data.issue_d = pd.to_datetime(data.issue_d, format='%b-%y')

# Seprating Month Year from dates for future analysis

data["issue_d_year"] = pd.to_datetime(data.issue_d, format='%b-%y').dt.year
data["issue_d_month"] = pd.to_datetime(data.issue_d, format='%b-%y').dt.month
```

In [17]:

```
# Seprating Categorical data , Numerical data, Date data , Extra data for future use

cat_data = ["term","grade","sub_grade","emp_length","purpose","home_ownership","loan_status","pub_rec_bankruptcies","verification_sta
num_data = ["loan_amnt","funded_amnt","funded_amnt_inv","int_rate","installment","annual_inc","dti"]
# extra_data = ["id","member_id","url","purpose","title","zip_code","addr_state"]
date_data = ["issue_d","issue_d_year","issue_d_month"]

```

In [18]:

```
data.shape
```

Out[18]:

```
(36781, 21)
```

In [19]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 36781 entries, 0 to 39680
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   loan_amnt             36781 non-null  int64
 1   funded_amnt           36781 non-null  int64
 2   funded_amnt_inv       36781 non-null  float64
 3   term                  36781 non-null  object
 4   int_rate              36781 non-null  object
 5   installment           36781 non-null  float64
 6   grade                 36781 non-null  object
 7   sub_grade             36781 non-null  object
 8   emp_length            36781 non-null  object
 9   home_ownership        36781 non-null  object
 10  annual_inc            36781 non-null  float64
 11  verification_status   36781 non-null  object
 12  issue_d               36781 non-null  datetime64[ns]
 13  loan_status           36781 non-null  object
 14  purpose               36781 non-null  object
 15  dti                   36781 non-null  float64
 16  earliest_cr_line      36781 non-null  object
 17  last_pymnt_d          36781 non-null  object
 18  pub_rec_bankruptcies  36781 non-null  float64
 19  issue_d_year          36781 non-null  int32
 20  issue_d_month         36781 non-null  int32
dtypes: datetime64[ns](1), float64(5), int32(2), int64(2), object(11)
memory usage: 5.9+ MB
```

In [20]:

```
data.nunique()
```

Out[20]:

```
loan_amnt                856
funded_amnt             1010
funded_amnt_inv         7606
term                       2
int_rate                 336
installment            14389
grade                      7
sub_grade                 35
emp_length                11
home_ownership             4
annual_inc              4938
verification_status        3
issue_d                   52
loan_status                2
purpose                   14
dti                     2848
earliest_cr_line         513
last_pymnt_d              97
pub_rec_bankruptcies       3
issue_d_year               5
issue_d_month             12
dtype: int64
```

In [21]:

```
# Checking datatypes of Numerical Variables

for num_col in num_data:
    print("Col",num_col,"------>>",data[num_col].dtypes)

```

```
Col loan_amnt ------>> int64
Col funded_amnt ------>> int64
Col funded_amnt_inv ------>> float64
Col int_rate ------>> object
Col installment ------>> float64
Col annual_inc ------>> float64
Col dti ------>> float64
```

In [22]:

```
# Here convert the Object into Float

data.int_rate = data.int_rate.str.replace("%","")
data.int_rate = data.int_rate.astype("float")

```

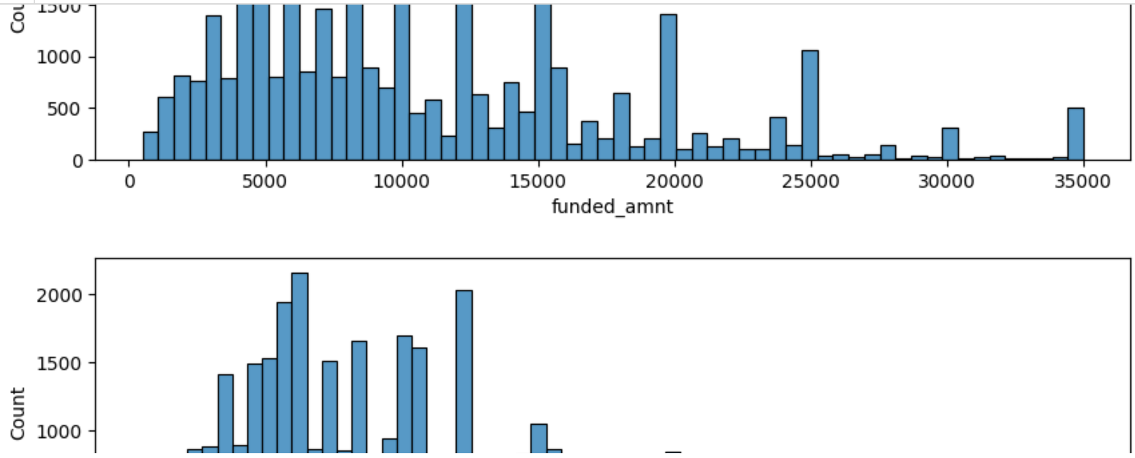
In [23]:

```python
for num_col in num_data:
    print("Col",num_col,"------>>",data[num_col].dtypes)
```

```
Col loan_amnt ------>> int64
Col funded_amnt ------>> int64
Col funded_amnt_inv ------>> float64
Col int_rate ------>> float64
Col installment ------>> float64
Col annual_inc ------>> float64
Col dti ------>> float64
```

In [24]:

```python
# Draw the Histogram for all the Numrical Data

for num_col in num_data:
    plt.figure(figsize=(10,3))

    sns.histplot(data[num_col])

    plt.show()

```

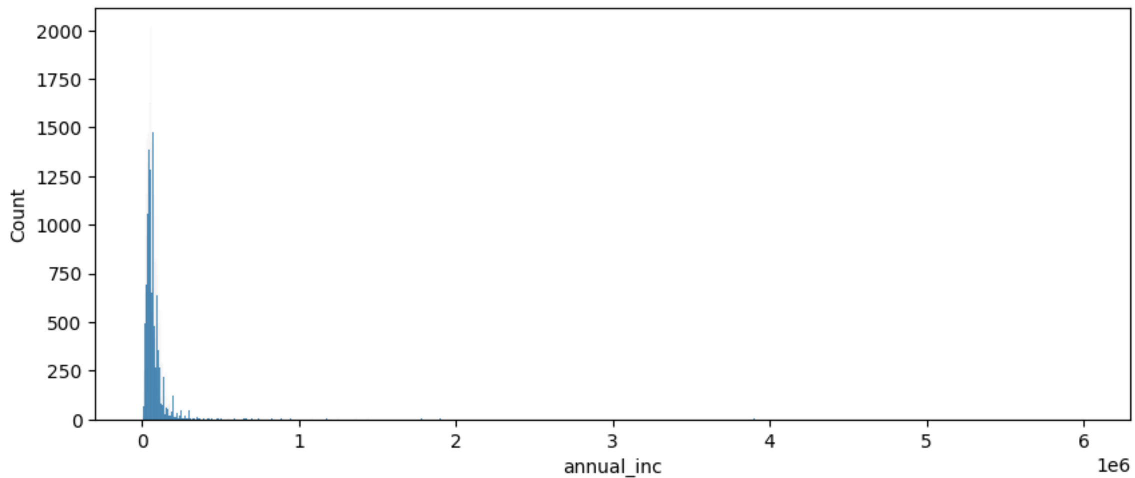


In [ ]:

```python

```

In [25]:

```python
## Here Annual Salary have Outliers so we haveto remove that

plt.figure(figsize=(10,4))

sns.histplot(data["annual_inc"])

plt.show()
```



In [26]:

```
data["annual_inc"].describe()
```

Out[26]:

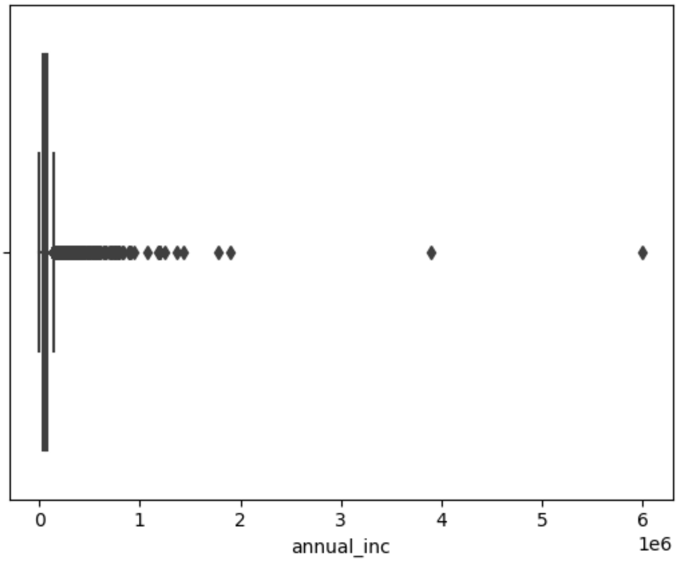
```
count    3.678100e+04
mean     6.944215e+04
std      6.406979e+04
min      4.000000e+03
25%      4.100400e+04
50%      6.000000e+04
75%      8.300000e+04
max      6.000000e+06
Name: annual_inc, dtype: float64
```

In [27]:

```
# Here plotting BoxPlot for detecting Outliers

sns.boxplot(x=data["annual_inc"])
```

Out[27]:

```
<Axes: xlabel='annual_inc'>
```



In [28]:

```
# Here we Remove Outliers

data = data[data["annual_inc"] < data["annual_inc"].quantile(0.95)]
```

In [29]:

```
data.shape
```

Out[29]:

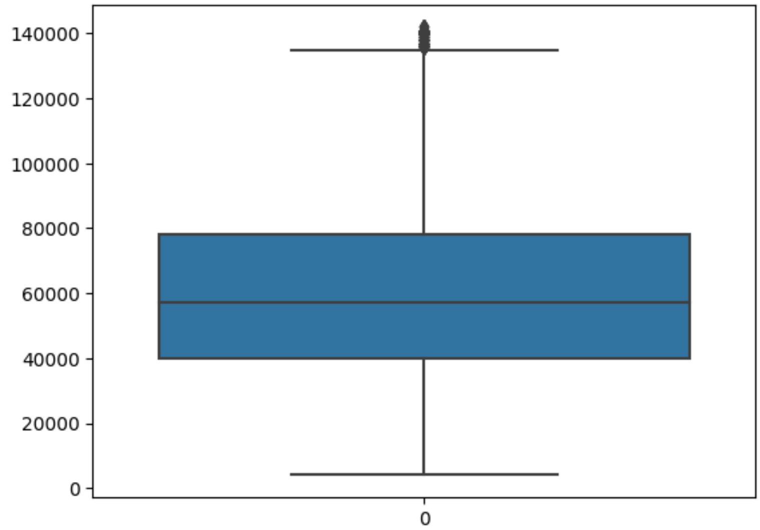
```
(34938, 21)
```

In [30]:

```
sns.boxplot(data["annual_inc"])
```

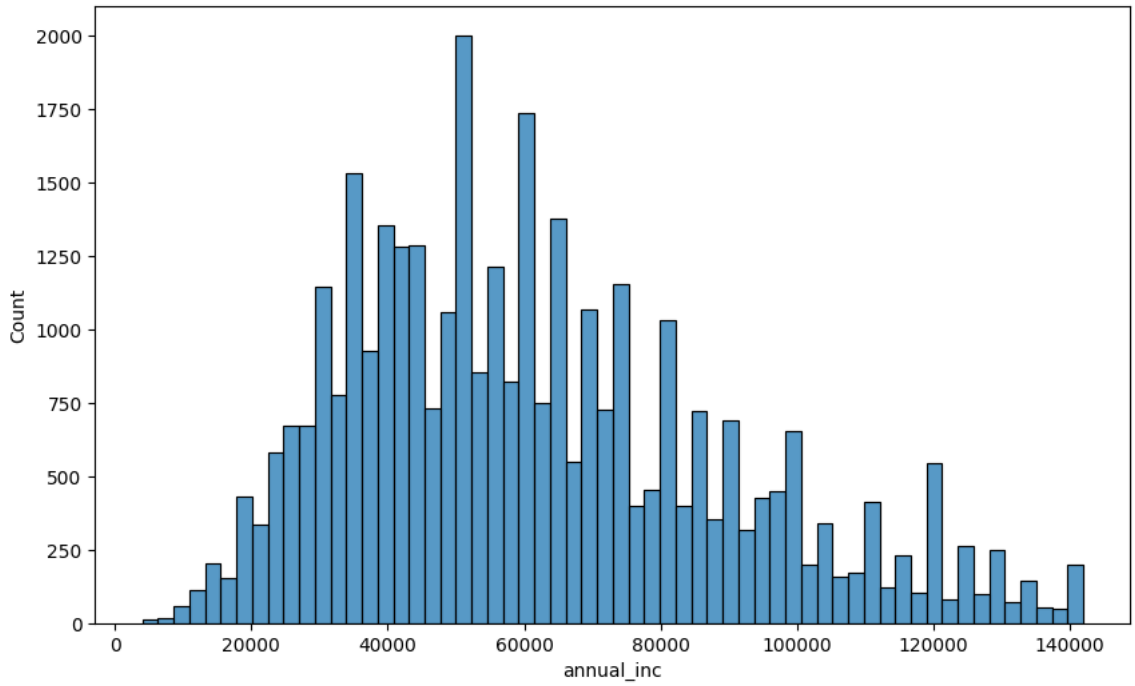
Out[30]:

```
<Axes: >
```



In [31]:

```
plt.figure(figsize=(10,6))

sns.histplot(data["annual_inc"])

plt.show()
```

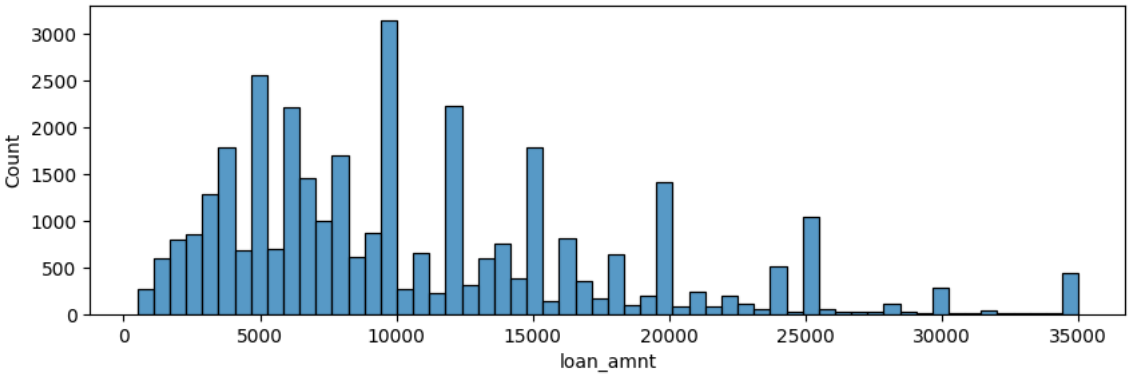


Univariate Analysis

Univariate Analysis on Numerical Data

In [39]:

```
# Draw the Histogram and Boxplot for all the Numrical Data

for num_col in num_data:
    plt.figure(figsize=(10,3))

    sns.histplot(data[num_col])
    plt.show()

    sns.boxplot(data[num_col])

    plt.show()

```



In [75]:

```
print(data[data.loan_amnt.between(0, 5000)]["loan_amnt"].count())
print(data[data.loan_amnt.between(5000, 10000)]["loan_amnt"].count())
print(data[data.loan_amnt.between(10000, 15000)]["loan_amnt"].count())
print(data[data.loan_amnt.between(15000, 20000)]["loan_amnt"].count())
print(data[data.loan_amnt.between(20000, 25000)]["loan_amnt"].count())
print(data[data.loan_amnt.between(25000, 30000)]["loan_amnt"].count())
print(data[data.loan_amnt.between(30000, 35000)]["loan_amnt"].count())
```

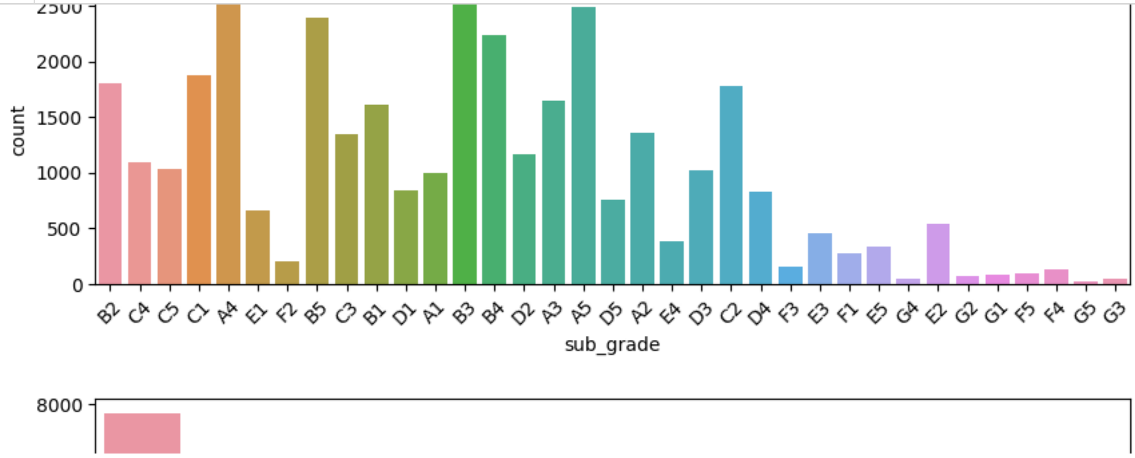
```
8685
13707
9643
5553
3658
1593
787
```

- **As Per the distribution of loan amount people are likely to take loan between range 5k to 10k**
- **When Interest Rate is high the count is going low means people are likely to avoid High interest rate loans.**

Univariate Analysis on Categorical Data

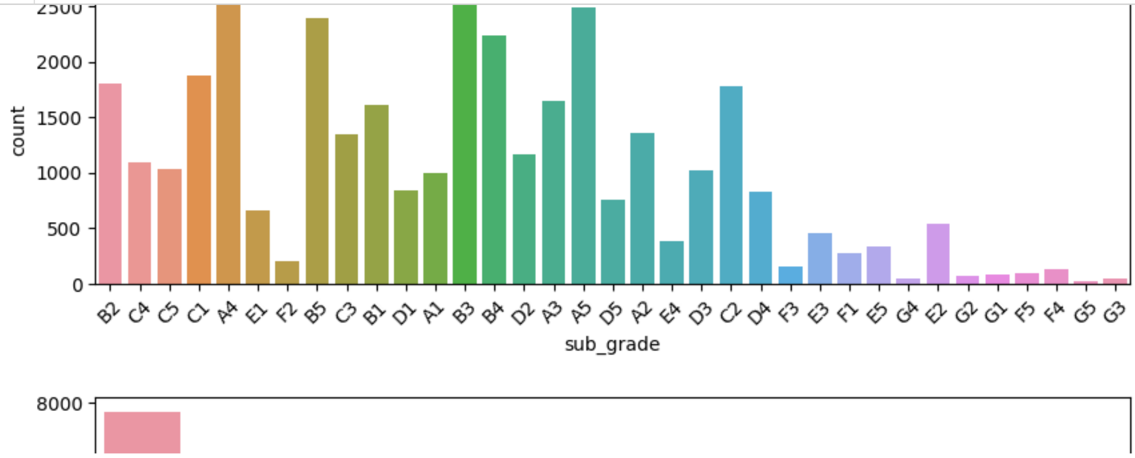
In [82]:

```python
# Draw the Countplot for all the Categorical Data

for num_col in cat_data:
    plt.figure(figsize=(10,3))

    g = sns.countplot(x=data[num_col])

    g.set_xticklabels(
    labels=data[num_col].unique(), rotation=45)

    plt.show()
```



In [146]:

```python
# Draw the Countplot for the Categorical Data whose Loan status is 'Charged Off'

for num_col in cat_data:
    plt.figure(figsize=(10,3))

    g = sns.countplot(x=data[num_col],data = data[data.loan_status == 'Charged Off'])

    g.set_xticklabels(
    labels=data[num_col].unique(), rotation=45)

    plt.show()


```



- **People are highly go for 36 Month Tenure rather than 60 Months**
- **Most approved loan are from Grade B.**
- **People with more than 10+ years of experience are taking more loan or LC approving more loan to them.**
- **People who have Debt Consolidation are the most who takes Loan.**
- **Very few ratio of people who have their own house and takes loan.**

Segmented Univariate Analysis

In [85]:

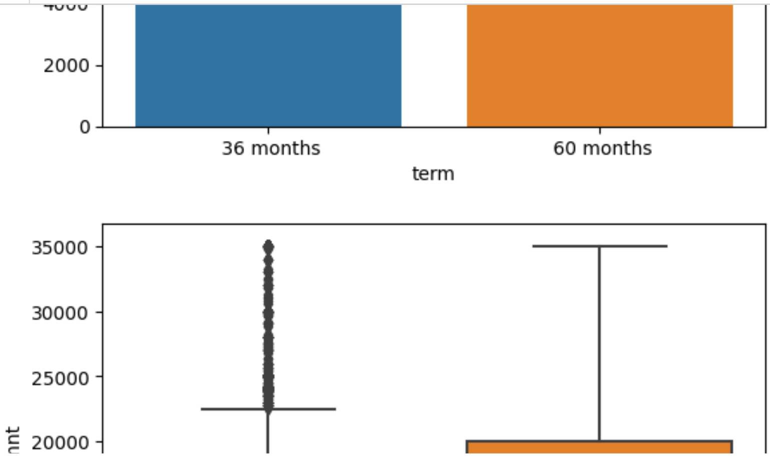
```
data.columns
```

Out[85]:

```
Index(['loan_amnt', 'funded_amnt', 'funded_amnt_inv', 'term', 'int_rate',
       'installment', 'grade', 'sub_grade', 'emp_length', 'home_ownership',
       'annual_inc', 'verification_status', 'issue_d', 'loan_status',
       'purpose', 'dti', 'earliest_cr_line', 'last_pymnt_d',
       'pub_rec_bankruptcies', 'issue_d_year', 'issue_d_month'],
      dtype='object')
```

In [100]:

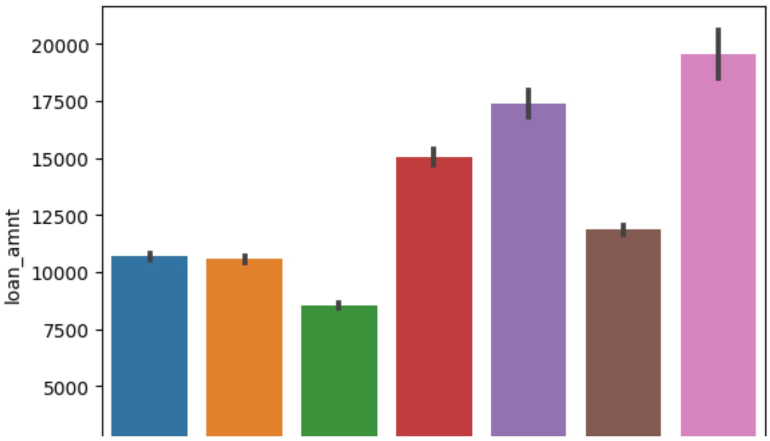
```
# Draw the Barplot and Boxplot where "Term" on X-axis and all other Numerical data on Y-Axis sequencially.

for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    sns.barplot(x = 'term',y = num_col,data = data)
    plt.show()

    sns.boxplot(data = data,x = 'term',y = num_col)
    plt.show()
```



- **Higher the loan amount higher the tenure of the loan**

In [101]:

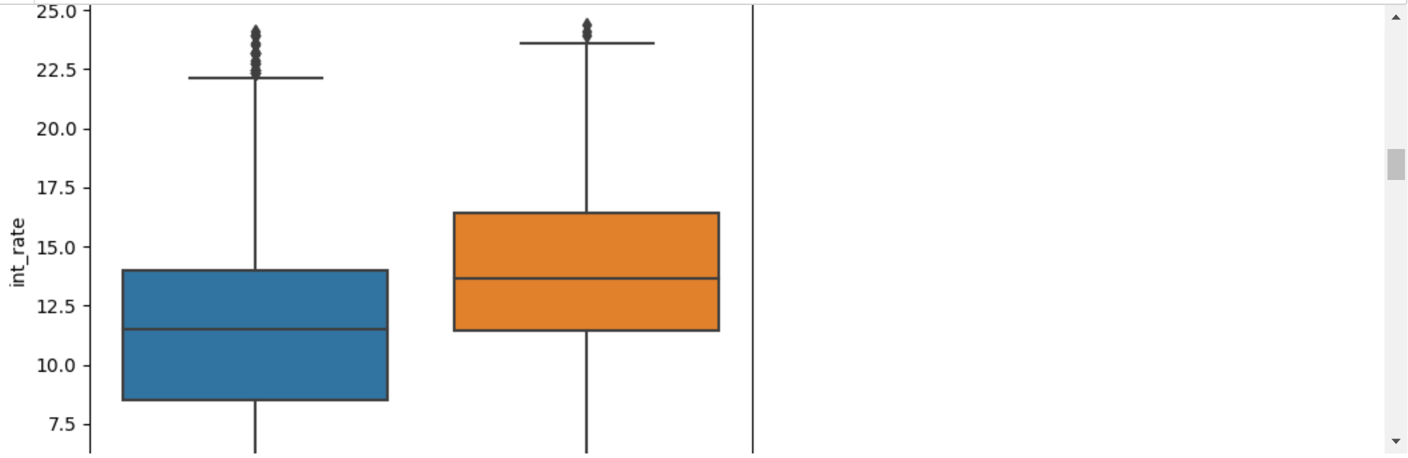
```
# Draw the Barplot and Boxplot where "grade" on X-axis and all other Numerical data on Y-Axis sequencially.

for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    sns.barplot(x = 'grade',y = num_col,data = data)
    plt.show()

    sns.boxplot(data = data,x = 'grade',y = num_col)
    plt.show()
```



- **G grade loans have the highest loan amount recieved with high interest ratio**

In [102]:

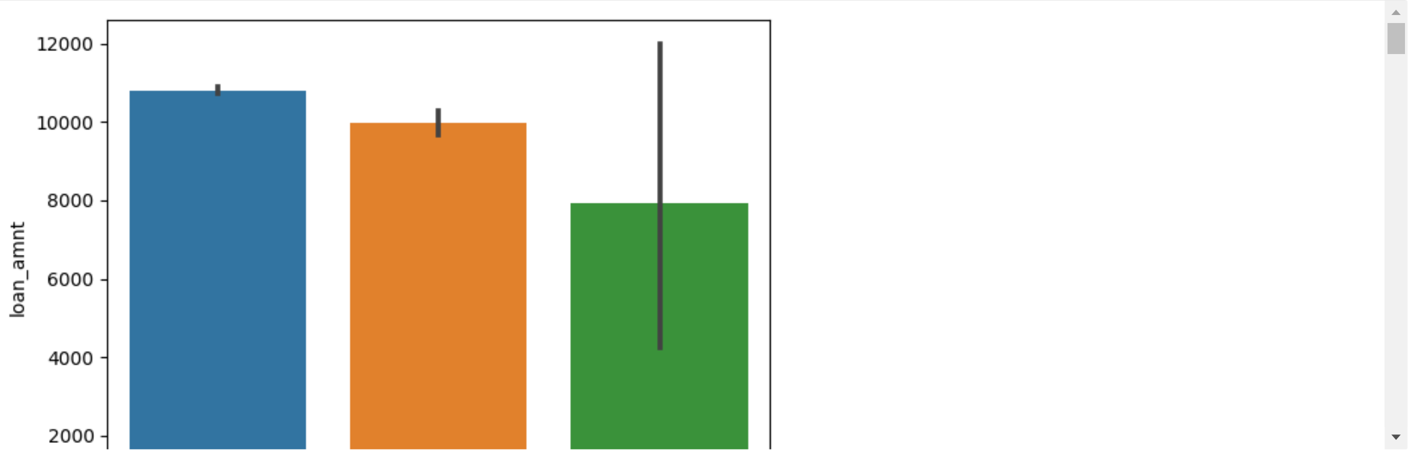
```
# Draw the Barplot and Boxplot where "loan_status" on X-axis and all other Numerical data on Y-Axis sequencially.

for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    sns.barplot(x = 'loan_status',y = num_col,data = data)
    plt.show()

    sns.boxplot(data = data,x = 'loan_status',y = num_col)
    plt.show()
```



- **People who have charged off the loan has high interest rate and their annual income is slightly low compare to Fully paid.**

In [103]:

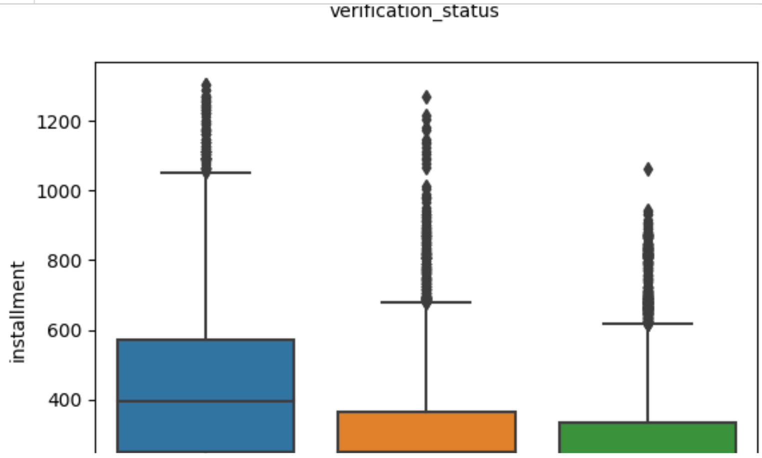
```
# Draw the Barplot and Boxplot where "pub_rec_bankruptcies" on X-axis and all other Numerical data on Y-Axis sequencially.

for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    sns.barplot(x = 'pub_rec_bankruptcies',y = num_col,data = data)
    plt.show()

    sns.boxplot(data = data,x = 'pub_rec_bankruptcies',y = num_col)
    plt.show()
```



- **pub_rec_bankruptcies has 3 category. When you analyse category 2.0 it has lowest loan_amount_spred and has highest amount of interest rate so people in this category are likely to get default.**

In [104]:

```
# Draw the Barplot and Boxplot where "verification_status" on X-axis and all other Numerical data on Y-Axis sequencially.


for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    sns.barplot(x = 'verification_status',y = num_col,data = data)
    plt.show()

    sns.boxplot(data = data,x = 'verification_status',y = num_col)
    plt.show()
```



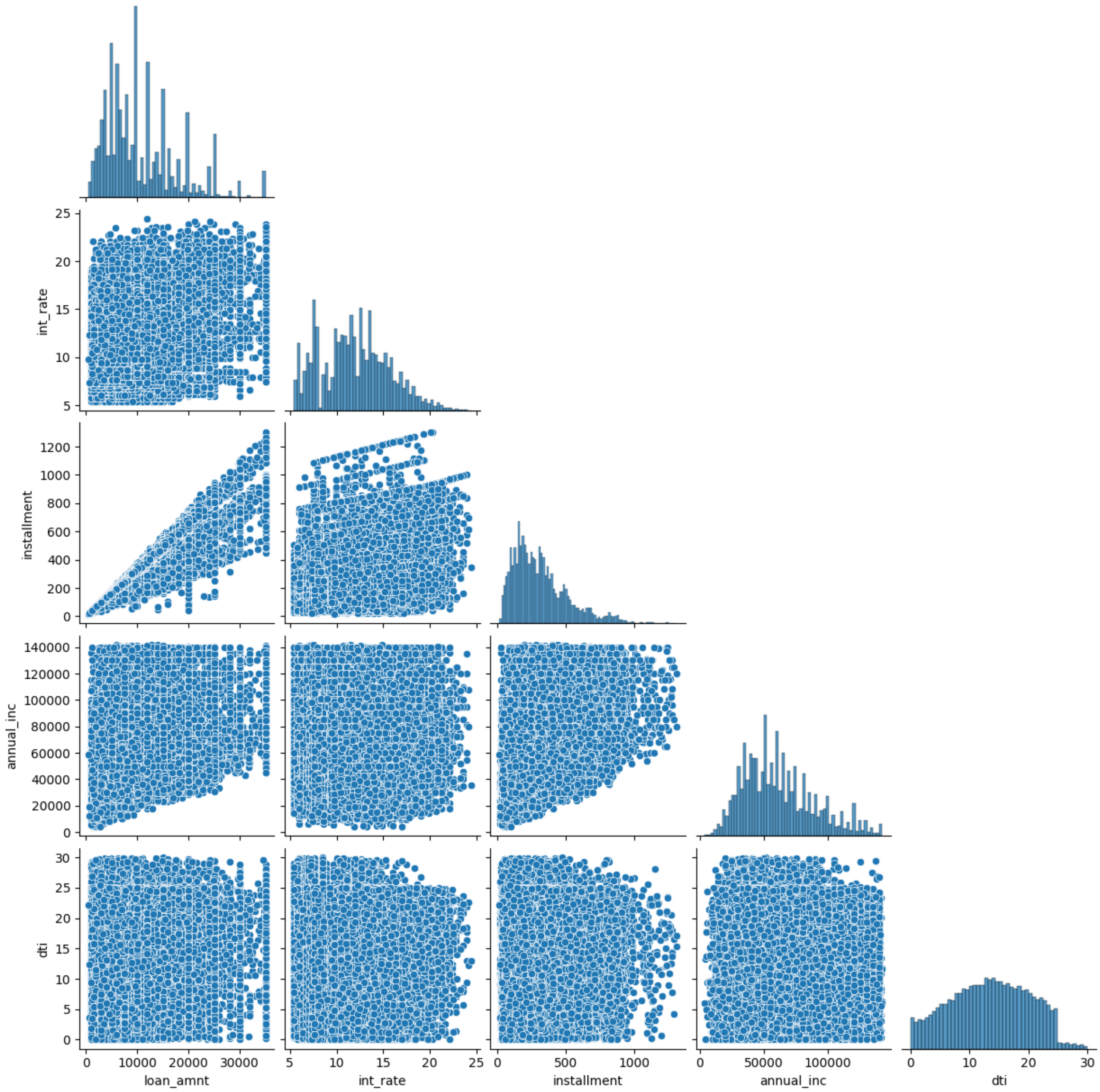
- **People whose income is verified are have highest loan amount recieved**

Bivariate Analysis

Bivariate Analysis on Numerical Data

In [109]:

```
# Draw pairplot for all the numerical data so that we can find co-relation between them.

sns.pairplot(data[["loan_amnt","int_rate","installment","annual_inc","dti"]], corner=True)
plt.show()
```



In [113]:

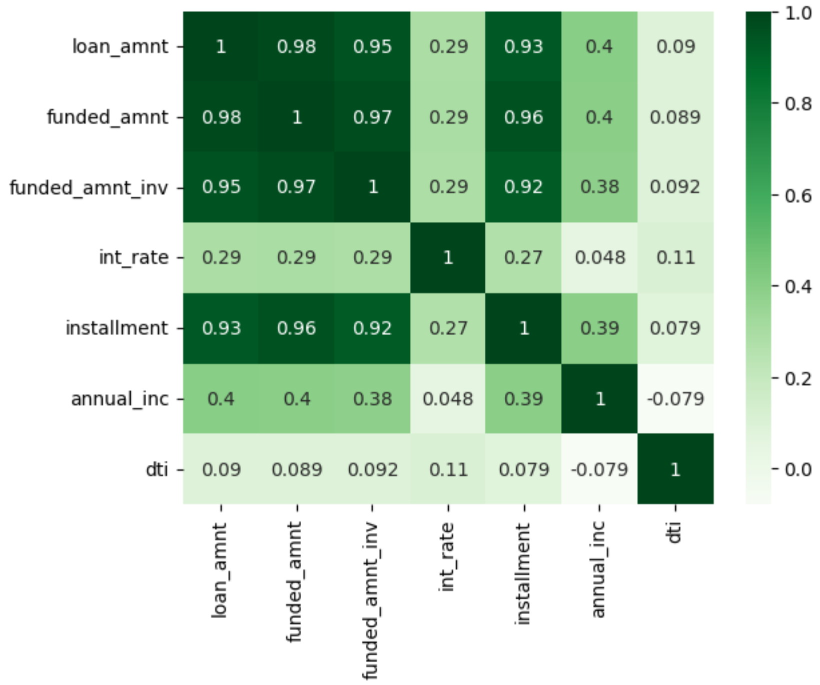
```
corr_data = data[["loan_amnt","funded_amnt","funded_amnt_inv","int_rate","installment","annual_inc","dti"]].corr()
```

In [114]:

```
sns.heatmap(corr_data,cmap="Greens", annot=True)
```

Out[114]:

```
<Axes: >
```

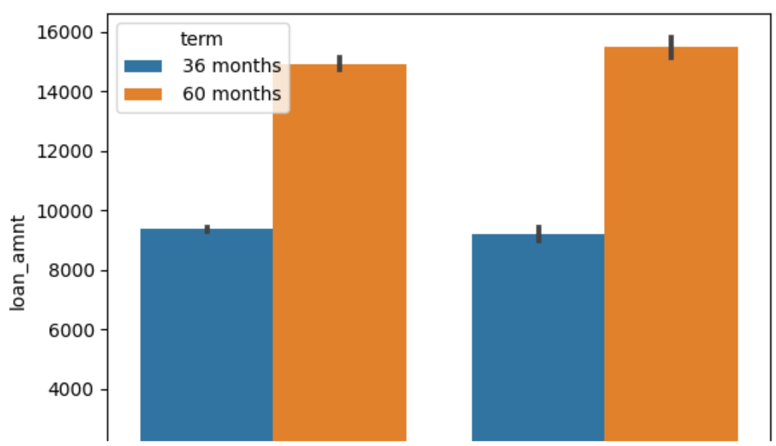


- **Loan amount, Funded amount, funded amount inv and installment are highly positive co-related**

Bivariate Analysis on Categorical Data

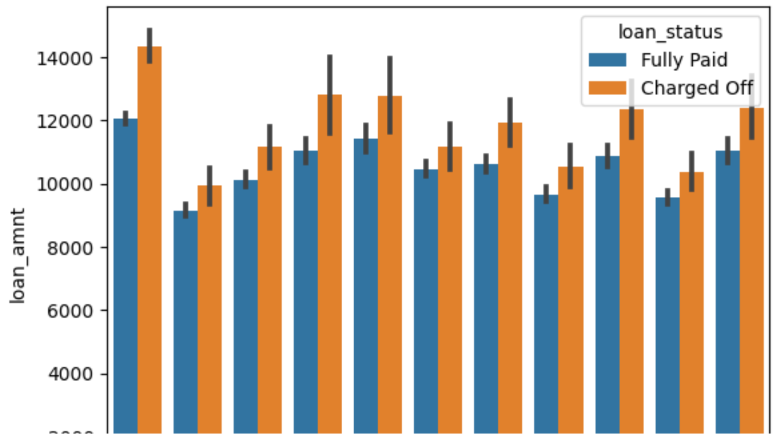
In [140]:

```
# Draw the Barplot where "loan_status" on X-axis and all other Numerical data on Y-Axis sequencially and hue is "Term".

for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    sns.barplot(x = 'loan_status',y = num_col,data = data,hue="term")
    plt.show()
```



In [160]:

```
# Draw the Barplot where "emp_length" on X-axis and all other Numerical data on Y-Axis sequencially and hue is "Loan_status".

for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    sns.barplot(x = 'emp_length',y = num_col,data = data,hue="loan_status")
    plt.show()
```



In [138]:

```
pd.pivot_table(data,index="loan_status",columns="emp_length",values="loan_amnt")
```

Out[138]:

emp_length	1 year	10+ years	2 years	3 years	4 years	5 years	6 years	7 years	8 years	9 year
loan_status										
Charged Off	10539.917453	14350.729335	10387.099812	11184.990440	11168.042453	11934.871495	12371.020761	12407.012195	12816.888298	12764.38356
Fully Paid	9650.356577	12056.927020	9588.775072	10136.920581	10467.473414	10632.596042	10879.456150	11053.690909	11039.491150	11424.89919

In [163]:

```
pd.pivot_table(data,index="loan_status",columns="emp_length",values="loan_amnt").mean(axis=1)
```

Out[163]:

```
loan_status
Charged Off    11806.662389
Fully Paid     10553.841331
dtype: float64
```

In [129]:

```
pd.pivot_table(data,index="emp_length",columns="loan_status",values="int_rate")
```

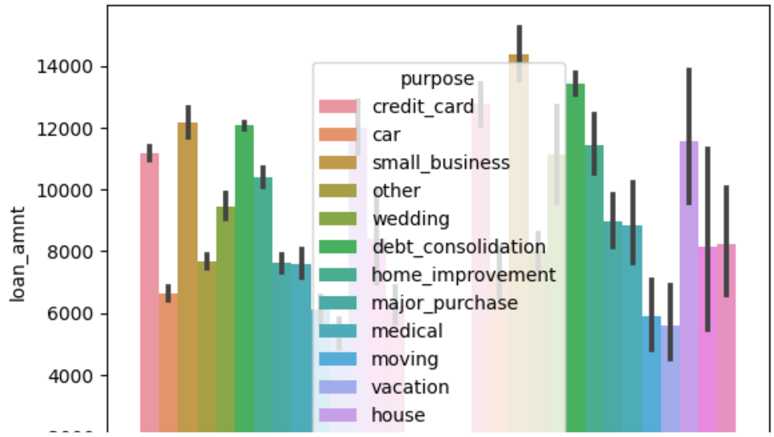
Out[129]:

loan_status	Charged Off	Fully Paid
emp_length		
1 year	13.680519	11.733292
10+ years	14.060981	11.513089
2 years	13.828041	11.697232
3 years	13.915583	11.603918
4 years	13.941816	11.748750
5 years	13.782874	11.630485
6 years	14.010623	11.551259
7 years	14.050772	11.716349
8 years	13.709947	11.415628
9 years	13.740000	11.556038
< 1 year	13.492757	11.609410

- **Applicant who recieved loan with interest rate higher than average 11% are likely to get default.**
- **Applicant who recieved loan with higer than average 10k are likely to get default.**

In [137]:

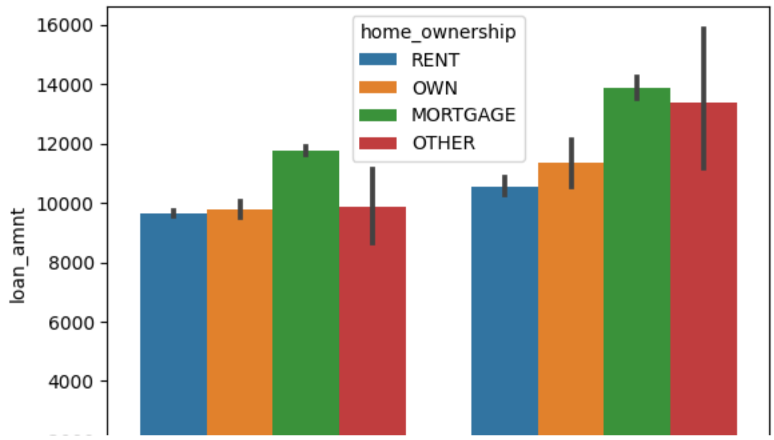
```
# Draw the Barplot where "loan_status" on X-axis and all other Numerical data on Y-Axis sequencially and hue is "purpose".


for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    h = sns.barplot(x = 'loan_status',y = num_col,data = data,hue="purpose")

    h.set_xticklabels(
    labels=data["loan_status"].unique(), rotation=90)

    plt.show()
```



- **Applicant who recieved loan for home purpose and take loan with higher interest rate are get defaulted.**

In [136]:

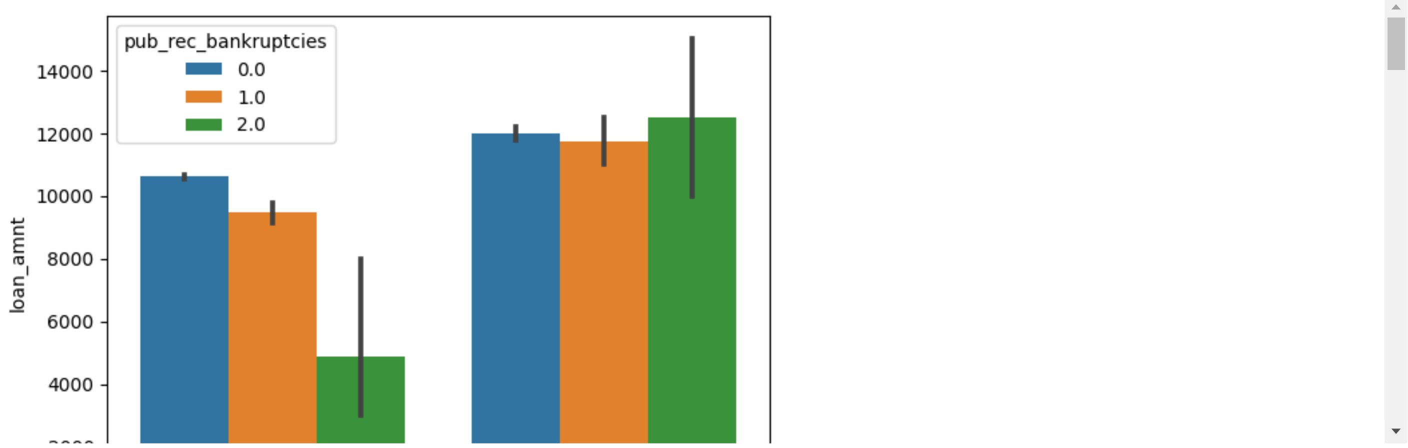
```
# Draw the Barplot where "loan_status" on X-axis and all other Numerical data on Y-Axis sequencially and hue is "home_ownership".


for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    h = sns.barplot(x = 'loan_status',y = num_col,data = data,hue="home_ownership")

    h.set_xticklabels(
    labels=data["loan_status"].unique(), rotation=90)

    plt.show()
```



- **Applicants whose home ownership is 'MORTGAGE and have income between 60 to 70 k and have high amount of loan are likely to get default.**

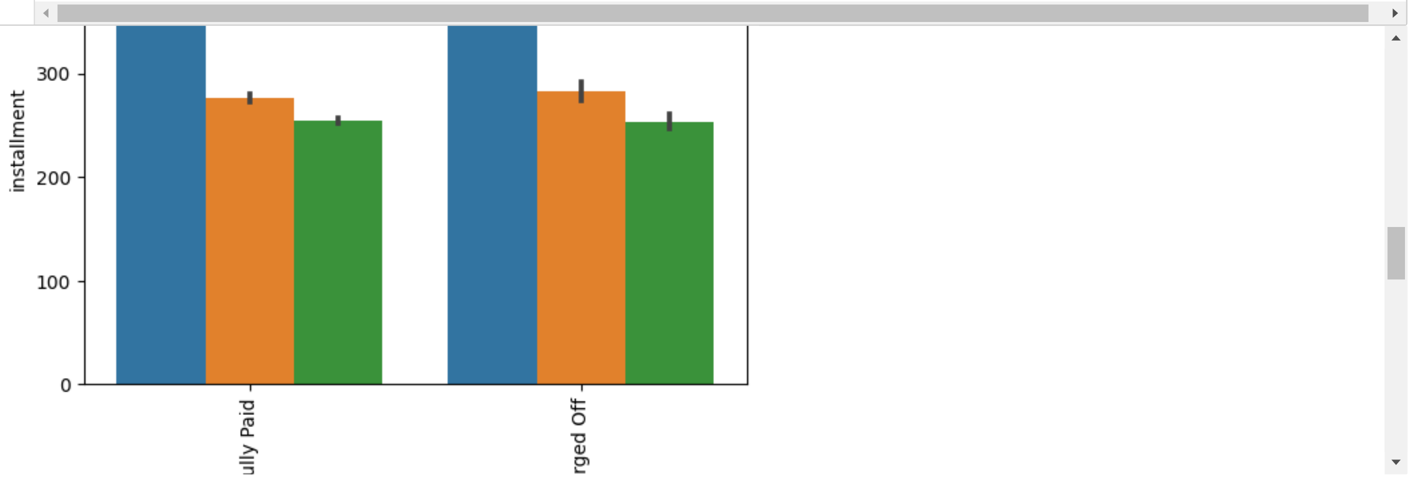
In [141]:

```
# Draw the Barplot where "loan_status" on X-axis and all other Numerical data on Y-Axis sequencially and hue is "pub_rec_bankruptcies

for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    h = sns.barplot(x = 'loan_status',y = num_col,data = data,hue="pub_rec_bankruptcies")

    h.set_xticklabels(
    labels=data["loan_status"].unique(), rotation=90)

    plt.show()
```



In [142]:

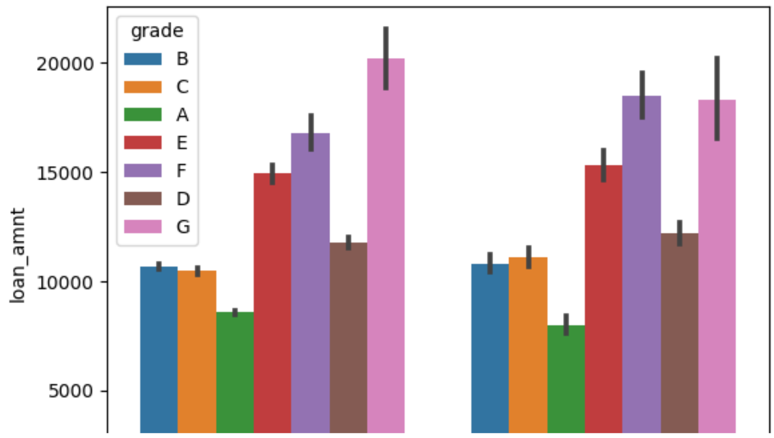
```
# Draw the Barplot where "loan_status" on X-axis and all other Numerical data on Y-Axis sequencially and hue is "verification_status"


for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    h = sns.barplot(x = 'loan_status',y = num_col,data = data,hue="verification_status")

    h.set_xticklabels(
    labels=data["loan_status"].unique(), rotation=90)

    plt.show()
```



- **Applicants whose income is verified has recieved high loan amount compare to non verified and that why it's has high chances of default.**

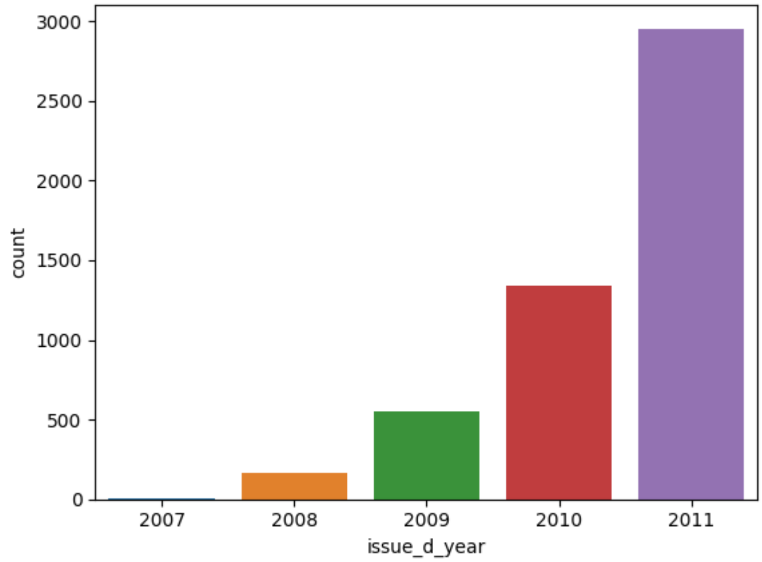
In [167]:

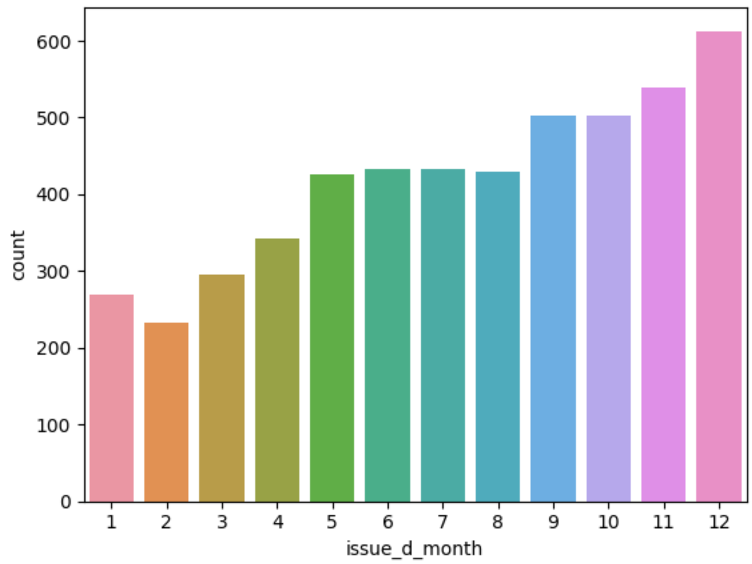
```
# Draw the Barplot where "loan_status" on X-axis and all other Numerical data on Y-Axis sequencially and hue is "grade".

for num_col in ["loan_amnt","int_rate","installment","annual_inc","dti"]:
    h = sns.barplot(x = 'loan_status',y = num_col,data = data,hue="grade")

    h.set_xticklabels(
    labels=data["loan_status"].unique(), rotation=90)

    plt.show()
```



In [180]:

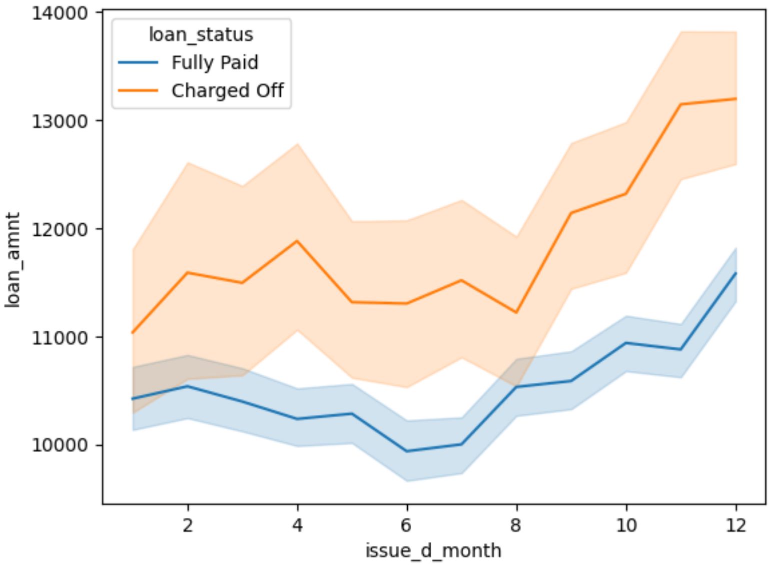
```
# Draw the Countplot for "issue_d_year"  and "issue_d_month" whose loan status is 'Charged Off'

sns.countplot(x='issue_d_year', data=data[data['loan_status']=='Charged Off'])
plt.show()

sns.countplot(x='issue_d_month', data=data[data['loan_status']=='Charged Off'])
plt.show()
```

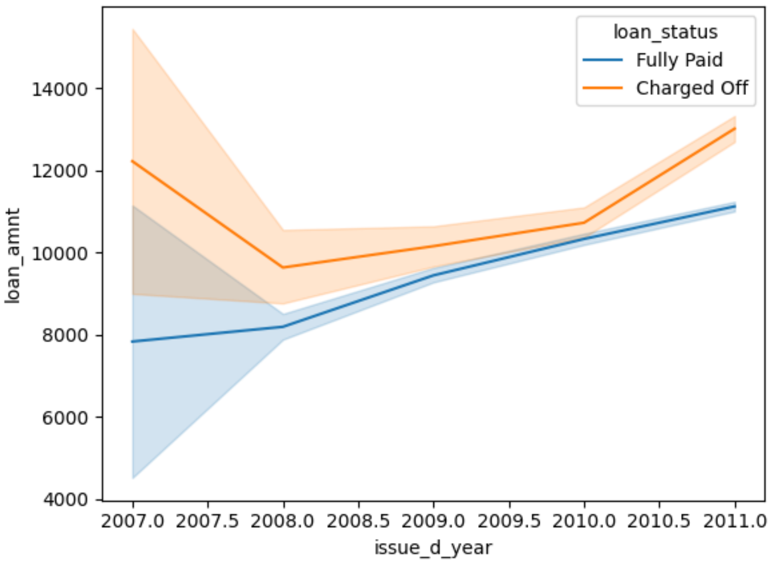




In [179]:

```
# Draw the Lineplot  for "issue_d_year"  and "issue_d_month" whose hue is'loan_status'

sns.lineplot(data =data,y='loan_amnt', x='issue_d_month', hue ='loan_status')
plt.show()

sns.lineplot(data =data,y='loan_amnt', x='issue_d_year', hue ='loan_status')
plt.show()
```





- **2011 year have the highest number of defaulters compare to other years and december month have heighest number of defaulters.**

Summary

Below is the list of possibility for Defaulting

- **G grade loans have the highest loan amount recieved with high interest ratio so they are likely to get default**
- **People who have charged off the loan has high interest rate and their annual income is slightly low compare to Fully paid.**
- **pub_rec_bankruptcies has 3 category. When you analyse category 2.0 it has lowest loan_amount_spred and has highest amount of interest rate so people in this category are likely to get default.**
- **Applicant who recieved loan with interest rate higher than average 11% are likely to get default.**
- **Applicant who recieved loan with higer than average 10k are likely to get default.**
- **Applicant who recieved loan for home purpose and take loan with higher interest rate are get defaulted.**
- **Applicants whose home ownership is 'MORTGAGE and have income between 60 to 70 k and have high amount of loan are likely to get default.**
- **Applicants whose income is verified has recieved high loan amount compare to non verified and that why it's has high chances of default.**

- **2011 year have the highest number of defaulters compare to other years.**
- **Surprisingly applicant who took loan in december month have heighest number of defaulters.**