Lending Club Case Study

Reading the CSV File

In [1]:
```
import pandas  as pd
import seaborn as sb
import numpy   as np
import matplotlib.pyplot as plt #to plot some parameters in seaborn

import plotly.offline as py
py.init_notebook_mode(connected=True) # this code, allow us to work with offline plotly version
import plotly.graph_objs as go # it's like "plt" of matplot
import plotly.tools as tls # It's useful to we get some tools of plotly
import warnings # This library will be used to ignore some warnings
from collections import Counter # To do counter of some features
import plotly.io as pio
#pio.renderers.default = "colab" #Colab configs for plotly
```

In [2]:
```
loan = pd.read_csv("loan.csv")
```

```
/var/folders/p6/klf5stcd60n3__hy6dqwl0xh0000gn/T/ipykernel_36579/3592418794.py:1: DtypeWarning:

Columns (47) have mixed types. Specify dtype option on import or set low_memory=False.
```

In [3]:
```
loan.head()
```

Out[3]:

	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_past_12m	pct_tl_nvr_dlq	percent_bc_gt_75	p
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87	B	B2	...	NaN	NaN	NaN	NaN	
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83	C	C4	...	NaN	NaN	NaN	NaN	
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33	C	C5	...	NaN	NaN	NaN	NaN	
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31	C	C1	...	NaN	NaN	NaN	NaN	
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.79	B	B5	...	NaN	NaN	NaN	NaN	

5 rows × 111 columns

In [4]:
```
loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39717 entries, 0 to 39716
Columns: 111 entries, id to total_il_high_credit_limit
dtypes: float64(74), int64(13), object(24)
memory usage: 33.6+ MB
```

In [5]:
```
loan.describe()
```

Out[5]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	installment	annual_inc	dti	delinq_2yrs	inq_last_6mths	...	num_tl_90g_dpd_24m	num_tl_op_past_
count	3.971700e+04	3.971700e+04	39717.000000	39717.000000	39717.000000	39717.000000	3.971700e+04	39717.000000	39717.000000	39717.000000	...	0.0	
mean	6.831319e+05	8.504636e+05	11219.443815	10947.713196	10397.448868	324.561922	6.896893e+04	13.315130	0.146512	0.869200	...	NaN	
std	2.106941e+05	2.656783e+05	7456.670694	7187.238670	7128.450439	208.874874	6.379377e+04	6.678594	0.491812	1.070219	...	NaN	
min	5.473400e+04	7.069900e+04	500.000000	500.000000	0.000000	15.690000	4.000000e+03	0.000000	0.000000	0.000000	...	NaN	
25%	5.162210e+05	6.667800e+05	5500.000000	5400.000000	5000.000000	167.020000	4.040400e+04	8.170000	0.000000	0.000000	...	NaN	
50%	6.656650e+05	8.508120e+05	10000.000000	9600.000000	8975.000000	280.220000	5.900000e+04	13.400000	0.000000	1.000000	...	NaN	
75%	8.377550e+05	1.047339e+06	15000.000000	15000.000000	14400.000000	430.780000	8.230000e+04	18.600000	0.000000	1.000000	...	NaN	
max	1.077501e+06	1.314167e+06	35000.000000	35000.000000	35000.000000	1305.190000	6.000000e+06	29.990000	11.000000	8.000000	...	NaN	

8 rows × 87 columns

In [6]:
```
df = pd.DataFrame(loan)
list(df.columns)
```

Out[6]:
```
['id',
 'member_id',
 'loan_amnt',
 'funded_amnt',
 'funded_amnt_inv',
 'term',
 'int_rate',
 'installment',
 'grade',
 'sub_grade',
 'emp_title',
 'emp_length',
 'home_ownership',
 'annual_inc',
 'verification_status',
 'issue_d',
 'loan_status',
 'pymnt_plan',
 'url',
 'desc',
 'purpose',
 'title',
 'zip_code',
 'addr_state',
 'dti',
 'delinq_2yrs',
 'earliest_cr_line',
```

```
'inq_last_6mths',
'mths_since_last_delinq',
'mths_since_last_record',
'open_acc',
'pub_rec',
'revol_bal',
'revol_util',
'total_acc',
'initial_list_status',
'out_prncp',
'out_prncp_inv',
'total_pymnt',
'total_pymnt_inv',
'total_rec_prncp',
'total_rec_int',
'total_rec_late_fee',
'recoveries',
'collection_recovery_fee',
'last_pymnt_d',
'last_pymnt_amnt',
'next_pymnt_d',
'last_credit_pull_d',
'collections_12_mths_ex_med',
'mths_since_last_major_derog',
'policy_code',
'application_type',
'annual_inc_joint',
'dti_joint',
'verification_status_joint',
'acc_now_delinq',
'tot_coll_amt',
'tot_cur_bal',
'open_acc_6m',
'open_il_6m',
'open_il_12m',
'open_il_24m',
'mths_since_rcnt_il',
'total_bal_il',
'il_util',
'open_rv_12m',
'open_rv_24m',
'max_bal_bc',
'all_util',
'total_rev_hi_lim',
'inq_fi',
'total_cu_tl',
'inq_last_12m',
'acc_open_past_24mths',
'avg_cur_bal',
'bc_open_to_buy',
'bc_util',
'chargeoff_within_12_mths',
'delinq_amnt',
'mo_sin_old_il_acct',
'mo_sin_old_rev_tl_op',
'mo_sin_rcnt_rev_tl_op',
'mo_sin_rcnt_tl',
```

```
 'mort_acc',
 'mths_since_recent_bc',
 'mths_since_recent_bc_dlq',
 'mths_since_recent_inq',
 'mths_since_recent_revol_delinq',
 'num_accts_ever_120_pd',
 'num_actv_bc_tl',
 'num_actv_rev_tl',
 'num_bc_sats',
 'num_bc_tl',
 'num_il_tl',
 'num_op_rev_tl',
 'num_rev_accts',
 'num_rev_tl_bal_gt_0',
 'num_sats',
 'num_tl_120dpd_2m',
 'num_tl_30dpd',
 'num_tl_90g_dpd_24m',
 'num_tl_op_past_12m',
 'pct_tl_nvr_dlq',
 'percent_bc_gt_75',
 'pub_rec_bankruptcies',
 'tax_liens',
 'tot_hi_cred_lim',
 'total_bal_ex_mort',
 'total_bc_limit',
 'total_il_high_credit_limit']
```

Data Cleaning

Drop Loan behaviourial fields as per the suggestion 1) delinq_2yrs
2) earliest_cr_line
3) inq_last_6mths
4) open_acc
5) pub_rec
6) revol_bal
7) revol_util
8) total_acc
9) out_prncp
10) out_prncp_inv
11) total_pymnt
12) total_pymnt_inv
13) total_rec_prncp
14) total_rec_int
15) total_rec_late_fee
16) recoveries
17) collection_recovery_fee
18) last_pymnt_d
19) last_pymnt_amnt
20) last_credit_pull_d
21) application_type

In [7]:
```
df = df.drop(['delinq_2yrs', 'earliest_cr_line', 'inq_last_6mths', 'open_acc', 'pub_rec', 'revol_bal', 'revol_util', 'total_acc', 'out_prncp', 'out_prncp_inv', 'total_py
```

Drop the columns which contains same values in all rows

In [8]:
```
for col in df.columns:  # Loop through columns
  if len(df[col].unique()) == 1:  # Find unique values in column along with their length and if length is == 1 then it contains same values
    df.drop([col], axis=1, inplace=True)  # Drop the column
```

In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39717 entries, 0 to 39716
Data columns (total 31 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   id                          39717 non-null  int64
 1   member_id                   39717 non-null  int64
 2   loan_amnt                   39717 non-null  int64
 3   funded_amnt                 39717 non-null  int64
 4   funded_amnt_inv             39717 non-null  float64
 5   term                        39717 non-null  object
 6   int_rate                    39717 non-null  object
 7   installment                 39717 non-null  float64
 8   grade                       39717 non-null  object
 9   sub_grade                   39717 non-null  object
 10  emp_title                   37258 non-null  object
 11  emp_length                  38642 non-null  object
 12  home_ownership              39717 non-null  object
 13  annual_inc                  39717 non-null  float64
 14  verification_status         39717 non-null  object
 15  issue_d                     39717 non-null  object
 16  loan_status                 39717 non-null  object
 17  url                         39717 non-null  object
 18  desc                        26777 non-null  object
 19  purpose                     39717 non-null  object
 20  title                       39706 non-null  object
 21  zip_code                    39717 non-null  object
 22  addr_state                  39717 non-null  object
 23  dti                         39717 non-null  float64
 24  mths_since_last_delinq      14035 non-null  float64
 25  mths_since_last_record      2786 non-null   float64
 26  next_pymnt_d                1140 non-null   object
 27  collections_12_mths_ex_med  39661 non-null  float64
 28  chargeoff_within_12_mths    39661 non-null  float64
 29  pub_rec_bankruptcies        39020 non-null  float64
 30  tax_liens                   39678 non-null  float64
dtypes: float64(10), int64(4), object(17)
memory usage: 9.4+ MB
```

In [10]:
```
df.describe()
```

Out[10]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	installment	annual_inc	dti	mths_since_last_delinq	mths_since_last_record	collections_12_mths_ex_m
count	3.971700e+04	3.971700e+04	39717.000000	39717.000000	39717.000000	39717.000000	3.971700e+04	39717.000000	14035.000000	2786.000000	3966
mean	6.831319e+05	8.504636e+05	11219.443815	10947.713196	10397.448868	324.561922	6.896893e+04	13.315130	35.900962	69.698134	
std	2.106941e+05	2.656783e+05	7456.670694	7187.238670	7128.450439	208.874874	6.379377e+04	6.678594	22.020060	43.822529	
min	5.473400e+04	7.069900e+04	500.000000	500.000000	0.000000	15.690000	4.000000e+03	0.000000	0.000000	0.000000	
25%	5.162210e+05	6.667800e+05	5500.000000	5400.000000	5000.000000	167.020000	4.040400e+04	8.170000	18.000000	22.000000	
50%	6.656650e+05	8.508120e+05	10000.000000	9600.000000	8975.000000	280.220000	5.900000e+04	13.400000	34.000000	90.000000	
75%	8.377550e+05	1.047339e+06	15000.000000	15000.000000	14400.000000	430.780000	8.230000e+04	18.600000	52.000000	104.000000	
max	1.077501e+06	1.314167e+06	35000.000000	35000.000000	35000.000000	1305.190000	6.000000e+06	29.990000	120.000000	129.000000	

Drop URL which is a non-significant field

In [11]:
```
df = df.drop(columns = 'url')
```

In [12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39717 entries, 0 to 39716
Data columns (total 30 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   id                          39717 non-null  int64  
 1   member_id                   39717 non-null  int64  
 2   loan_amnt                   39717 non-null  int64  
 3   funded_amnt                 39717 non-null  int64  
 4   funded_amnt_inv             39717 non-null  float64
 5   term                        39717 non-null  object 
 6   int_rate                    39717 non-null  object 
 7   installment                 39717 non-null  float64
 8   grade                       39717 non-null  object 
 9   sub_grade                   39717 non-null  object 
 10  emp_title                   37258 non-null  object 
 11  emp_length                  38642 non-null  object 
 12  home_ownership              39717 non-null  object 
 13  annual_inc                  39717 non-null  float64
 14  verification_status         39717 non-null  object 
 15  issue_d                     39717 non-null  object 
 16  loan_status                 39717 non-null  object 
 17  desc                        26777 non-null  object 
 18  purpose                     39717 non-null  object 
 19  title                       39706 non-null  object 
 20  zip_code                    39717 non-null  object 
 21  addr_state                  39717 non-null  object 
 22  dti                         39717 non-null  float64
 23  mths_since_last_delinq      14035 non-null  float64
 24  mths_since_last_record      2786 non-null   float64
 25  next_pymnt_d                1140 non-null   object 
 26  collections_12_mths_ex_med  39661 non-null  float64
 27  chargeoff_within_12_mths    39661 non-null  float64
 28  pub_rec_bankruptcies        39020 non-null  float64
 29  tax_liens                   39678 non-null  float64
dtypes: float64(10), int64(4), object(16)
memory usage: 9.1+ MB
```

Remove the word years in emp_length

In [13]:
```
df['emp_length'] = df['emp_length'].str.replace(' years','')
df['emp_length'] = df['emp_length'].str.replace(' year','')
df['emp_length'] = df['emp_length'].str.replace('+','')
df['emp_length'] = df['emp_length'].str.replace('< ','')
#df['emp_length'] = df['emp_length'].str.replace('nan','0')
df['emp_length'] = df['emp_length'].fillna('0')
```

```
/var/folders/p6/klf5stcd60n3__hy6dqwl0xh0000gn/T/ipykernel_36579/2446633840.py:3: FutureWarning:

The default value of regex will change from True to False in a future version. In addition, single character regular expressions will *not* be treated as literal string
s when regex=True.
```

Variables:

1) Categorical:

i) Ordered - term, grade, sub_grade, loan_status

ii) Unordered - emp_title, home_ownership, verification_status, purpose, title

2) Quantitative/Numeric:

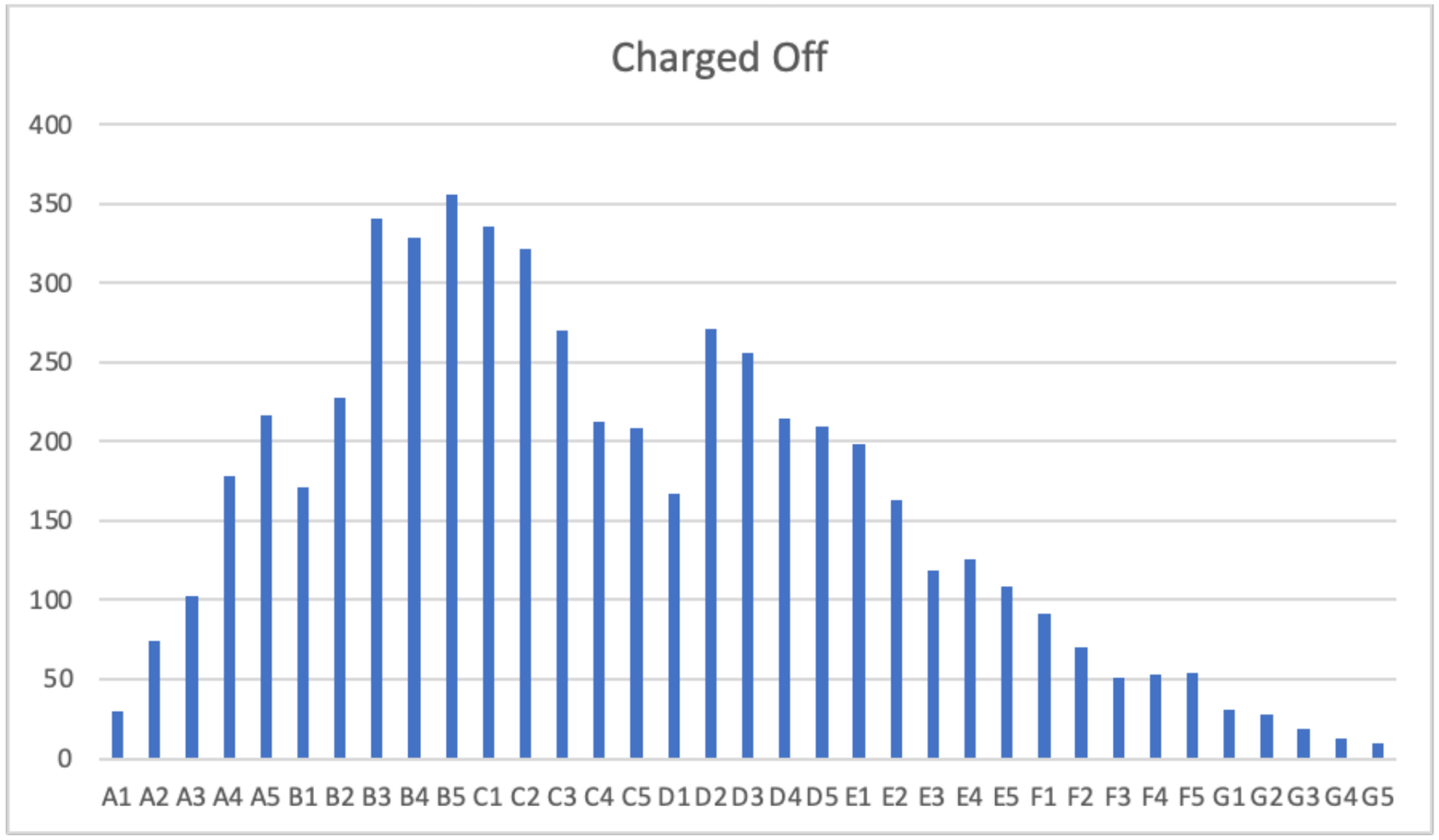
loan_amnt, funded_amnt, funded_amnt_inv, int_rate, installment, emp_length, annual_inc, dti

(issue_d, desc, zip_code, addr_state, mths_since_last_delinq, mths_since_last_record, next_pymnt_d, collections_12_mths_ex_med,chargeoff_within_12_mths,pub_rec_bankruptcies, tax_liens)

Observation

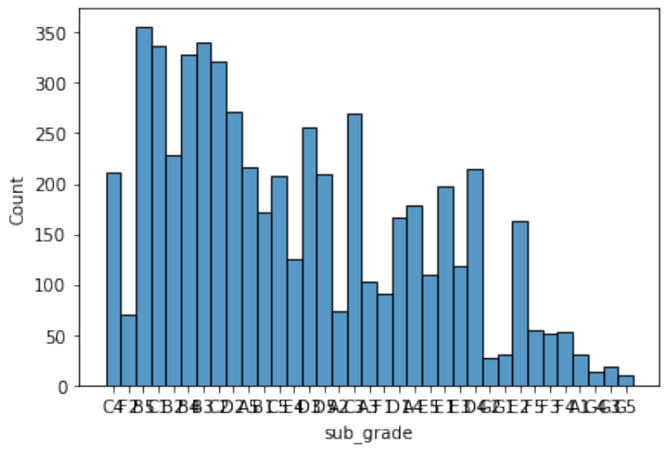
Univariate Analysis

1) Employees in B,C,D grades are defaulting more compared to other grades



In [14]:
```
sb.histplot(df[df["loan_status"] == 'Charged Off'].sub_grade,bins=10)
```

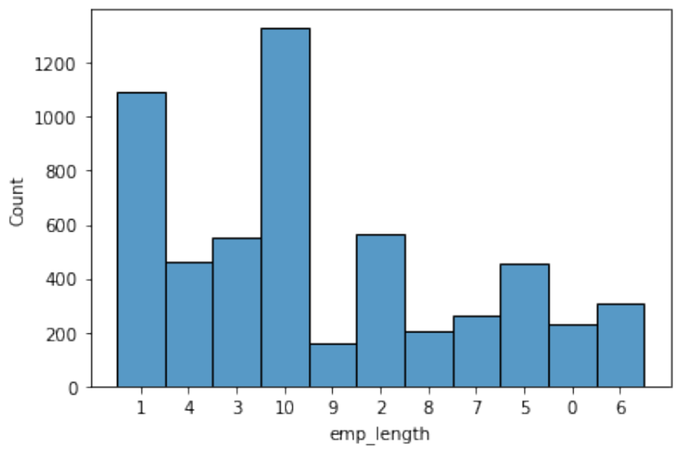
Out[14]:
```
<AxesSubplot:xlabel='sub_grade', ylabel='Count'>
```



2) Employess more than 10 years of experience are Charged Off

In [15]:
```
sb.histplot(df[df["loan_status"] == 'Charged Off'].emp_length,bins=10)
```

Out[15]:
```
<AxesSubplot:xlabel='emp_length', ylabel='Count'>
```



3) Employess who does not own house is Charged Off most of the times

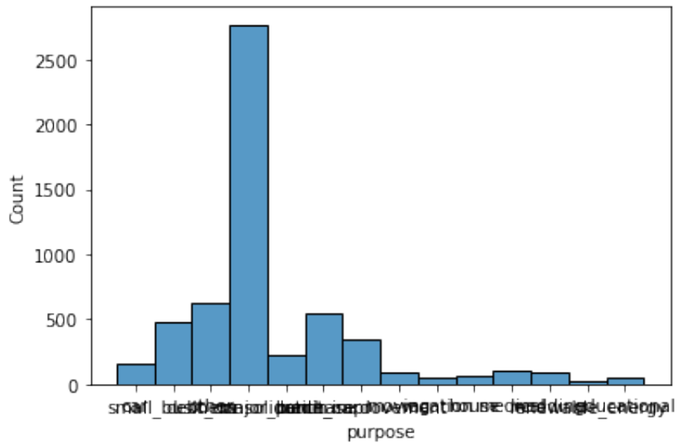
In [16]:
```
sb.histplot(df[df["loan_status"] == 'Charged Off'].home_ownership,bins=2)
```

Out[16]:
```
<AxesSubplot:xlabel='home_ownership', ylabel='Count'>
```

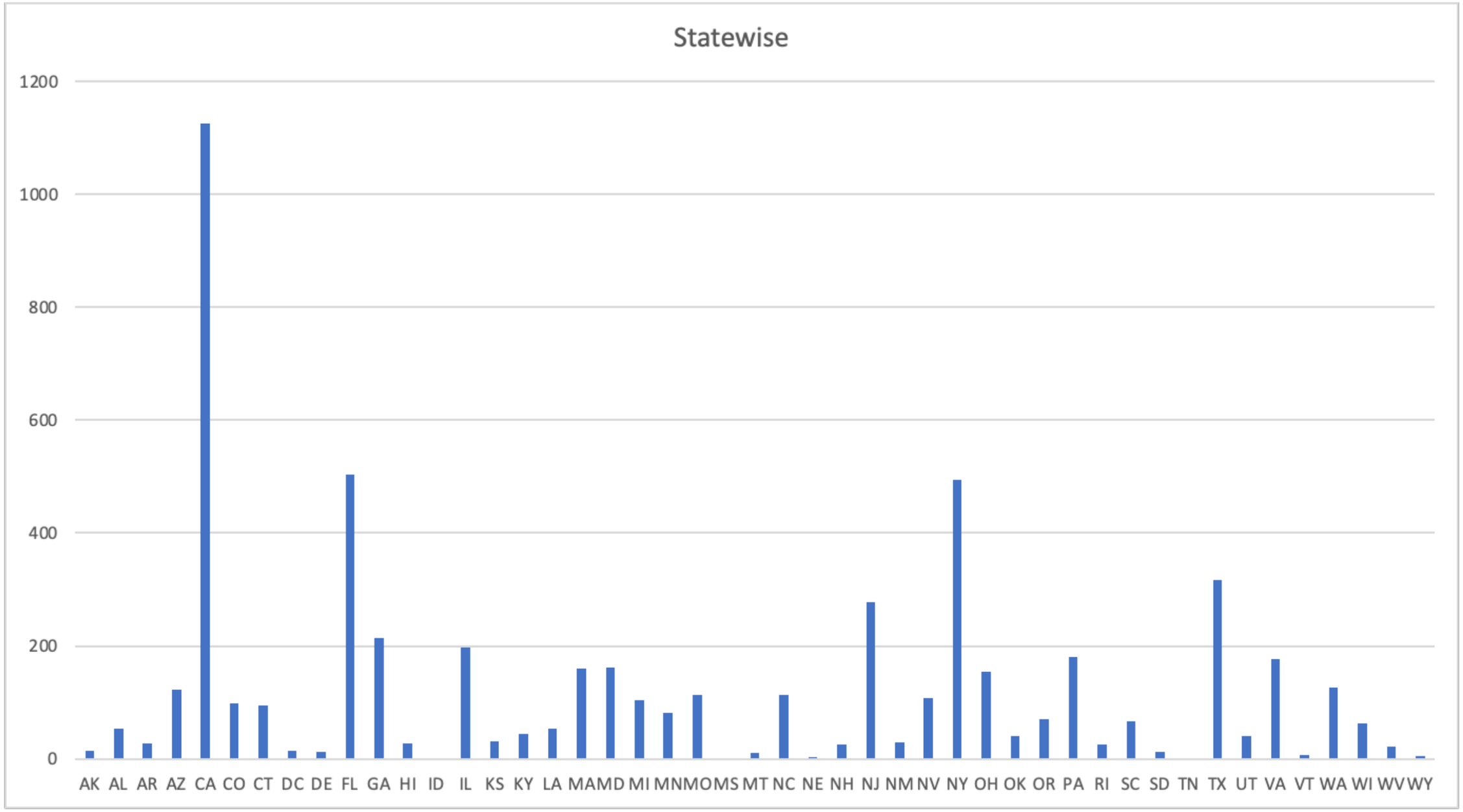
4) Most of the employees are getting loan for Debt Consolidation

In [17]:
```
sb.histplot(df[df["loan_status"] == 'Charged Off'].purpose,bins=2)
```

Out[17]:
```
<AxesSubplot:xlabel='purpose', ylabel='Count'>
```

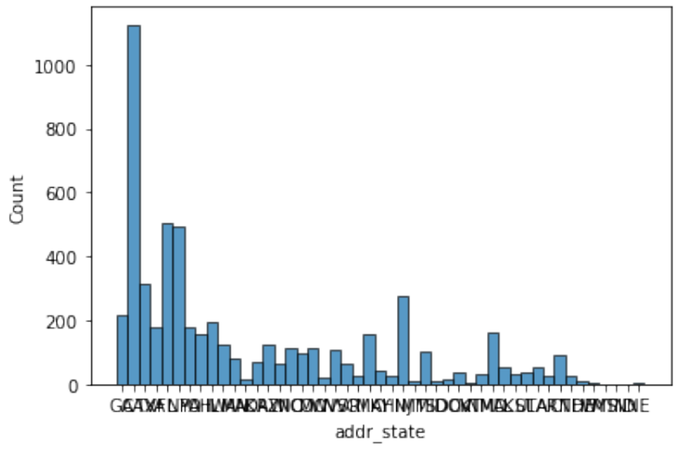


5) Employees from CA, NY and FL are Charged Off more



In [18]:
```
sb.histplot(df[df["loan_status"] == 'Charged Off'].addr_state,bins=2)
```

Out[18]:
```
<AxesSubplot:xlabel='addr_state', ylabel='Count'>
```

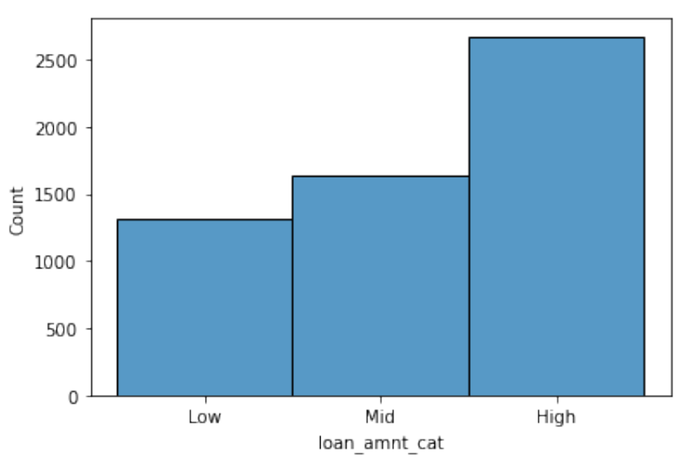


Segmented Univariate Analysis

1) Mostly the loan amount higher than 10000 are defaulted

In [19]:
```
loan_conditions = [ (df['loan_amnt'] > 10000), (df['loan_amnt'] >5000), (df['loan_amnt'] <= 5000) ]
loan_cond_values = ['High', 'Mid', 'Low']
df['loan_amnt_cat'] = np.select(loan_conditions, loan_cond_values)
sb.histplot(df[df["loan_status"] == 'Charged Off'].loan_amnt_cat,bins=2)
```

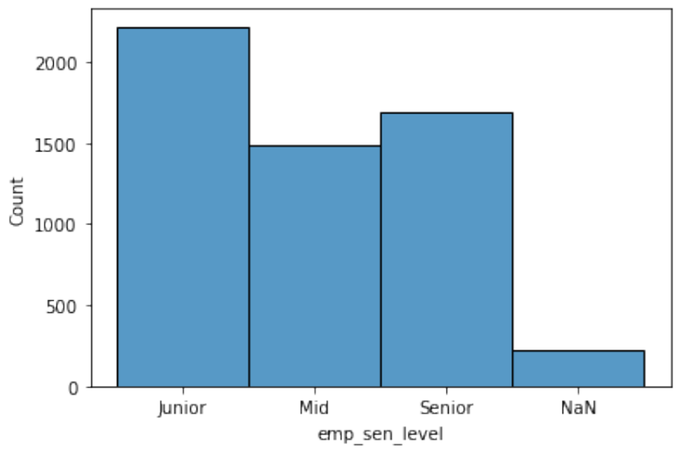
Out[19]:
```
<AxesSubplot:xlabel='loan_amnt_cat', ylabel='Count'>
```



2) Employees lesser than 5 years of experience are Charged Off more

In [20]:
```
emp_len_conditions = [ (df['emp_length'] == '10'), (df['emp_length'] == '9'), (df['emp_length'] == '8'), (df['emp_length'] == '7'), (df['emp_length'] == '6'), (df['emp_l
emp_len_cond_values = ['Senior', 'Senior', 'Senior','Mid','Mid','Mid','Mid','Junior','Junior','Junior','NaN']
df['emp_sen_level'] = np.select(emp_len_conditions, emp_len_cond_values)
sb.histplot(df[df["loan_status"] == 'Charged Off'].emp_sen_level,bins=10)
```

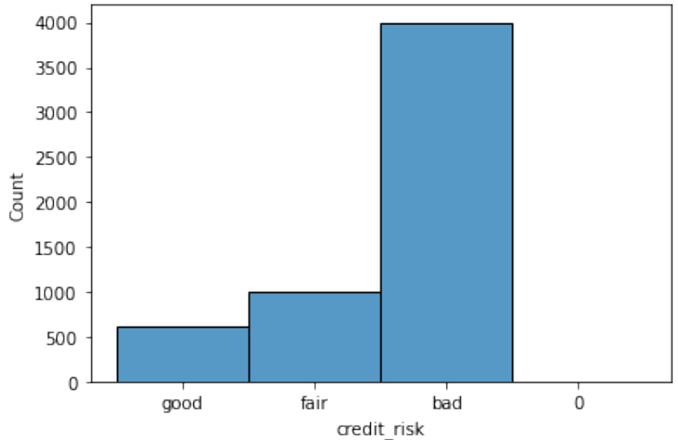
Out[20]:
```
<AxesSubplot:xlabel='emp_sen_level', ylabel='Count'>
```



3) Employees with lower Credit Risk (Higher DTI) is Charged off more

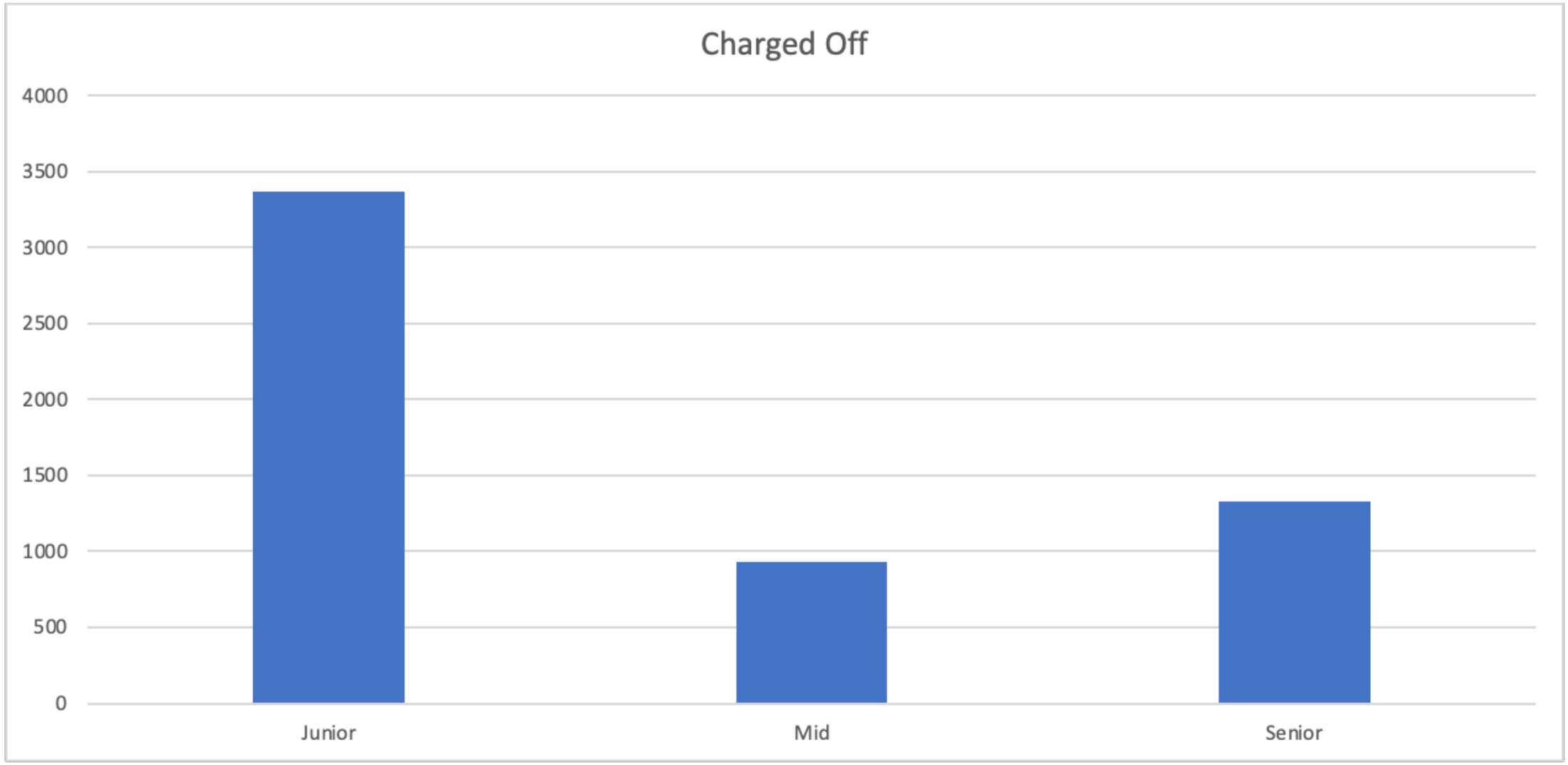
In [21]:
```
dti_conditions  = [ (df['dti'] > 10), (df['dti'] > 5), (df['dti'] < 5) ]
dti_cond_values = ['bad', 'fair', 'good']
df['credit_risk'] = np.select(dti_conditions, dti_cond_values)
sb.histplot(df[df["loan_status"] == 'Charged Off'].credit_risk,bins=4)
```

Out[21]:
```
<AxesSubplot:xlabel='credit_risk', ylabel='Count'>
```



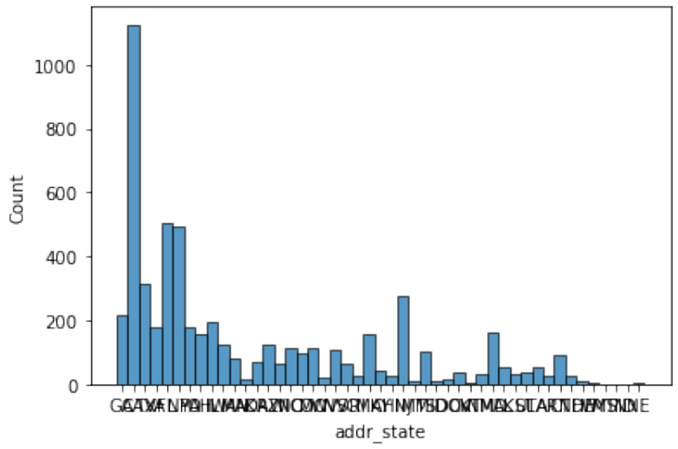
BiVariate Analysis

1) Chances of default is higher in the employees who are less than or equal to 5 years. However employess more than 10 years of experience are Charged off more than anyone else

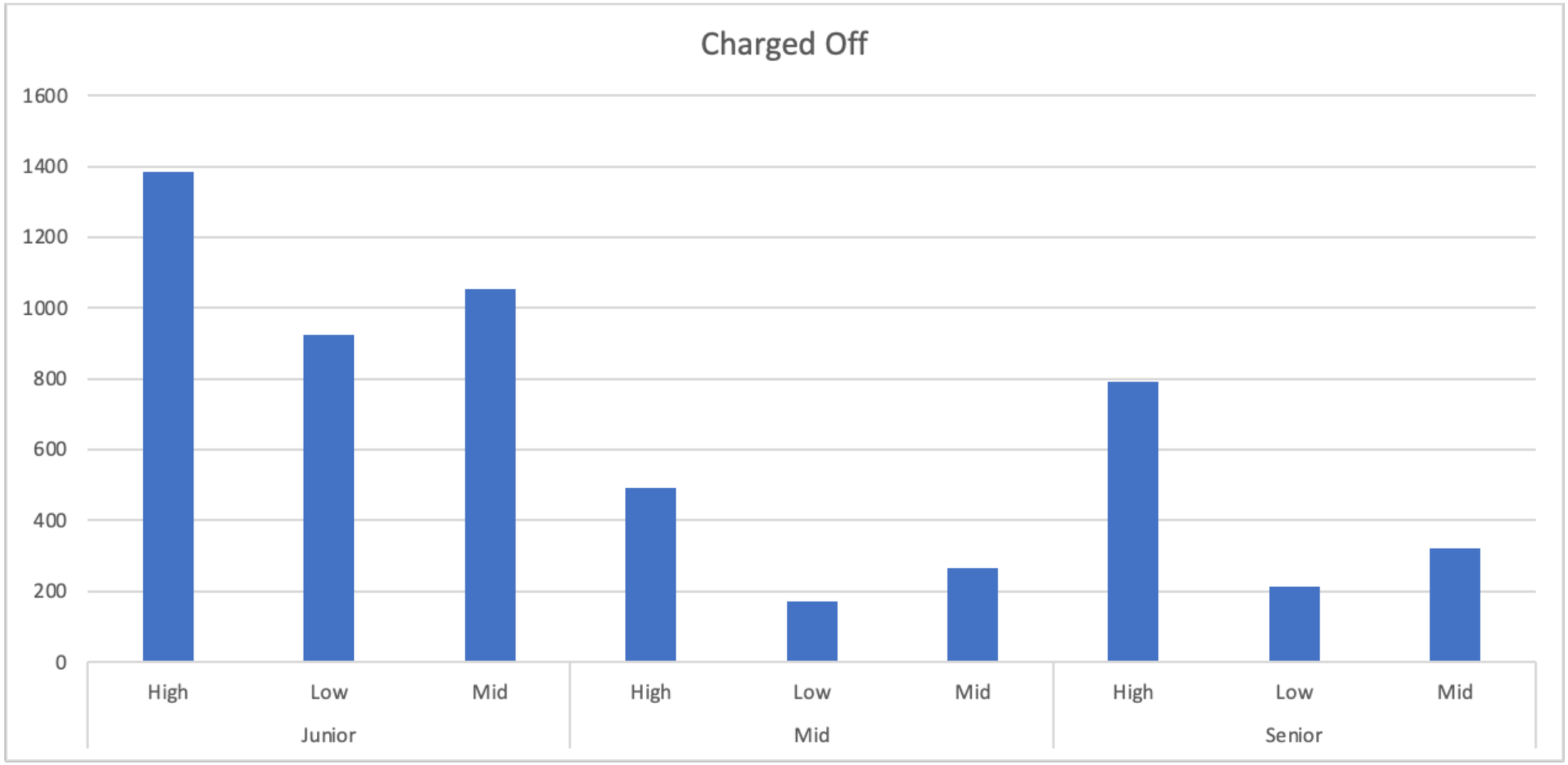


In [22]:
```
sb.histplot(df[df["loan_status"] == 'Charged Off'].addr_state,bins=10)
```

Out[22]:
```
<AxesSubplot:xlabel='addr_state', ylabel='Count'>
```

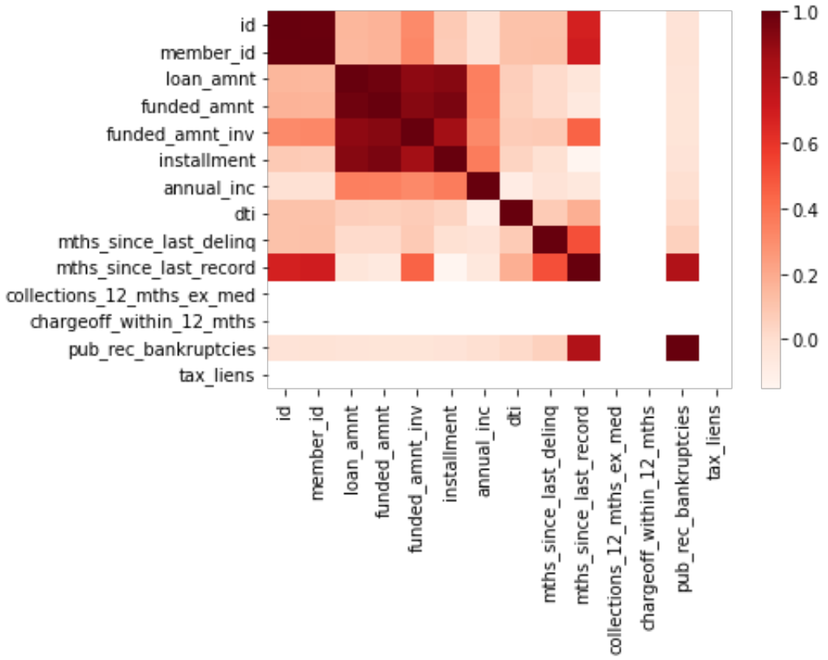

1000
800
600
400
200
0
Count
addr_state

2) Loans which are more than 10000 are mostly defaulted among all employees



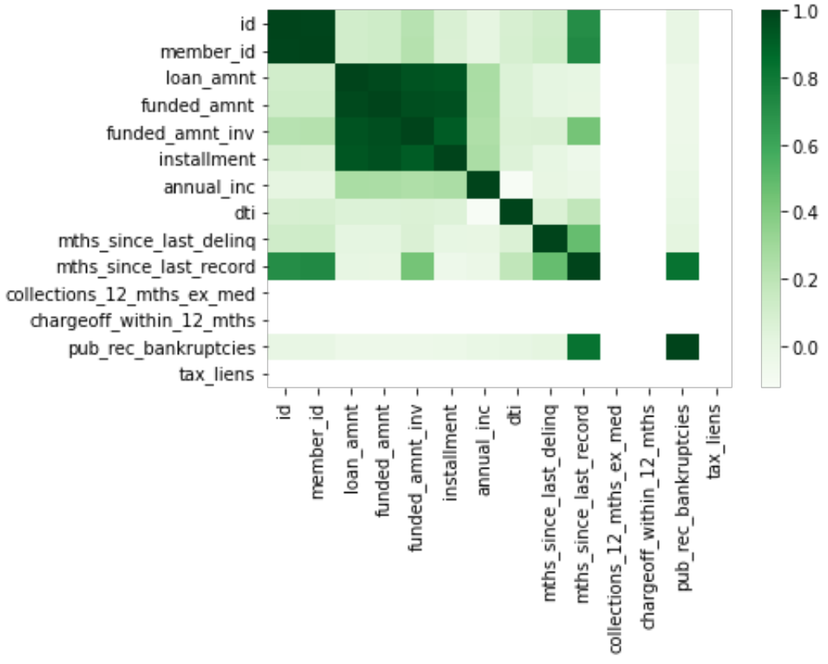
In [23]:
```
sb.heatmap(df[df["loan_status"] == 'Charged Off'].corr(), cmap="Reds")
```

Out[23]:
```
<AxesSubplot:>
```

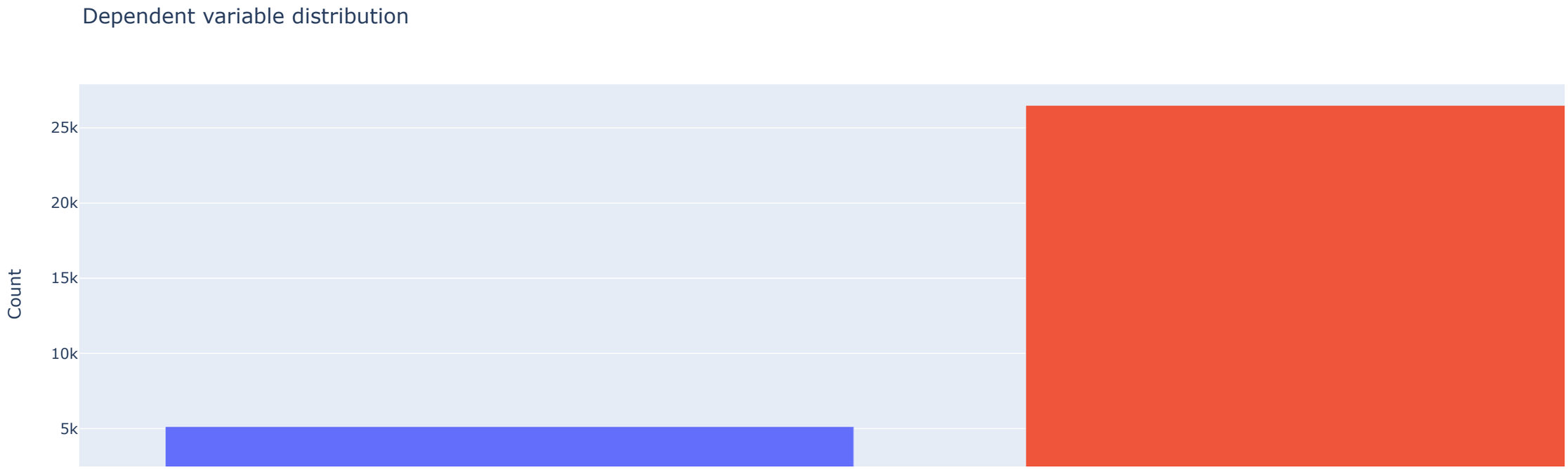


In [24]:
```
sb.heatmap(df[df["loan_status"] == 'Fully Paid'].corr(),cmap="Greens")
```

Out[24]:
```
<AxesSubplot:>
```

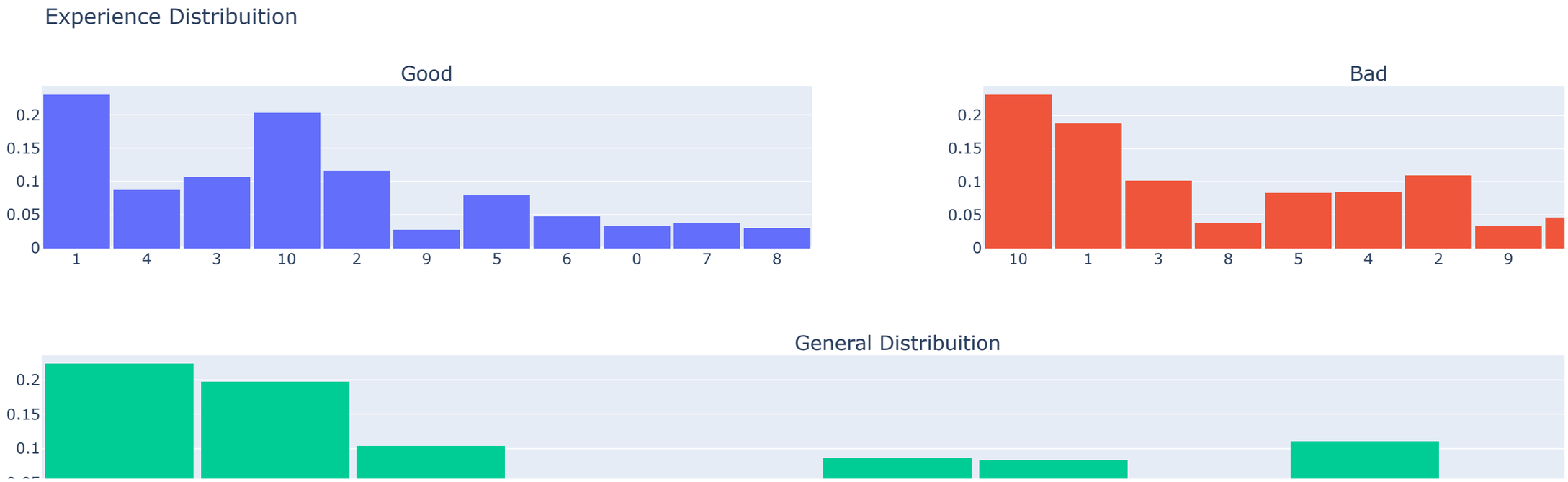


In [25]:
```
tr0 = go.Bar(
            x = df[df["credit_risk"]== 'good']["credit_risk"].value_counts().index.values,
            y = df[df["credit_risk"]== 'good']["credit_risk"].value_counts().values,
            name='Good credit'
    )

tr1 = go.Bar(
            x = df[df["credit_risk"]== 'bad']["credit_risk"].value_counts().index.values,
            y = df[df["credit_risk"]== 'bad']["credit_risk"].value_counts().values,
            name='Bad credit'
    )

data = [tr0, tr1]

layout = go.Layout(

)

layout = go.Layout(
    yaxis=dict(
        title='Count'
    ),
    xaxis=dict(
        title='Risk Variable'
    ),
    title='Dependent variable distribution'
)

fig = go.Figure(data=data, layout=layout)

py.iplot(fig, filename='grouped-bar')
```


Dependent variable distribution
Count
25k
20k
15k
10k
5k

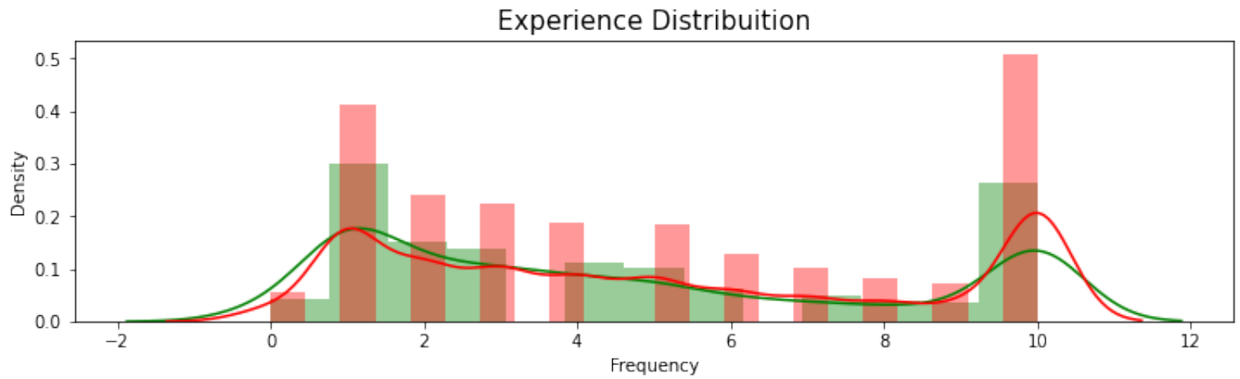
In [26]:
```
df_good        = df.loc[df["credit_risk"] == 'good']['emp_length'].values.tolist()
df_bad         = df.loc[df["credit_risk"] == 'bad' ]['emp_length'].values.tolist()
df_emp_length  = df['emp_length'].values.tolist()

#First plot
tr0 = go.Histogram(
    x=df_good,
    histnorm='probability',
    name="Good Credit"
)
#Second plot
tr1 = go.Histogram(
    x=df_bad,
    histnorm='probability',
    name="Bad Credit"
)
#Third plot
tr2 = go.Histogram(
    x=df_emp_length,
    histnorm='probability',
    name="Overall Experience"
)

#Creating the grid
fig = tls.make_subplots(rows=2, cols=2, specs=[[{}, {}], [{'colspan': 2}, None]],
                          subplot_titles=('Good','Bad', 'General Distribuition'))

#setting the figs
fig.append_trace(tr0, 1, 1)
fig.append_trace(tr1, 1, 2)
fig.append_trace(tr2, 2, 1)

fig['layout'].update(showlegend=True, title='Experience Distribuition', bargap=0.05)
py.iplot(fig, filename='custom-sized-subplot-with-subplot-titles')
```

```
/opt/anaconda3/lib/python3.9/site-packages/plotly/tools.py:461: DeprecationWarning:

plotly.tools.make_subplots is deprecated, please use plotly.subplots.make_subplots instead
```

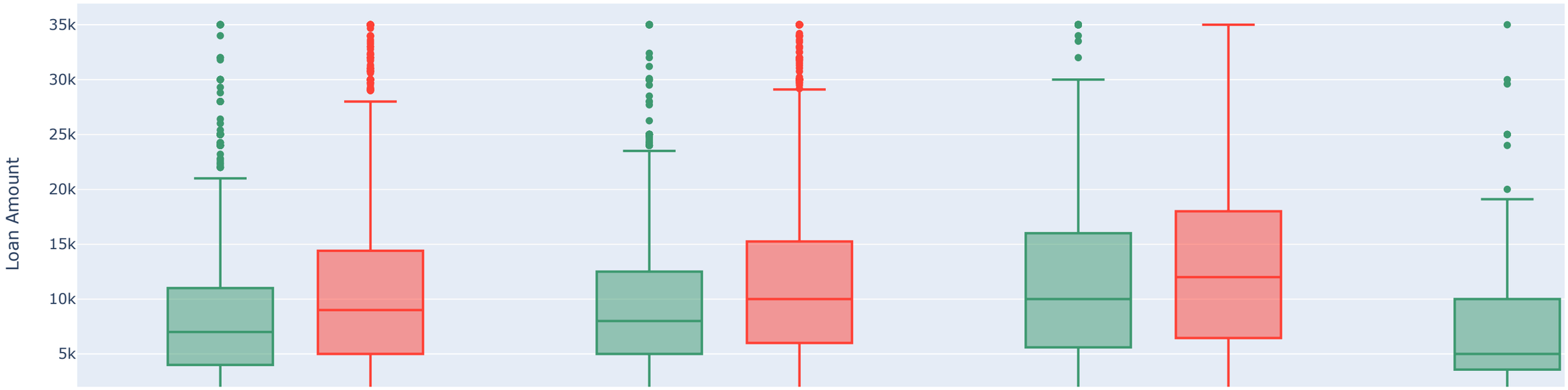


In [27]:
```
df_good = df[df["credit_risk"] == 'good']
df_bad  = df[df["credit_risk"] == 'bad']

fig, ax = plt.subplots(nrows=2, figsize=(12,8))
plt.subplots_adjust(hspace = 0.4, top = 0.8)

g1 = sb.distplot(df_good["emp_length"], ax=ax[0],
             color="g")
g1 = sb.distplot(df_bad["emp_length"], ax=ax[0],
             color='r')
g1.set_title("Experience Distribuition", fontsize=15)
g1.set_xlabel("Experience")
g1.set_xlabel("Frequency")

g2 = sb.countplot(x="emp_length",data=df,
              palette="hls", ax=ax[1],
              hue = "credit_risk")
g2.set_title("Experience Counting by Credit Risk", fontsize=15)
g2.set_xlabel("Experience")
plt.show()
```

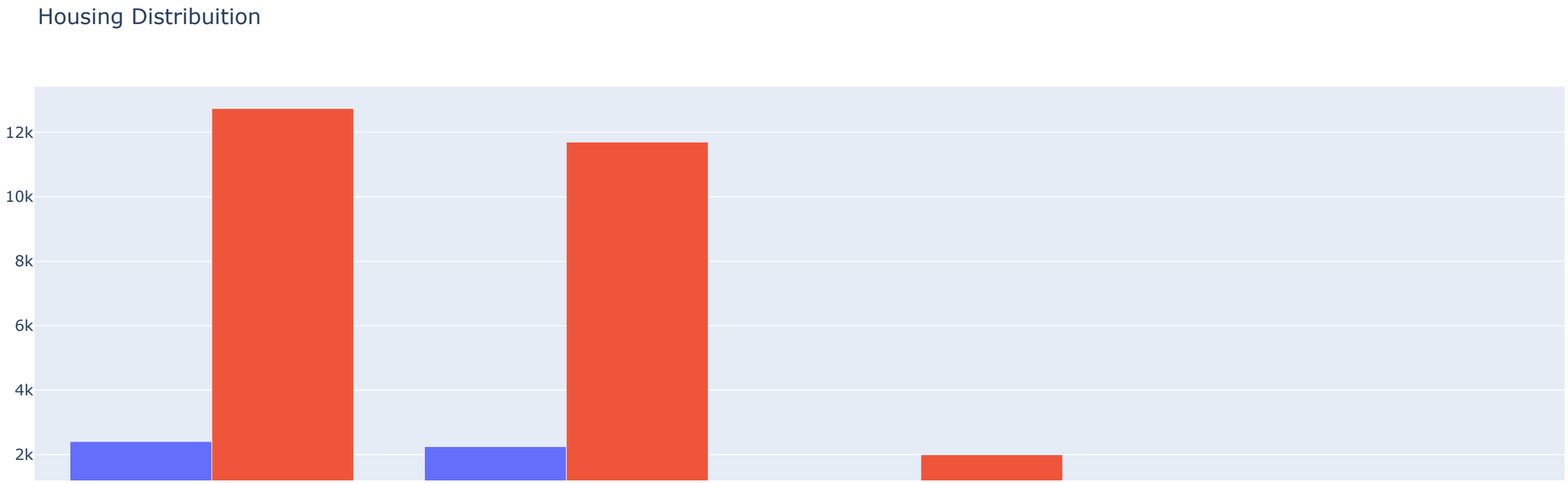
```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/distributions.py:2619: FutureWarning:

`distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexib
ility) or `histplot` (an axes-level function for histograms).

/opt/anaconda3/lib/python3.9/site-packages/seaborn/distributions.py:2619: FutureWarning:

`distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexib
ility) or `histplot` (an axes-level function for histograms).
```



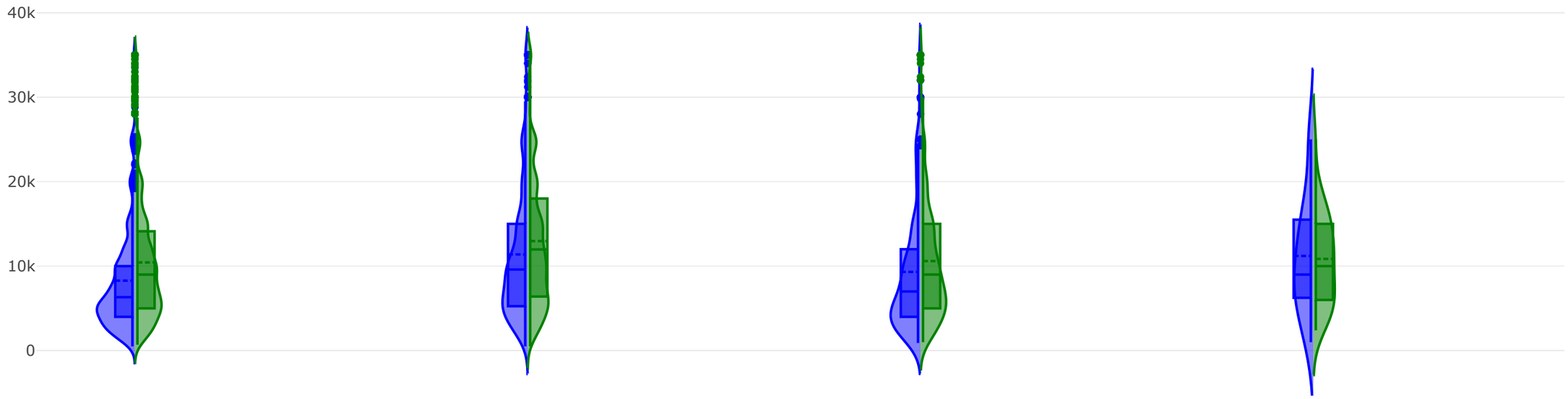
In [28]:
```
df_good = df[df["credit_risk"] == 'good']
df_bad  = df[df["credit_risk"] == 'bad']

tr0 = go.Box(
    y=df_good["loan_amnt"],
    x=df_good["emp_sen_level"],
    name='Good credit',
    marker=dict(
        color='#3D9970'
    )
)

tr1 = go.Box(
    y=df_bad['loan_amnt'],
    x=df_bad['emp_sen_level'],
    name='Bad credit',
    marker=dict(
        color='#FF4136'
    )
)

data = [tr0, tr1]

layout = go.Layout(
    yaxis=dict(
        title='Loan Amount',
        zeroline=False
    ),
    xaxis=dict(
        title='Seniority'
    ),
    boxmode='group'
)
fig = go.Figure(data=data, layout=layout)

py.iplot(fig, filename='box-age-cat')
```


Loan Amount
35k
30k
25k
20k
15k
10k
5k

In [29]:
```
#First plot
tr0 = go.Bar(
    x = df[df["credit_risk"]== 'good']["home_ownership"].value_counts().index.values,
    y = df[df["credit_risk"]== 'good']["home_ownership"].value_counts().values,
    name='Good credit'
)

#Second plot
tr1 = go.Bar(
    x = df[df["credit_risk"]== 'bad']["home_ownership"].value_counts().index.values,
    y = df[df["credit_risk"]== 'bad']["home_ownership"].value_counts().values,
    name="Bad Credit"
)

data = [tr0, tr1]

layout = go.Layout(
    title='Housing Distribuition'
)


fig = go.Figure(data=data, layout=layout)

py.iplot(fig, filename='Housing-Grouped')
```


Housing Distribuition
12k
10k
8k
6k
4k
2k

In [30]:
```
#Distribuition of Loan amount by Home Ownership
fig = {
    "data": [
        {
            "type": 'violin',
            "x": df_good['home_ownership'],
            "y": df_good['loan_amnt'],
            "legendgroup": 'Good Credit',
            "scalegroup": 'No',
            "name": 'Good Credit',
            "side": 'negative',
            "box": {
                "visible": True
            },
            "meanline": {
                "visible": True
            },
            "line": {
                "color": 'blue'
            }
        },
        {
            "type": 'violin',
            "x": df_bad['home_ownership'],
            "y": df_bad['loan_amnt'],
            "legendgroup": 'Bad Credit',
            "scalegroup": 'No',
            "name": 'Bad Credit',
            "side": 'positive',
            "box": {
                "visible": True
            },
            "meanline": {
                "visible": True
            },
            "line": {
                "color": 'green'
            }
        }
    ],
    "layout" : {
        "yaxis": {
            "zeroline": False,
        },
        "violingap": 0,
        "violinmode": "overlay"
    }
}


py.iplot(fig, filename = 'violin/split', validate = False)
```


40k
30k
20k
10k
0

In [31]:
```
#First plot
tr0 = go.Bar(
    x = df[df["credit_risk"]== 'good']["grade"].value_counts().index.values,
    y = df[df["credit_risk"]== 'good']["grade"].value_counts().values,
    name='Good credit'
)

#First plot 2
tr1 = go.Bar(
    x = df[df["credit_risk"]== 'bad']["grade"].value_counts().index.values,
    y = df[df["credit_risk"]== 'bad']["grade"].value_counts().values,
    name="Bad Credit"
)

#Second plot
tr2 = go.Box(
    x = df[df["credit_risk"]== 'good']["grade"],
    y = df[df["credit_risk"]== 'good']["loan_amnt"],
    name=tr0.name
)

#Second plot 2
tr3 = go.Box(
    x = df[df["credit_risk"]== 'bad']["grade"],
    y = df[df["credit_risk"]== 'bad']["loan_amnt"],
    name=tr1.name
)

data = [tr0, tr1, tr2,tr3]



fig = tls.make_subplots(rows=1, cols=2,
                        subplot_titles=('Grade', 'Loan Amount by Grade'))

fig.append_trace(tr0, 1, 1)
fig.append_trace(tr1, 1, 1)
fig.append_trace(tr2, 1, 2)
fig.append_trace(tr3, 1, 2)

fig['layout'].update(height=400, width=800, title='Grade Distribuition', boxmode='group')
py.iplot(fig, filename='sex-subplot')
```

```
/opt/anaconda3/lib/python3.9/site-packages/plotly/tools.py:461: DeprecationWarning:

plotly.tools.make_subplots is deprecated, please use plotly.subplots.make_subplots instead
```

Grade Distribuition