In [2]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [3]:
```
%time data = pd.read_table('XYZCorp_LendingData.txt',parse_dates=['issue_d']
```

```
CPU times: user 54.2 s, sys: 1.16 s, total: 55.4 s
Wall time: 57.7 s
```

Dividing the data into train and test

In [4]:
```
train_data = data[data['issue_d'] < '2015-6-01']
test_data = data[data['issue_d'] >= '2015-6-01']
```

In [5]:
```
train = train_data.copy()
test = test_data.copy()
```

In [6]:
```
train.head()
```

Out[6]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	su
0	1077501	1296599	5000.0	5000.0	4975.0	36 months	10.65	162.87	B	
1	1077430	1314167	2500.0	2500.0	2500.0	60 months	15.27	59.83	C	
2	1077175	1313524	2400.0	2400.0	2400.0	36 months	15.96	84.33	C	
3	1076863	1277178	10000.0	10000.0	10000.0	36 months	13.49	339.31	C	
4	1075358	1311748	3000.0	3000.0	3000.0	60 months	12.69	67.79	B	

5 rows × 73 columns

In [7]:
```
train['default_ind'].value_counts()
```

Out[7]:
```
0    552822
1     46156
Name: default_ind, dtype: int64
```

In [8]:
```
train.describe()
```

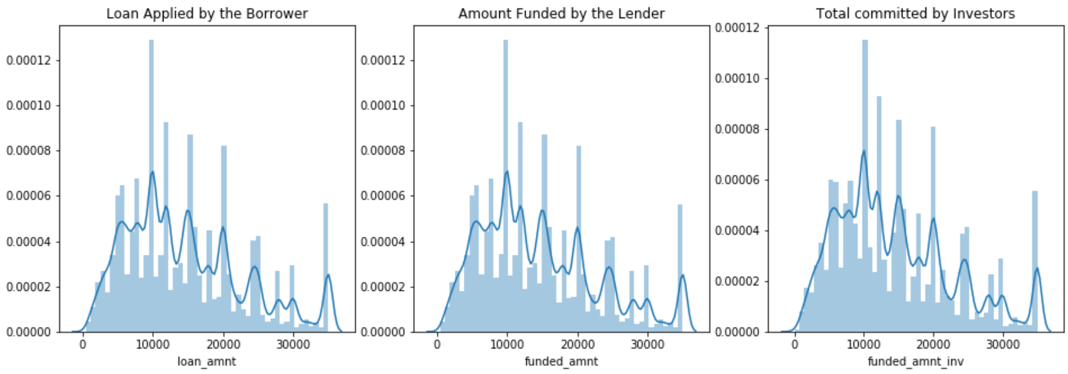
Out[8]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	int_rate	inst
count	5.989780e+05	5.989780e+05	598978.000000	598978.000000	598978.000000	598978.000000	598978.
mean	2.044157e+07	2.231985e+07	14540.642519	14521.789031	14478.973948	13.520911	434.
std	1.619182e+07	1.711491e+07	8336.476483	8327.529212	8337.695086	4.370961	242.
min	5.473400e+04	7.069900e+04	500.000000	500.000000	0.000000	5.320000	15.
25%	5.937838e+06	7.205072e+06	8000.000000	8000.000000	8000.000000	10.160000	259.
50%	1.564996e+07	1.763377e+07	12600.000000	12525.000000	12500.000000	13.330000	381.
75%	3.671239e+07	3.943412e+07	20000.000000	20000.000000	20000.000000	16.290000	568.
max	5.095230e+07	5.433202e+07	35000.000000	35000.000000	35000.000000	28.990000	1409.

8 rows × 52 columns

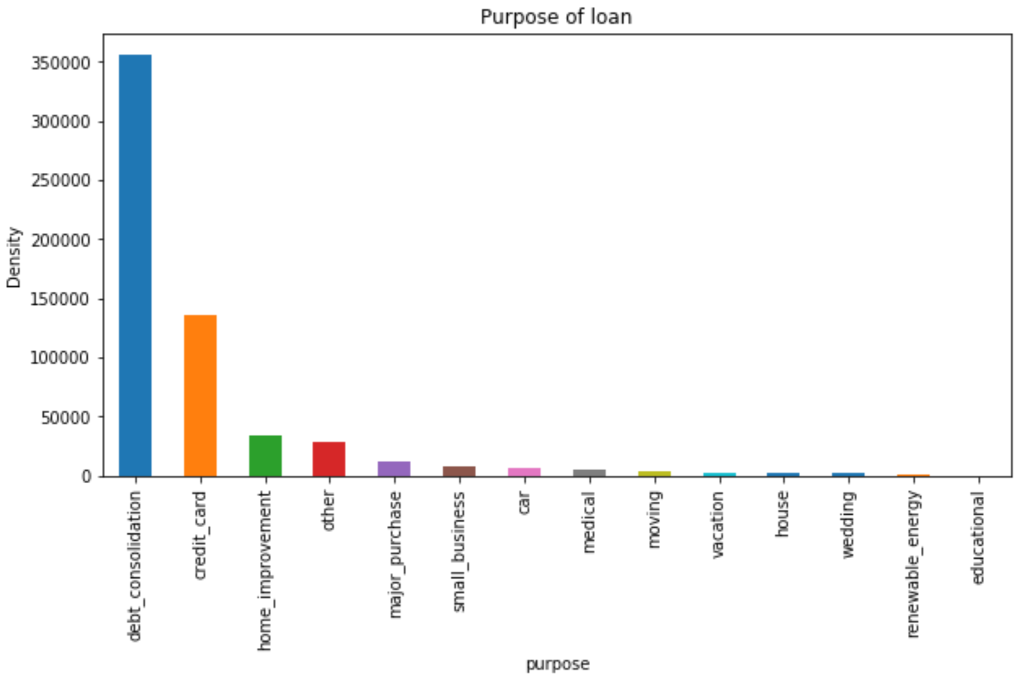
In [9]:
```
fig, ax = plt.subplots(1, 3, figsize=(16,5))

sns.distplot(train['loan_amnt'], ax=ax[0])
sns.distplot(train['funded_amnt'], ax=ax[1])
sns.distplot(train['funded_amnt_inv'], ax=ax[2])
ax[1].set_title("Amount Funded by the Lender")
ax[0].set_title("Loan Applied by the Borrower")
ax[2].set_title("Total committed by Investors")
```

Out[9]:
```
Text(0.5,1,'Total committed by Investors')
```



- Most of the loans issued were in the range of 10,000 to 20,000 USD.
- Loans were issued in an incremental manner. (Possible due to a recovery in the U.S economy)
- The loans applied by potential borrowers, the amount issued to the borrowers and the amount funded by investors are similarly distributed, meaning that it is most likely that qualified borrowers are going to get the loan they had applied for.

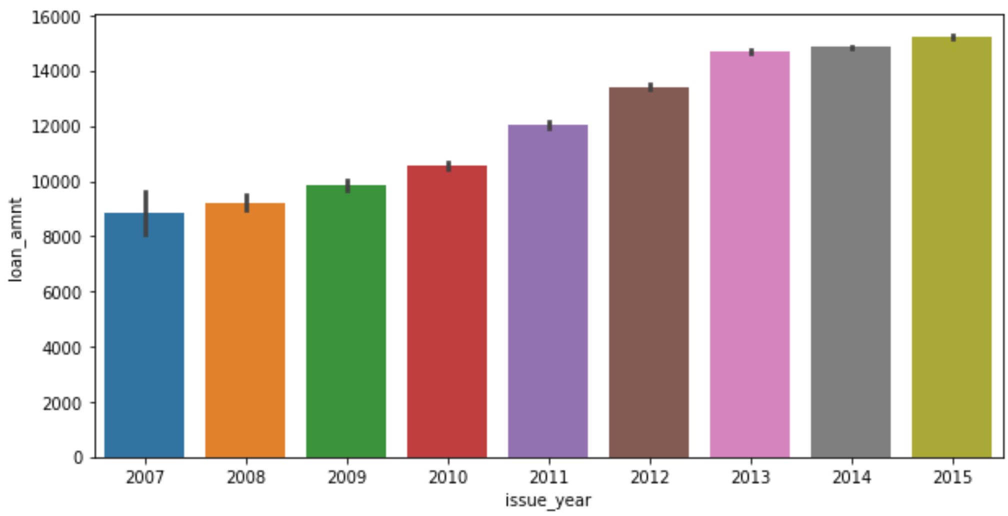
In [10]:
```
train.purpose.value_counts(ascending=False).plot.bar(figsize=(10,5))
plt.xlabel('purpose'); plt.ylabel('Density'); plt.title('Purpose of loan');
```



Debt Consolidation - more than 350K loans (~58%)
Credit Card —more than 130K (~20%)
Home Improvement—more than 135K (~6%)
Other Purposes—less than 30K (~4%)

In [11]:
```
plt.figure(figsize=(10,5))
train['issue_year'] = train['issue_d'].dt.year
sns.barplot(x='issue_year',y='loan_amnt',data=train)
```

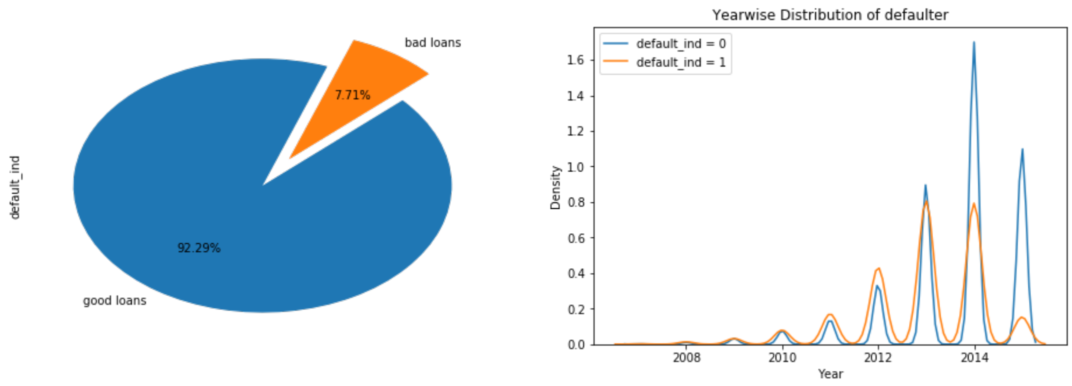
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7efbd48dff98>



- The year of 2015 was the year were most loans were issued.

In [12]:
```
fig, ax = plt.subplots(1, 2, figsize=(16,5))
train['default_ind'].value_counts().plot.pie(explode=[0,0.25],labels=['good
                                             autopct='%1.2f%%',startangle=7(
sns.kdeplot(train.loc[train['default_ind']==0,'issue_year'],label='default_i
sns.kdeplot(train.loc[train['default_ind']==1,'issue_year'],label='default_i
plt.xlabel('Year'); plt.ylabel('Density'); plt.title('Yearwise Distribution
```

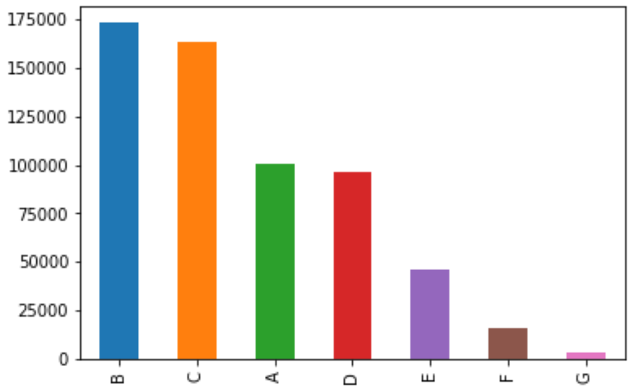
Out[12]: Text(0.5,1,'Yearwise Distribution of defaulter')



- Most of the loan default is done in year 2013 and 2014

In [13]:
```
train.grade.value_counts().plot.bar()
```

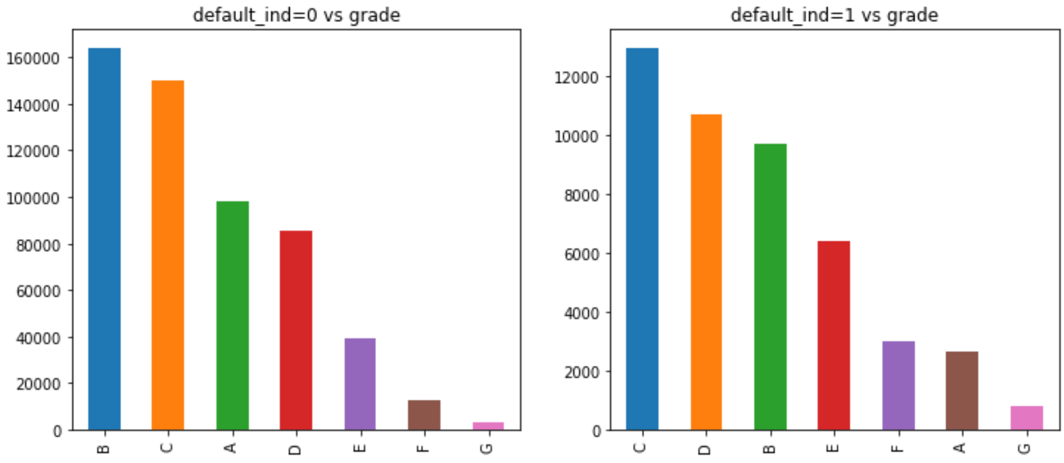
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7efbd47dfa20>



- Most people have Grade **B**

In [14]:
```
fig,array=plt.subplots(1,2,figsize=(12,5))
train.loc[train['default_ind']==0,'grade'].value_counts().plot.bar(ax=array
train.loc[train['default_ind']==1,'grade'].value_counts().plot.bar(ax=array
array[0].set_title('default_ind=0 vs grade').array[1].set_title('default_ind
```

Out[14]:
```
(Text(0.5,1,'default_ind=0 vs grade'), Text(0.5,1,'default_ind=1 vs grade
'))
```



- Most people with Grade **C** have done the Default

In [15]:
```
#Converting Emp Length into Integer
train.emp_length.unique()
train.loc[train['emp_length']=='10+ years','emp_len'] = 10
train.loc[train['emp_length']=='<1 year','emp_len'] = .5
train.loc[train['emp_length']=='1 year','emp_len'] = 1
train.loc[train['emp_length']=='3 years','emp_len'] = 3
train.loc[train['emp_length']=='8 years','emp_len'] = 8
train.loc[train['emp_length']=='9 years','emp_len'] = 9
train.loc[train['emp_length']=='4 years','emp_len'] = 4
train.loc[train['emp_length']=='5 years','emp_len'] = 5
train.loc[train['emp_length']=='6 years','emp_len'] = 6
train.loc[train['emp_length']=='2 years','emp_len'] = 2
train.loc[train['emp_length']=='7 years','emp_len'] = 7
train.loc[train['emp_length']=='nan','emp_len'] = 0
```

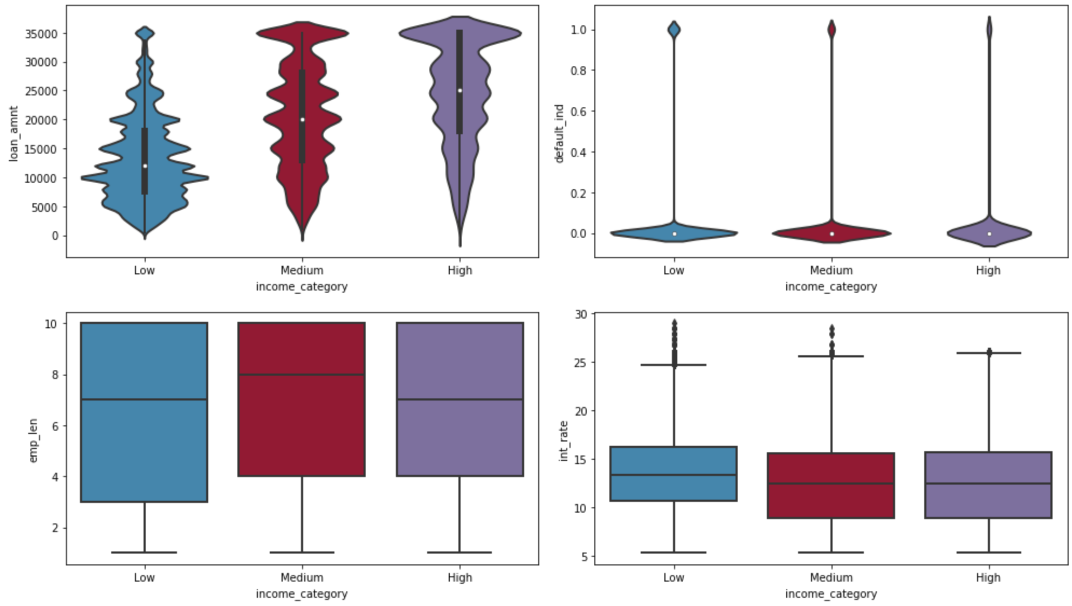
In [16]:
```
print(train.int_rate.mean())
print(train.annual_inc.mean())
```

```
13.520910684598922
73972.8004821713
```

In [17]:
```
train['income_category'] = np.nan
train.loc[train['annual_inc'] <= 100000,'income_category'] = 'Low'
train.loc[(train['annual_inc'] > 100000) & (train['annual_inc'] <= 200000),
train.loc[train['annual_inc'] > 200000,'income_category'] = 'High'
```

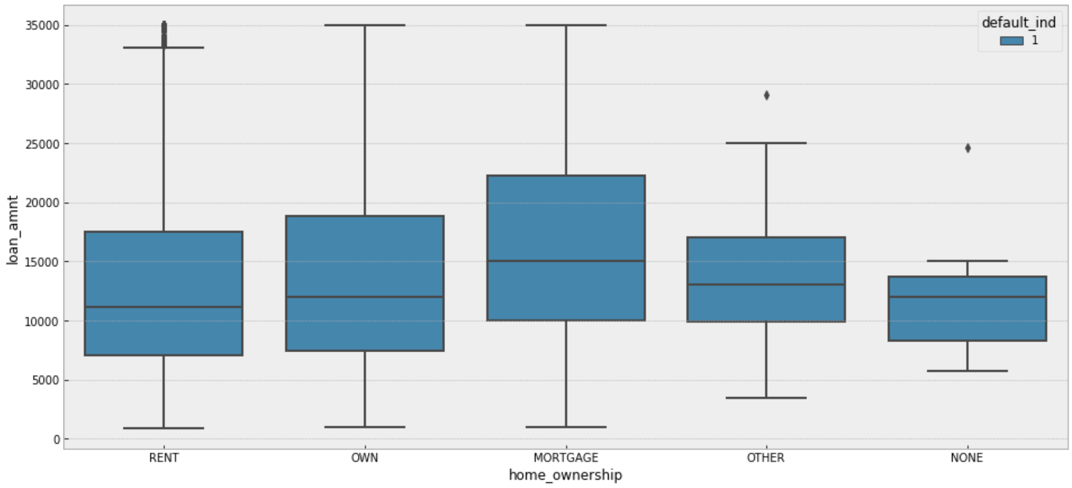
In [18]:

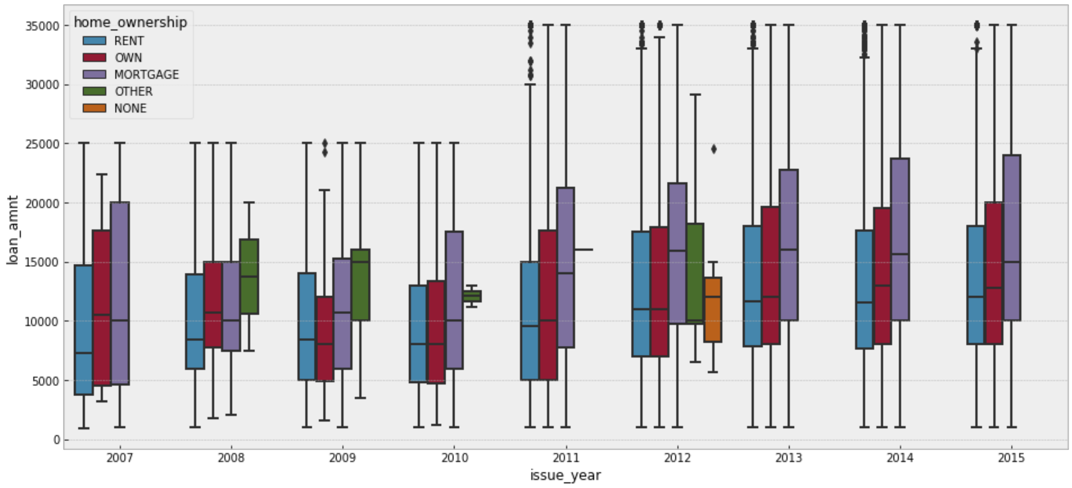
```
fig, ((ax1, ax2), (ax3, ax4))= plt.subplots(nrows=2, ncols=2, figsize=(14,8
plt.style.use('bmh')
sns.violinplot(x="income_category", y="loan_amnt", data=train, ax=ax1 )
sns.violinplot(x="income_category", y="default_ind", data=train, ax=ax2)
sns.boxplot(x="income_category", y="emp_len", data=train, ax=ax3)
sns.boxplot(x="income_category", y="int_rate", data=train, ax=ax4)
plt.tight_layout(h_pad=1.5)
```



In [19]:
```
defaulter = train.loc[train['default_ind']==1]
plt.figure(figsize=(16,16))
plt.subplot(211)
sns.boxplot(data=defaulter,x = 'home_ownership',y='loan_amnt',hue='default_i
plt.subplot(212)
sns.boxplot(data=defaulter,x='issue_year',y='loan_amnt',hue='home_ownership
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7efbd348a2b0>





In [20]:

```python
def to_datepart(df,fldname,drop=False):
    fld = df[fldname]
    fld_dtype = fld.dtype
    targ_pre = re.sub('[Dd]ate$', '', fldname)
    attr = ['Month', 'Week', 'Day', 'Dayofweek', 'Dayofyear',
            'Is_month_end', 'Is_month_start', 'Is_quarter_end', 'Is_quarter_
            'Is_year_end', 'Is_year_start']
    for n in attr: df[targ_pre + n] = getattr(fld.dt, n.lower())
    df[targ_pre + 'Elapsed'] = fld.astype(np.int64)
    if drop: df.drop(fldname, axis=1, inplace=True)

import re
to_datepart(train,'issue_d',drop=True)
to_datepart(test,'issue_d',drop=True)

def treat_missing(df):
    for c in df.columns:
        if df[c].dtype == 'object':
            df.fillna(df[c].mode()[0],inplace=True)
        else:
            df.fillna(df[c].median(),inplace=True)
```

In [21]:

```python
treat_missing(train)
treat_missing(test)
```

In [22]:

```python
def train_cat(df):
    for n,c in df.items():
        if df[n].dtype == 'object': df[n] = c.astype('category').cat.as_orde

train_cat(train)
train_cat(test)
```

In [23]:

```python
to_drop = ['sub_grade','emp_title','desc','title','zip_code',
           'addr_state','earliest_cr_line','last_pymnt_d','last_credit_pull_

train.drop(to_drop,axis=1,inplace=True)
test.drop(to_drop,axis=1,inplace=True)
```

In [24]:

```python
#label encoding
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for c in train.columns:
    if train[c].dtype == 'object':
        if len(list(train[c].unique())) <= 2:
            train[c] = le.fit_transform(train[c])
            test[c] = le.transform(test[c])
```

In [25]:

```python
print(train.shape)
print(test.shape)
train = pd.get_dummies(train)
test = pd.get_dummies(test)
print(train.shape)
print(test.shape)
```

```
(598978, 78)
(256991, 75)
(598978, 123)
(256991, 118)
```

In [26]:
```
# train_label = train['default_ind']
# Align the training and testing data, keep only columns present in both da
train, test = train.align(test, join = 'inner', axis = 1)
```

In [27]:
```
print(train.shape)
print(test.shape)
```

```
(598978, 111)
(256991, 111)
```

In [28]:
```
X = train.copy()
y = X.pop('default_ind')

def split_vals(a,n):return a[:n].copy(),a[n:].copy()

n_valid = len(test)  # same as test set size
n_trn = len(X)-n_valid
raw_train,raw_valid = split_vals(train,n_trn)
X_train, X_valid = split_vals(X, n_trn)
y_train, y_valid = split_vals(y, n_trn)
X_train.shape, y_train.shape, X_valid.shape
```

Out[28]:
```
((341987, 110), (341987,), (256991, 110))
```

In [34]:
```
from sklearn.ensemble import RandomForestClassifier
m = RandomForestClassifier(n_jobs=-1,n_estimators=100)
m.fit(X_train,y_train)
from sklearn.metrics import confusion_matrix,precision_score,recall_score,r
y_pred = m.predict(X_valid)
print(confusion_matrix(y_valid,y_pred))
print('Precision', precision_score(y_valid,y_pred))
print('Recall',recall_score(y_valid,y_pred))
print('AUC Score',roc_auc_score(y_valid,y_pred))
```

```
Confusion Matrix [[226885  18579]
 [   391  11136]]
Precision 0.37476022211004545
Recall 0.9660796391081808
AUC Score 0.9451951661629617
```

In [*]:
```
y_test = test.pop('default_ind')
y_pred = m.predict(test)
from sklearn.metrics import classification_report
print(confusion_matrix(y_test,y_pred))
print(precision_score(y_test,y_pred))
print(classification_report(y_test,y_pred))
print(recall_score(y_test,y_pred))
print(roc_auc_score(y_test,y_pred))
```

RECOMMENDATIONS AND CONCLUSION:

We have successfully built an machine learning algorithm to predict the people who might default on their loans. Also, we might want to look on other techniques or variables to improve the prediction power of the algorithm. One of the drawbacks is just the limited number of people who defaulted on their loan in the 8 years of data (2007-2015) present on the dataset. We can use an updated data frame which consist next 3 years values (2015-2018) and see how many of the current loans were paid off or defaulted or even charged off. Then these new data points can be used for predicting them or even used to train the model again to improve its accuracy
Since the algorithm puts around 40% of non-defaulters in the default class, we might want to look further into this issue to make the model more robust.

Business Insights and Recommendations:

The facts from our analysis shows that Applicants who has taken the Loan for 'small business' has the highest probability of charge off of 14%. Hence, bank should take extra caution like take some asset or guarantee while approving the loan for purpose of 'small business' Banks should consider "Grade" as a major variable while providing loans. Also, As the annual income is decreasing the probability that person will default is in-creasing with highest of 7% at (0 to 25000) salary bracket. The banks should either start with less principal loan amount and check the credibility. Finally, As the interest rate is increasing the probability that person will default with highest of 9% at 15% & above bracket. Banks should consider minimizing their interest range for Applicants who are self-employed & less than 1 year of experience as they are more probable of charged off.

In [ ]:

```
```