In [102]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

Training Data:

Janurary 2014 to June 2016

In [103]:
```
df = pd.read_csv('train_lending_club.csv')
```

In [104]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 236846 entries, 0 to 236845
Data columns (total 27 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   issue_d                   236846 non-null  object 
 1   sub_grade                 236846 non-null  object 
 2   term                      236846 non-null  object 
 3   home_ownership            236846 non-null  object 
 4   fico_range_low            236846 non-null  float64
 5   total_acc                 236846 non-null  float64
 6   pub_rec                   236846 non-null  float64
 7   revol_util                236846 non-null  float64
 8   annual_inc                236846 non-null  float64
 9   int_rate                  236846 non-null  float64
 10  dti                       236846 non-null  float64
 11  purpose                   236846 non-null  object 
 12  mort_acc                  236846 non-null  float64
 13  loan_amnt                 236846 non-null  float64
 14  application_type          236846 non-null  object 
 15  installment               236846 non-null  float64
 16  verification_status       236846 non-null  object 
 17  pub_rec_bankruptcies      236846 non-null  float64
 18  addr_state                236846 non-null  object 
 19  initial_list_status       236846 non-null  object 
 20  fico_range_high           236846 non-null  float64
 21  revol_bal                 236846 non-null  float64
 22  id                        236846 non-null  int64  
 23  open_acc                  236846 non-null  float64
 24  emp_length                236846 non-null  float64
 25  loan_status               236846 non-null  int64  
 26  time_to_earliest_cr_line  236846 non-null  float64
dtypes: float64(16), int64(2), object(9)
memory usage: 48.8+ MB
```

Data Cleaning Function

In [105]:
```
def cleaning_data(df):

    # rescale the annual_income column: using log
    annual_inc = np.log(df['annual_inc'])
    # add this column
    df['log_annual_inc'] = annual_inc

    # take the average of the "low-" and "high-" range fico scores for each bo
rrrower
    FICO = df[['fico_range_low', 'fico_range_high']].mean(axis=1)
    # add this column
    df['fico'] = FICO

    # drop irrelevant columns
    df2 = df.drop(columns = ['issue_d', 'sub_grade', 'term', 'home_ownership',
'fico_range_low', 'annual_inc',
                             'application_type','verification_status', 'addr_s
tate', 'initial_list_status',
                             'fico_range_high', 'id'])

    # handle the missing/underfined data
    df2.replace(to_replace = [np.inf, -np.inf],
                value = np.nan,
                inplace = True)

    # drop NaNs
    df2.dropna(inplace= True)

    # check for NaN
    print( " \n Checking for NaNs: \n \n", df2.isna().sum() )

    return df2
```

In [106]:
```
# call the data into the function


loans = cleaning_data(df)
```

```
 Checking for NaNs:

 total_acc                 0
pub_rec                  0
revol_util               0
int_rate                 0
dti                      0
purpose                  0
mort_acc                 0
loan_amnt                0
installment              0
pub_rec_bankruptcies     0
revol_bal                0
open_acc                 0
emp_length               0
loan_status              0
time_to_earliest_cr_line    0
log_annual_inc           0
fico                     0
dtype: int64

C:\Newfolder\lib\site-packages\pandas\core\arraylike.py:396: RuntimeWarning:
divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

In [107]:
```
# view the cleaned data


loans.head()
```

Out[107]:

	total_acc	pub_rec	revol_util	int_rate	dti	purpose	mort_acc	loan_amnt	installm
0	18.0	0.0	86.8	16.99	15.16	credit_card	1.0	17775.0	441
1	26.0	0.0	103.5	15.61	16.74	credit_card	4.0	29175.0	703
2	47.0	0.0	11.4	7.90	20.34	debt_consolidation	1.0	6000.0	187
3	26.0	0.0	56.2	16.99	23.15	debt_consolidation	7.0	15600.0	387
4	15.0	1.0	67.1	14.98	17.88	vacation	1.0	10000.0	346

Exploratory Data Analysis

In [108]:
```
# check basic statistics of the data

loans.describe()
```

Out[108]:

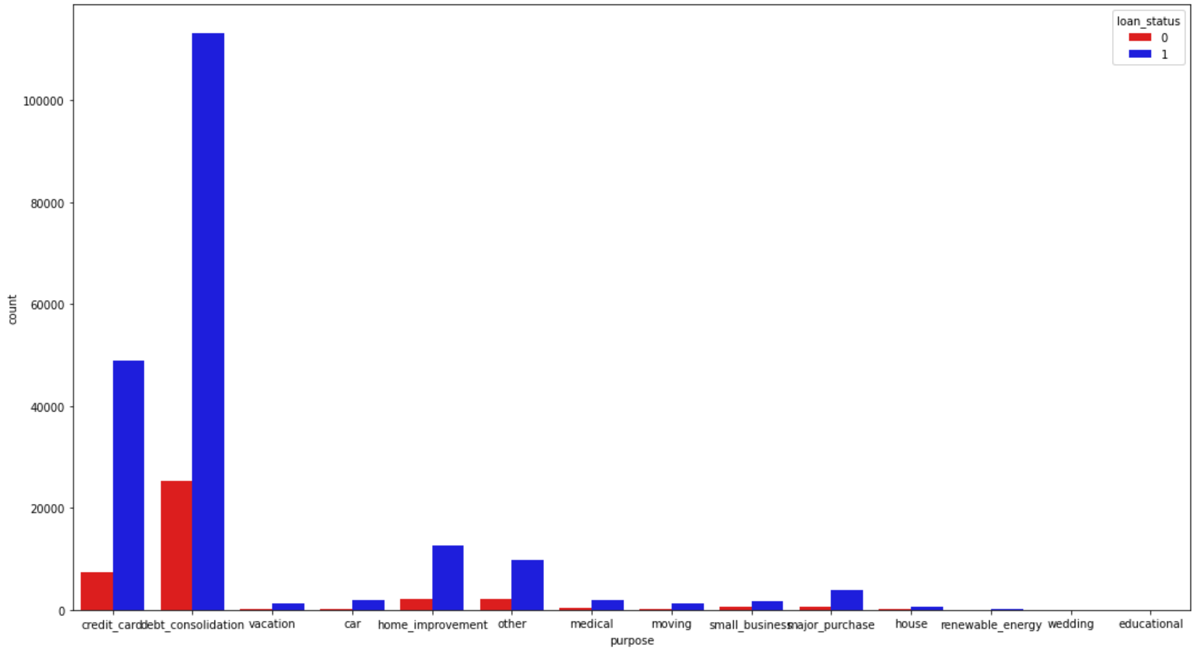
	total_acc	pub_rec	revol_util	int_rate	dti	mort_ac
count	236840.000000	236840.000000	236840.000000	236840.000000	236840.000000	236840.00000
mean	25.573391	0.239351	52.846637	12.603131	18.534255	1.73330
std	12.196261	0.673020	24.012396	4.481979	9.214346	2.04463
min	2.000000	0.000000	0.000000	5.320000	0.000000	0.00000
25%	17.000000	0.000000	35.000000	9.170000	12.050000	0.00000
50%	24.000000	0.000000	53.000000	12.290000	17.890000	1.00000
75%	32.000000	0.000000	71.200000	15.310000	24.520000	3.00000
max	169.000000	86.000000	182.800000	30.990000	999.000000	47.00000

How many loans were paid in full, based on loan pupose?

In [109]:
```
plt.figure(figsize= (18, 10))
sns.countplot(x = loans['purpose'],

              hue = df['loan_status'],
              palette = ['red', 'blue'])
```

Out[109]: <Axes: xlabel='purpose', ylabel='count'>

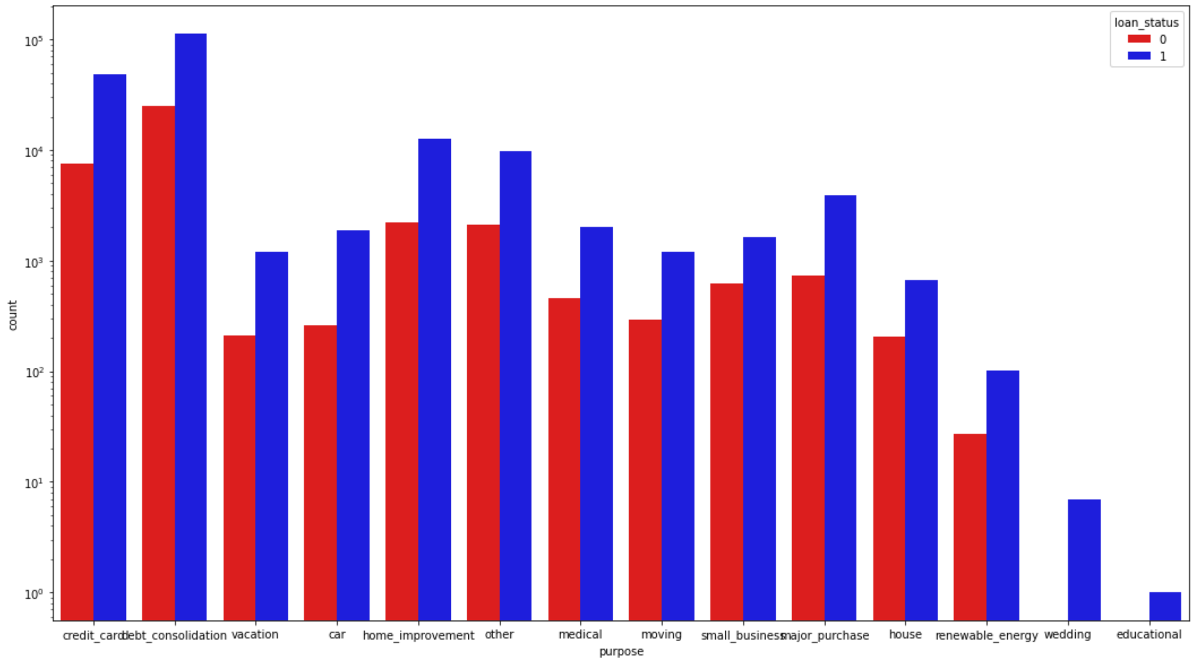


In [110]:
```
# RESCALE to show the counts of less dominant "loan purpose" like education

plt.figure(figsize= (18, 10))
sns.countplot(x = loans['purpose'],
              hue = df['loan_status'],

              palette = ['red', 'blue'])

# to help with the scaling (so all data/bars/plots can show):
plt.yscale('log')  # Apply log scale
```



Insights:

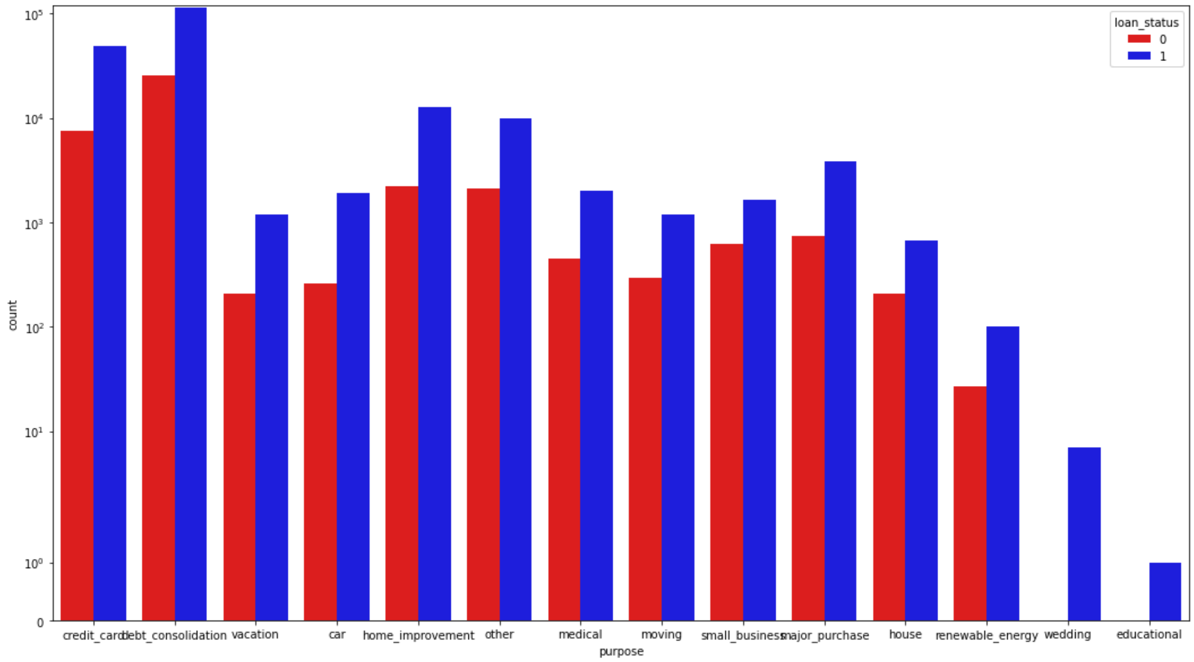
- Loans that are Fully paid = 0, and Not fully paid = 1
- Between 2014 - 2016, majority of borrowers used the money for _debt_consolidation_ and *credit cards*
- Education had the least number of loans collected
- No loan under *Education* and *Wedding* was paid in full with the latter having more debt

In [111]:
```
# RESCALE to show the counts of less dominant "loan purpose" like education

plt.figure(figsize= (18, 10))
sns.countplot(x = loans['purpose'],
              hue = df['loan_status'],

              palette = ['red', 'blue'])

# to help with the scaling (so all data/bars/plots can show):
plt.yscale('symlog')  # Apply log scale
```



Deeper Dive in to Education & Wedding

In [112]:
```
# filter the data by 'purpose'
# to just education and wedding

loans[ (loans['purpose'] == 'educational') | (loans['purpose'] == 'wedding')
].sort_values(by= 'int_rate')
```

Out[112]:

	total_acc	pub_rec	revol_util	int_rate	dti	purpose	mort_acc	loan_amnt	installmer
89151	56.0	1.0	42.8	9.99	8.11	wedding	0.0	3600.0	116.1
93948	77.0	0.0	75.2	11.53	19.62	educational	0.0	2200.0	72.5
40915	23.0	0.0	33.8	12.49	24.16	wedding	0.0	6000.0	200.7
52727	20.0	0.0	97.8	14.99	11.80	wedding	0.0	14000.0	485.2
4969	8.0	0.0	60.7	18.92	1.74	wedding	0.0	5500.0	201.3
14329	49.0	5.0	28.1	18.92	10.91	wedding	3.0	5000.0	183.0
39738	21.0	0.0	75.6	25.89	30.42	wedding	1.0	14950.0	601.4
96135	14.0	0.0	8.1	25.99	8.33	wedding	0.0	23100.0	691.4

Insights:

- There are more borrowers for wedding than for education (see 'purpose' column)
- Interest rate for wedding borrowers went as high as ~26% and education was less than half of that

What is the average interest rate for each *Purpose* ?

In [113]:
```
loans['int_rate'].groupby(by = loans['purpose']).mean().sort_values()
```

Out[113]:
```
purpose
credit_card           10.976304
educational           11.530000
car                   11.888936
major_purchase        12.367448
home_improvement      12.512215
debt_consolidation    12.983961
vacation              13.880177
medical               14.145555
other                 14.233732
moving                15.367108
renewable_energy      15.905938
small_business        16.701099
house                 17.159396
wedding               18.170000
Name: int_rate, dtype: float64
```

Insights:

- On average, Weddings had more interest-rate than any other category. Housing and small business followed
- Credit card had the least amount of interest-rate among all categories

Is there a Correlation between FICO score and Interest Rate?

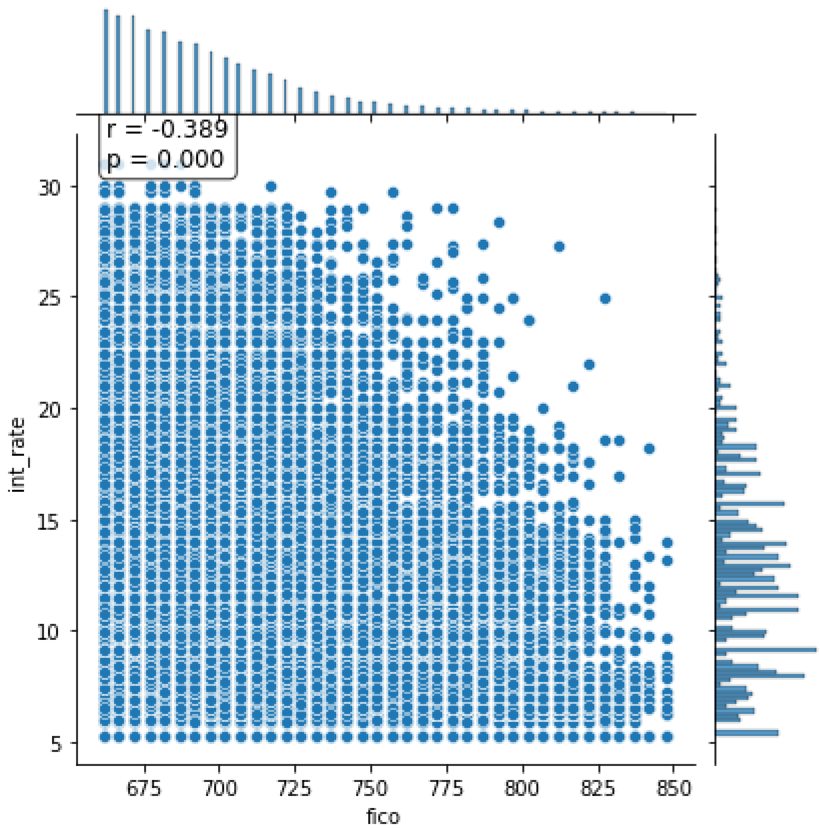
In [114]:
```
from scipy.stats import pearsonr
```

In [115]:
```python
g = sns.jointplot(data = loans,
                  x = 'fico',
                  y = 'int_rate')

# Calculate the correlation coefficient
r, p_value = pearsonr(loans['fico'], loans['int_rate'])

# Add the calculated correlation text to the plot
g.ax_joint.text(0.05, 0.95,
                f'r = {r:.3f}\np = {p_value:.3f}',
                transform = g.ax_joint.transAxes,
                fontsize = 12,
                bbox = dict(boxstyle = 'round',
                            facecolor = 'white',
                            alpha = 0.8))
```

Out[115]:
```
Text(0.05, 0.95, 'r = -0.389\np = 0.000')
```



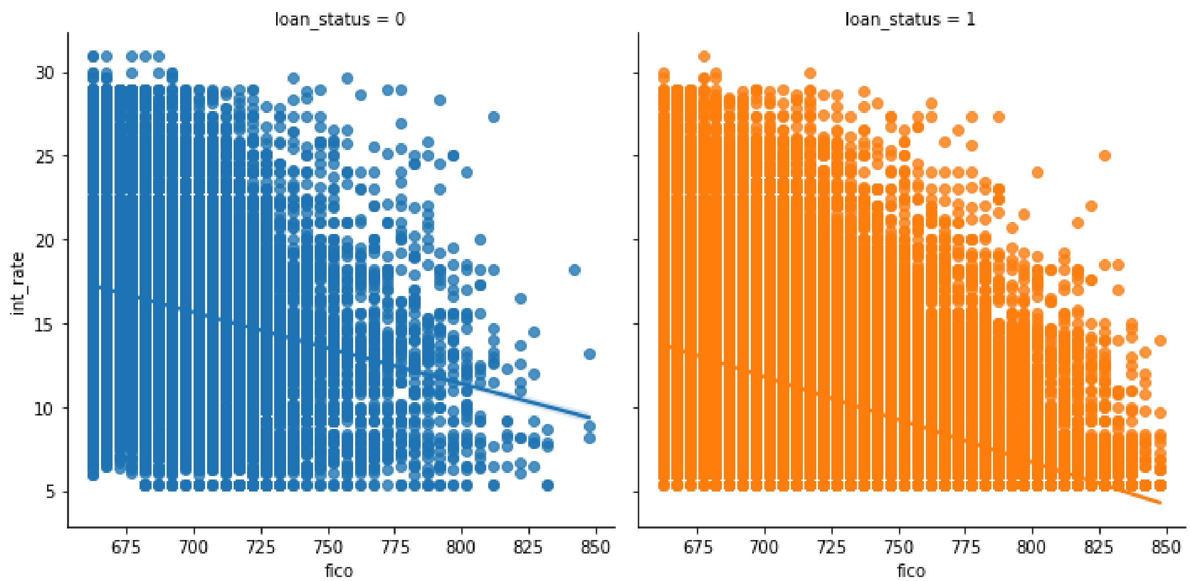
Insights:

- There is a weak negative correlation between FICO score and Interest Rate
- A low interest rate is not a strong indicator of high FICO score; and vice versa

FICO vs. Interest Rate: How does the trend differ in Loan Status?

In [116]:
```
sns.lmplot(data = loans,
           x = 'fico',
           y = 'int_rate',
           col = 'loan_status',
           hue = 'loan_status')
```

Out[116]: <seaborn.axisgrid.FacetGrid at 0x207078db8b0>



 # Get the correlation coefficient for each plot

In [117]:
```
# Fully paid loans: when loan_status is zero

loan_zero = loans[loans['loan_status'] == 0]
r_loan_zero, _ = pearsonr(loan_zero['fico'], loan_zero['int_rate'])

print("Fully Paid Loans (loan_status = 0), correlation coefficient is: ", roun
d(r_loan_zero, 3))
```

```
Fully Paid Loans (loan_status = 0), correlation coefficient is:  -0.225
```

In [118]:
```
# Not fully paid loans: when loan_status is one

loan_one = loans[loans['loan_status'] == 1]
r_loan_one, _ = pearsonr(loan_one['fico'], loan_one['int_rate'])

print("Not Fully Paid Loans (loan_status = 1), correlation coefficient is: ",
round(r_loan_one, 3))
```

```
Not Fully Paid Loans (loan_status = 1), correlation coefficient is:  -0.395
```

Insights

- For *Not Fully Paid Loans* , high FICO score scores minimally contributes to lowering the interest rate .
    - Similarly, a high interest rate does not necessarily predict that FICO score will be low
- There is NO connection between FICO score and interest rate for *Fully Paid Loans*

Data Preparation

Categorical Features

- Observe that the **purpose** column is "categorical"
- This implies, there is need for transformation (to numerical): using dummy variables -this way, the library *sklearn* will be able to understand them
- We do this using the function: pd.get_dummies( )
- This function, "drops" the **purpose** column and then creates a unique column for each category

In [119]:

```
## Observe the "purpose" column

loans['purpose'].value_counts()
```

Out[119]:

```
purpose
debt_consolidation    138368
credit_card            56322
home_improvement       14823
other                  11922
major_purchase          4616
medical                 2459
small_business          2274
car                     2152
moving                  1480
vacation                1410
house                    878
renewable_energy         128
wedding                    7
educational                1
Name: count, dtype: int64
```

```
In [120]: # create a new dataset with this new dummy variables

loans_final_df = pd.get_dummies(data = loans,
                                columns = ['purpose'],    # ensure this is inpu
tted as a list # see documentation
                                drop_first = True)

# since educational and wedding (Purpose) are only 8 in total, let's drop it
loans_final_df = loans_final_df.drop(columns = ['purpose_educational', 'purpos
e_wedding'])

# view this update
loans_final_df.head()
```

Out[120]:

	total_acc	pub_rec	revol_util	int_rate	dti	mort_acc	loan_amnt	installment	pub_rec_bank
0	18.0	0.0	86.8	16.99	15.16	1.0	17775.0	441.66	
1	26.0	0.0	103.5	15.61	16.74	4.0	29175.0	703.45	
2	47.0	0.0	11.4	7.90	20.34	1.0	6000.0	187.75	
3	26.0	0.0	56.2	16.99	23.15	7.0	15600.0	387.62	
4	15.0	1.0	67.1	14.98	17.88	1.0	10000.0	346.56	

5 rows × 27 columns

Model Training

```
In [121]: from sklearn.model_selection import train_test_split

X = loans_final_df.drop(['loan_status'], axis = 1)
y = loans_final_df['loan_status']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rando
m_state=42)
```

```
In [122]: # Create Instance of Decision classifier
from sklearn.ensemble import RandomForestClassifier

rndforest_100 = RandomForestClassifier(n_estimators= 100)
```

```
In [123]: # Fit data

rndforest_100.fit(X = X_train,
                  y = y_train)
```

```
Out[123]: ▾ RandomForestClassifier
RandomForestClassifier()
```

Prediction

In [124]:
```
pred_initial = rndforest_100.predict(X_test)
```

In [125]:
```
# create classification report from the predictions

from sklearn.metrics import classification_report, confusion_matrix, accuracy_
score


print(

    classification_report(y_true = y_test,
                          y_pred = pred_initial)

)

print(

    confusion_matrix(y_true = y_test,
                     y_pred = pred_initial)

)
```

```
              precision    recall  f1-score   support

           0       0.60      0.21      0.31     11938
           1       0.86      0.97      0.91     59114

    accuracy                           0.84     71052
   macro avg       0.73      0.59      0.61     71052
weighted avg       0.82      0.84      0.81     71052

[[ 2492  9446]
 [ 1649 57465]]
```

Key Insight:

- Performance of the model good with overall $accuracy = 84\%$
- Only < 5% of the data was misclassified. i.e.:
    - from 236,840 borrowers, the loan (payment) status of 11,091 were wrongly classified
- It is important to point out $recall = 97\%$, which tells us that:

```
* Of all the instances of **Not Fully Paid Loans**, 97% were correctly identifi
ed
* This can be a good thing as our model is very effective in (or sensitive to)
catching bad borrowers
```

- Although, the data is highly imbalance (see 'support'), hence the usefulness of *f1-score* $= 91\%$ striking a good balance
- Moving forward, let's try to tune our hyperparameter $n\_estimators$, in attempt to find the optimal number of estimators
- Perhaps this will improve the model's performance

In [126]:
```
# Test for higher number of estimators
rndforest_200 = RandomForestClassifier(n_estimators= 200)
rndforest_300 = RandomForestClassifier(n_estimators= 300)


# Fit data
rndforest_200.fit(X = X_train,
                  y = y_train)
rndforest_300.fit(X = X_train,
                  y = y_train)


# Predict
pred_200 = rndforest_200.predict(X_test)
pred_300 = rndforest_300.predict(X_test)
```

In [127]:
```
# Model Performance
print("Number of Estimators = 200: ")
print(classification_report(y_true = y_test,
                            y_pred = pred_200))

print(confusion_matrix(y_true = y_test,
                       y_pred = pred_200))


print(" \n \n Number of Estimators = 300: ")
print(classification_report(y_true = y_test,
                            y_pred = pred_300))

print(confusion_matrix(y_true = y_test,
                       y_pred = pred_300))
```

```
Number of Estimators = 200:
              precision    recall  f1-score   support

           0       0.62      0.20      0.31     11938
           1       0.86      0.97      0.91     59114

    accuracy                           0.84     71052
   macro avg       0.74      0.59      0.61     71052
weighted avg       0.82      0.84      0.81     71052

[[ 2434  9504]
 [ 1519 57595]]


 Number of Estimators = 300:
              precision    recall  f1-score   support

           0       0.62      0.20      0.30     11938
           1       0.86      0.97      0.91     59114

    accuracy                           0.84     71052
   macro avg       0.74      0.59      0.61     71052
weighted avg       0.82      0.84      0.81     71052

[[ 2390  9548]
 [ 1495 57619]]
```

Key Insight

- Performance of the model did not change significantly with 200 and 300 iterations, hence we
- finalize using the model with **100 estimators** having a good overall $accuracy = 84$

Apply this model on a fresh dataset

In [ ]:
```
# Get a new dataset and use it on the model
```

In [128]:
```
new_df = pd.read_csv('test_lending_club.csv')

new_df.head()
```

Out[128]:

	issue_d	sub_grade	term	home_ownership	fico_range_low	total_acc	pub_rec	revol_util
0	2016-07-01	A4	36 months	MORTGAGE	830.0	13.0	0.0	12.0
1	2016-07-01	B5	36 months	RENT	660.0	25.0	0.0	59.4
2	2016-07-01	D2	36 months	MORTGAGE	660.0	17.0	1.0	40.9
3	2016-07-01	A1	36 months	RENT	740.0	36.0	0.0	27.7
4	2016-07-01	C4	60 months	MORTGAGE	680.0	14.0	0.0	44.3

5 rows × 27 columns

NEW test Data

July 2016 to December 2018

In [129]:
```
len(new_df)
```

Out[129]: 95019

In [130]:
```
# Clean the dataset

new_loans = cleaning_data(new_df)
```

```
 Checking for NaNs:

 total_acc                 0
pub_rec                   0
revol_util                0
int_rate                  0
dti                       0
purpose                   0
mort_acc                  0
loan_amnt                 0
installment               0
pub_rec_bankruptcies      0
revol_bal                 0
open_acc                  0
emp_length                0
loan_status               0
time_to_earliest_cr_line  0
log_annual_inc            0
fico                      0
dtype: int64

C:\Newfolder\lib\site-packages\pandas\core\arraylike.py:396: RuntimeWarning:
divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

In [131]:
```
# create a new dataset with this new dummy variables

new_loans_df = pd.get_dummies(data = new_loans,
                              columns = ['purpose'],   # ensure this is inputt
ed as a list # see documentation
                              drop_first = True)

# this new data set does not have "Purpose: educational - and - wedding"

# view this update
new_loans_df.head()
```

Out[131]:

	total_acc	pub_rec	revol_util	int_rate	dti	mort_acc	loan_amnt	installment	pub_rec_bank
0	13.0	0.0	12.0	7.99	7.25	9.0	15000.0	469.98	
1	25.0	0.0	59.4	11.49	34.49	0.0	5000.0	164.86	
2	17.0	1.0	40.9	17.99	13.20	3.0	8000.0	289.18	
3	36.0	0.0	27.7	5.32	12.90	0.0	16000.0	481.84	
4	14.0	0.0	44.3	14.49	13.89	1.0	14000.0	329.33	

5 rows × 27 columns

In [132]:
```
# get predictors & drop response

X_new = new_loans_df.drop(['loan_status'], axis = 1)
```

In [133]:
```
# Use the already built model to predict response

prediction_new_loans = rndforest_100.predict(X_new)
```

In [134]:
```
# create a new column for the predicted response

new_loans['NEW loan_status'] = prediction_new_loans
```

In [135]:
```
# view the outcome

new_loans.head()
```

Out[135]:

	total_acc	pub_rec	revol_util	int_rate	dti	purpose	mort_acc	loan_amnt	installm
0	13.0	0.0	12.0	7.99	7.25	major_purchase	9.0	15000.0	469
1	25.0	0.0	59.4	11.49	34.49	other	0.0	5000.0	164
2	17.0	1.0	40.9	17.99	13.20	debt_consolidation	3.0	8000.0	289
3	36.0	0.0	27.7	5.32	12.90	debt_consolidation	0.0	16000.0	481
4	14.0	0.0	44.3	14.49	13.89	debt_consolidation	1.0	14000.0	329

Check to see the model performance in predicting the response

- original response variable (came in with with data), **y_true** = new_loans['loan_status']
- new prediction, **y_pred** = prediction_new_loans

In [ ]:
```

```

In [143]:
```
# Manually: build a simple function to calculate the *accuracy, *recall *preci
sion and *f1-score

def classification_metrics(y_true, y_pred):

    """
    tp - true positive
    fp - false positive
    fn - false negative
    tn - true negative

    Reference Wikipedia explanation on "Confusion Matrix" ---https://en.wikipe
dia.org/wiki/Confusion_matrix
    """
    # keep counts
    tp = fp = fn = tn = 0

    # on both y_true and y_pred, run through every element and make relevant c
omparisms
    for i in range(len(y_true)):
        if y_true[i] == 1 and y_pred[i] == 1:
            tp += 1    # update true positive

        elif y_true[i] == 0 and y_pred[i] == 1:
            fp += 1    # update false positive

        elif y_true[i] == 1 and y_pred[i] == 0:
            fn += 1    # update false negative

        elif y_true[i] == 0 and y_pred[i] == 0:
            tn += 1    # update true negative

    # implementing formulas
    accuracy = (tp + tn) / len(y_true)
    recall = tp / (tp + fn) if (tp + fn) > 0 else 0
    precision = tp / (tp + fp) if (tp + fp) > 0 else 0
    f1 = 2 * precision * recall / (precision + recall) if (precision + recall)
> 0 else 0

    return accuracy, recall, precision, f1
```

In [144]:
```
acc, rec, pre, f1 = classification_metrics(y_true = np.array(new_loans['loan_s
tatus']) ,
                              y_pred = np.array(prediction_new_loans))

print('Accuracy:', round(acc, 3))
print('Recall: ', round(rec, 3))
print('Precision: ', round(pre, 3))
print('F1-score: ', round(f1, 3))
```

```
Accuracy: 0.866
Recall:  0.97
Precision:  0.883
F1-score:  0.924
```

Key Insights:

- In our new data, overall, the model performed better than in training
    - **87% accuracy** vs. training model of 84%
    - 97% recall (same as in training)
    - **improved precision** of 88% vs. 86% in training
    - f1-score of 92%, a better balance than in training (91%)
- Note the above results takes the positive class as 1 (i.e. Loans that are not fully paid)
- Again, using 100 estimators for our hyperparameter

In [ ]:

```

```