Case Study

In [1]:

```
# Manipulation
import pandas as pd
import numpy as np

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
```

Part 1: Data Exploration and Evaluation

1.1 Load and Explore

In [2]:

```
df = pd.read_csv('loan.csv', usecols=['loan_amnt',
                                      'funded_amnt',
                                      'term',
                                      'int_rate',
                                      'grade',
                                      'annual_inc',
                                      'issue_d',
                                      'dti',
                                      'revol_bal',
                                      'total_pymnt',
                                      'loan_status'])
```

In [3]:

```
df.shape # get shape
```

Out[3]:

```
(887379, 11)
```

In [4]:

```
df.head(10) # get first 10 rows
```

Out[4]:

	loan_amnt	funded_amnt	term	int_rate	grade	annual_inc	issue_d	loan_status	d
0	5000.0	5000.0	36 months	10.65	B	24000.0	Dec-2011	Fully Paid	27.6
1	2500.0	2500.0	60 months	15.27	C	30000.0	Dec-2011	Charged Off	1.0
2	2400.0	2400.0	36 months	15.96	C	12252.0	Dec-2011	Fully Paid	8.7
3	10000.0	10000.0	36 months	13.49	C	49200.0	Dec-2011	Fully Paid	20.0
4	3000.0	3000.0	60 months	12.69	B	80000.0	Dec-2011	Current	17.9
5	5000.0	5000.0	36 months	7.90	A	36000.0	Dec-2011	Fully Paid	11.2
6	7000.0	7000.0	60 months	15.96	C	47004.0	Dec-2011	Current	23.5
7	3000.0	3000.0	36 months	18.64	E	48000.0	Dec-2011	Fully Paid	5.3
8	5600.0	5600.0	60 months	21.28	F	40000.0	Dec-2011	Charged Off	5.5
9	5375.0	5375.0	60 months	12.69	B	15000.0	Dec-2011	Charged Off	18.0

In [5]:

```
df.sample(10) # get 10 random rows
```

Out[5]:

	loan_amnt	funded_amnt	term	int_rate	grade	annual_inc	issue_d	loan_status
519837	12000.0	12000.0	36 months	9.17	B	40000.0	Nov-2015	Current
380439	21000.0	21000.0	36 months	8.39	A	80000.0	May-2014	Current
883813	15000.0	15000.0	36 months	15.59	D	55000.0	Jan-2015	Current
541289	18325.0	18325.0	36 months	13.67	C	53173.2	Nov-2015	Current
252175	7700.0	7700.0	36 months	13.66	C	41600.0	Nov-2014	Current
262792	30000.0	30000.0	60 months	12.99	C	71300.0	Nov-2014	Current
808013	28000.0	28000.0	36 months	7.89	A	144000.0	Mar-2015	Current
490597	10000.0	10000.0	60 months	18.49	E	68000.0	Dec-2015	Current
288999	31075.0	31075.0	60 months	24.50	F	82000.0	Oct-2014	Current
727183	20000.0	20000.0	60 months	13.99	C	70000.0	Jun-2015	In Grace Period

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 887379 entries, 0 to 887378
Data columns (total 11 columns):
loan_amnt      887379 non-null float64
funded_amnt    887379 non-null float64
term           887379 non-null object
int_rate       887379 non-null float64
grade          887379 non-null object
annual_inc     887375 non-null float64
issue_d        887379 non-null object
loan_status    887379 non-null object
dti            887379 non-null float64
revol_bal      887379 non-null float64
total_pymnt    887379 non-null float64
dtypes: float64(7), object(4)
memory usage: 74.5+ MB
```

- **There is a date variable: I will convert it to the correct type**

In [7]:

```
df['issue_d'] = pd.to_datetime(df['issue_d'])
```

In [8]:

```
# Check
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 887379 entries, 0 to 887378
Data columns (total 11 columns):
loan_amnt       887379 non-null float64
funded_amnt     887379 non-null float64
term            887379 non-null object
int_rate        887379 non-null float64
grade           887379 non-null object
annual_inc      887375 non-null float64
issue_d         887379 non-null datetime64[ns]
loan_status     887379 non-null object
dti             887379 non-null float64
revol_bal       887379 non-null float64
total_pymnt     887379 non-null float64
dtypes: datetime64[ns](1), float64(7), object(3)
memory usage: 74.5+ MB
```

1.2 Look at different levels of aggregations

In [9]:

```
means = df.groupby(['term', 'grade', 'loan_status', df['issue_d'].dt.year]).me
an()
```

In [10]:

```
means.head()
```

Out[10]:

				loan_amnt	funded_amnt	int_rate	annual_inc	
term	**grade**	**loan_status**	**issue_d**					
36 months	**A**	**Charged Off**	**2007**	2000.000000	2000.000000	7.750000	24000.000000	
			2008	8211.764706	7357.352941	8.345294	53167.764706	
			2009	7457.594937	7457.594937	8.916203	55953.139241	1
			2010	8045.045045	7545.945946	7.205856	54519.585586	1
			2011	7599.719888	7584.453782	7.382689	51672.414482	1

In [11]:

```
means.tail()
```

Out[11]:

				loan_amnt	funded_amnt	int_rate	annual_in
term	grade	loan_status	issue_d				
60 months	G	Late (31-120 days)	2011	14600.000000	14600.000000	21.590000	185000.00000
			2012	23000.000000	23000.000000	24.795000	67500.00000
			2013	24542.592593	24542.592593	25.557407	97346.22222
			2014	21221.785714	21221.785714	25.882000	77361.82000
			2015	21901.495726	21901.495726	26.670940	74822.00136

1.3 Check for Missing values and or repeated rows

In [12]:

```
df[df.duplicated()==True]
```

Out[12]:

loan_amnt	funded_amnt	term	int_rate	grade	annual_inc	issue_d	loan_status	dti	rev

Good news: There are no duplicated rows!

In [13]:

```
df.isnull().sum()
```

Out[13]:

```
loan_amnt       0
funded_amnt     0
term            0
int_rate        0
grade           0
annual_inc      4
issue_d         0
loan_status     0
dti             0
revol_bal       0
total_pymnt     0
dtype: int64
```

Only one column, annual income has missing values that too only 4 values.

- Now let's explore those missing values:

In [14]:

```
df[df.isnull().any(axis=1)]
```

Out[14]:

	loan_amnt	funded_amnt	term	int_rate	grade	annual_inc	issue_d	loan_status
42449	5000.0	5000.0	36 months	7.43	A	NaN	2007-08-01	Does not meet the credit policy. Status:Fully ...
42450	7000.0	7000.0	36 months	7.75	A	NaN	2007-08-01	Does not meet the credit policy. Status:Fully ...
42480	6700.0	6700.0	36 months	7.75	A	NaN	2007-07-01	Does not meet the credit policy. Status:Fully ...
42533	6500.0	6500.0	36 months	8.38	A	NaN	2007-06-01	Does not meet the credit policy. Status:Fully ...

- Compare with any random 4 rows to see the difference

In [15]:

```
df.sample(4) # get 4 random rows
```

Out[15]:

	loan_amnt	funded_amnt	term	int_rate	grade	annual_inc	issue_d	loan_status
423496	17000.0	17000.0	36 months	13.65	C	90000.0	2014-03-01	Current
704441	2200.0	2200.0	36 months	12.29	C	63000.0	2015-07-01	Current
431981	7000.0	7000.0	36 months	10.99	B	99000.0	2014-03-01	Fully Paid
536790	14000.0	14000.0	36 months	7.26	A	57000.0	2015-11-01	Current

- Loan status looks *interesting* here for the **rows with missing annual income...**

In [16]:

```
df[df.isnull().any(axis=1)]['loan_status']
```

Out[16]:

```
42449    Does not meet the credit policy. Status:Fully ...
42450    Does not meet the credit policy. Status:Fully ...
42480    Does not meet the credit policy. Status:Fully ...
42533    Does not meet the credit policy. Status:Fully ...
Name: loan_status, dtype: object
```

In [17]:

```
df['loan_status'].unique()
```

Out[17]:

```
array(['Fully Paid', 'Charged Off', 'Current', 'Default',
       'Late (31-120 days)', 'In Grace Period', 'Late (16-30 days)
',
       'Does not meet the credit policy. Status:Fully Paid',
       'Does not meet the credit policy. Status:Charged Off', 'Iss
ued'],
      dtype=object)
```

My evaluation

- Since these are less than **0.001%** of the rows, we can just drop them
- Imputing them doesn't make sense here since that will leak data

In [18]:

```
df_no_na = df.dropna(axis = 0)
```

In [19]:

```
df_no_na.shape # we have dropped those 4 rows
```

Out[19]:

```
(887375, 11)
```

1.3 Describe the distribution of features

1.3.1 Continuous features

In [20]:

```
df_cont = df_no_na.select_dtypes(include = ["float64"])
```

In [21]:

```
df_cont.sample(5)
```

Out[21]:

	loan_amnt	funded_amnt	int_rate	annual_inc	dti	revol_bal	total_pymnt
49483	5000.0	5000.0	6.62	120000.0	9.79	11359.0	5222.92
838711	23925.0	23925.0	21.67	75000.0	36.53	48272.0	6591.90
702975	3500.0	3500.0	11.53	125000.0	29.49	7782.0	3698.15
333877	10000.0	10000.0	8.39	80000.0	12.69	5337.0	5357.89
471437	35000.0	35000.0	9.17	93000.0	29.06	24962.0	0.00

In [22]:

```
# Let's look at the summary statistics first
df_cont.describe()
```

Out[22]:

	loan_amnt	funded_amnt	int_rate	annual_inc	dti	rev
count	887375.000000	887375.000000	887375.000000	8.873750e+05	887375.000000	8.87375
mean	14755.302719	14741.915678	13.246764	7.502759e+04	18.157113	1.69208
std	8435.455353	8429.897443	4.381862	6.469830e+04	17.190629	2.24268
min	500.000000	500.000000	5.320000	0.000000e+00	0.000000	0.00000
25%	8000.000000	8000.000000	9.990000	4.500000e+04	11.910000	6.44350
50%	13000.000000	13000.000000	12.990000	6.500000e+04	17.650000	1.18750
75%	20000.000000	20000.000000	16.200000	9.000000e+04	23.950000	2.08290
max	35000.000000	35000.000000	28.990000	9.500000e+06	9999.000000	2.90483

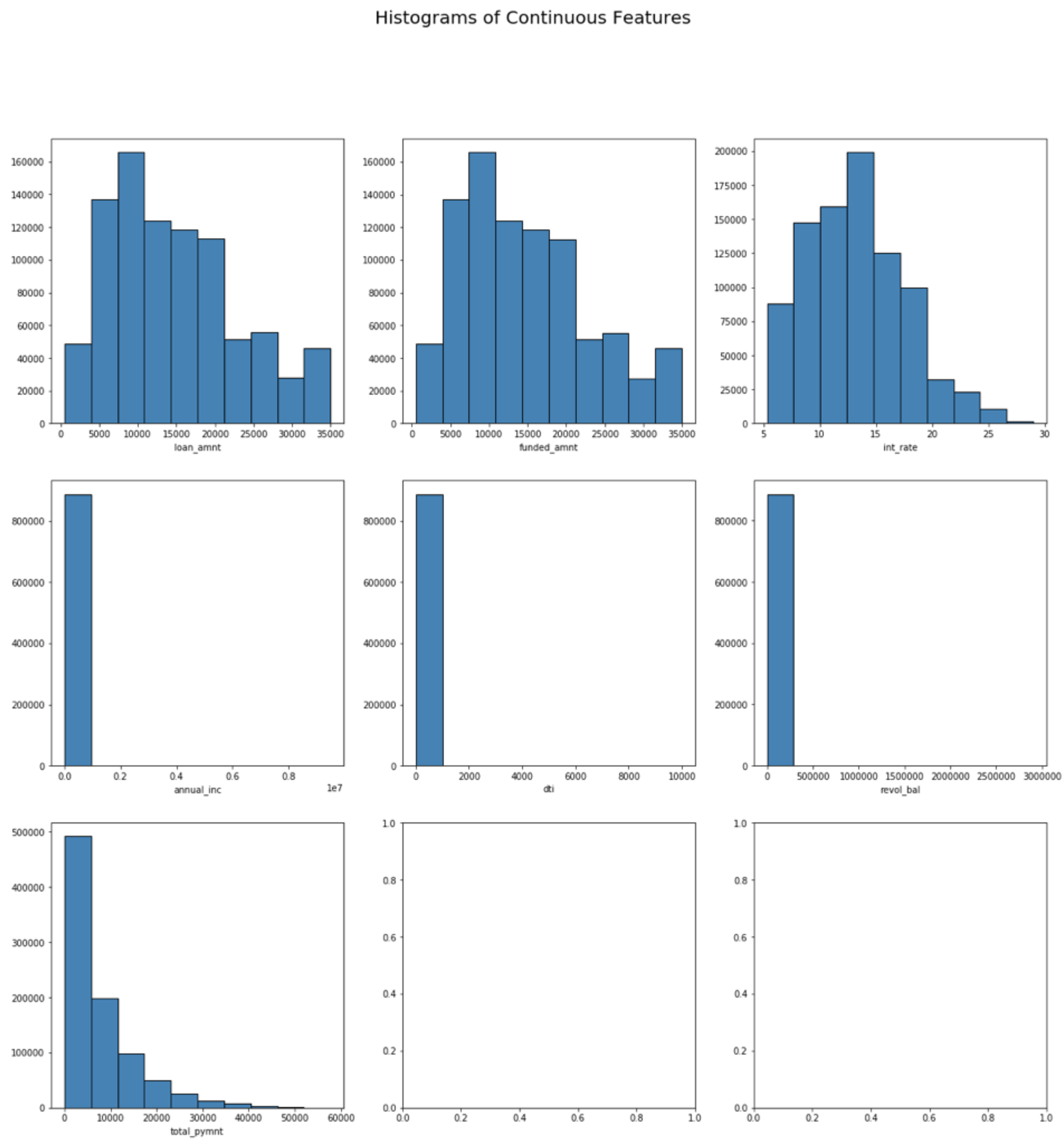
In [23]:

```
# Plot distributions of continuous features

fig, ax = plt.subplots(nrows = 3, ncols = 3, figsize = (20, 20))

for i, ax in enumerate(ax.ravel()):
    if i > 6:
        continue
    ax.hist(df_cont.iloc[:, i], color='steelblue', edgecolor='black', bins=10,
linewidth=1.0)
    ax.set_xlabel(df_cont.columns.values[i], color='k')

fig.suptitle('Histograms of Continuous Features', fontsize=20)
plt.show()
```



Comment: The distributions of the features are defined below

- Loan amount, Funded amount and Interest rate seem to have a slight poitive skew; however, we can approximate them to be normally distributed
- Total payment: Has an exponential distribution, higher values have exponentially lower counts
- Annual income, DTI and Revolv_bal also have exponential distributions, with very high values of lambda, i.e. the decay is much faster

1.3.2 Categorical features

- **Let's look at the unique values of the categorical columns**

In [24]:

```
# separate categorical features
df_cat = df_no_na.select_dtypes(include = ["object"])
```

In [25]:

```
df_cat.sample(5)
```

Out[25]:

	term	grade	loan_status
687465	36 months	D	Current
699920	60 months	G	Current
770543	36 months	B	Current
830349	60 months	B	Current
211313	36 months	A	Fully Paid

In [26]:

```
df_cat['term'].unique()
```

Out[26]:

```
array([' 36 months', ' 60 months'], dtype=object)
```

In [27]:

```
df_cat['grade'].unique()
```

Out[27]:

```
array(['B', 'C', 'A', 'E', 'F', 'D', 'G'], dtype=object)
```

In [28]:

```
df_cat['loan_status'].unique()
```

Out[28]:

```
array(['Fully Paid', 'Charged Off', 'Current', 'Default',
       'Late (31-120 days)', 'In Grace Period', 'Late (16-30 days)
',
       'Does not meet the credit policy. Status:Fully Paid',
       'Does not meet the credit policy. Status:Charged Off', 'Iss
ued'],
      dtype=object)
```

- **Summary statistics**

In [29]:

```
# Value Counts
for col in df_cat:
    print("Column Name: ", col )
    print(" ")
    print(df_cat[col].value_counts())
    print(" ")
```

```
Column Name:  term

 36 months    621121
 60 months    266254
Name: term, dtype: int64

Column Name:  grade

B    254535
C    245860
A    148198
D    139542
E     70705
F     23046
G      5489
Name: grade, dtype: int64

Column Name:  loan_status

Current                                                601779
Fully Paid                                             207723
Charged Off                                             45248
Late (31-120 days)                                      11591
Issued                                                   8460
In Grace Period                                          6253
Late (16-30 days)                                        2357
Does not meet the credit policy. Status:Fully Paid       1984
Default                                                  1219
Does not meet the credit policy. Status:Charged Off       761
Name: loan_status, dtype: int64
```

- **Visualisations**

In [30]:

```
# Plot distributions of continuous features

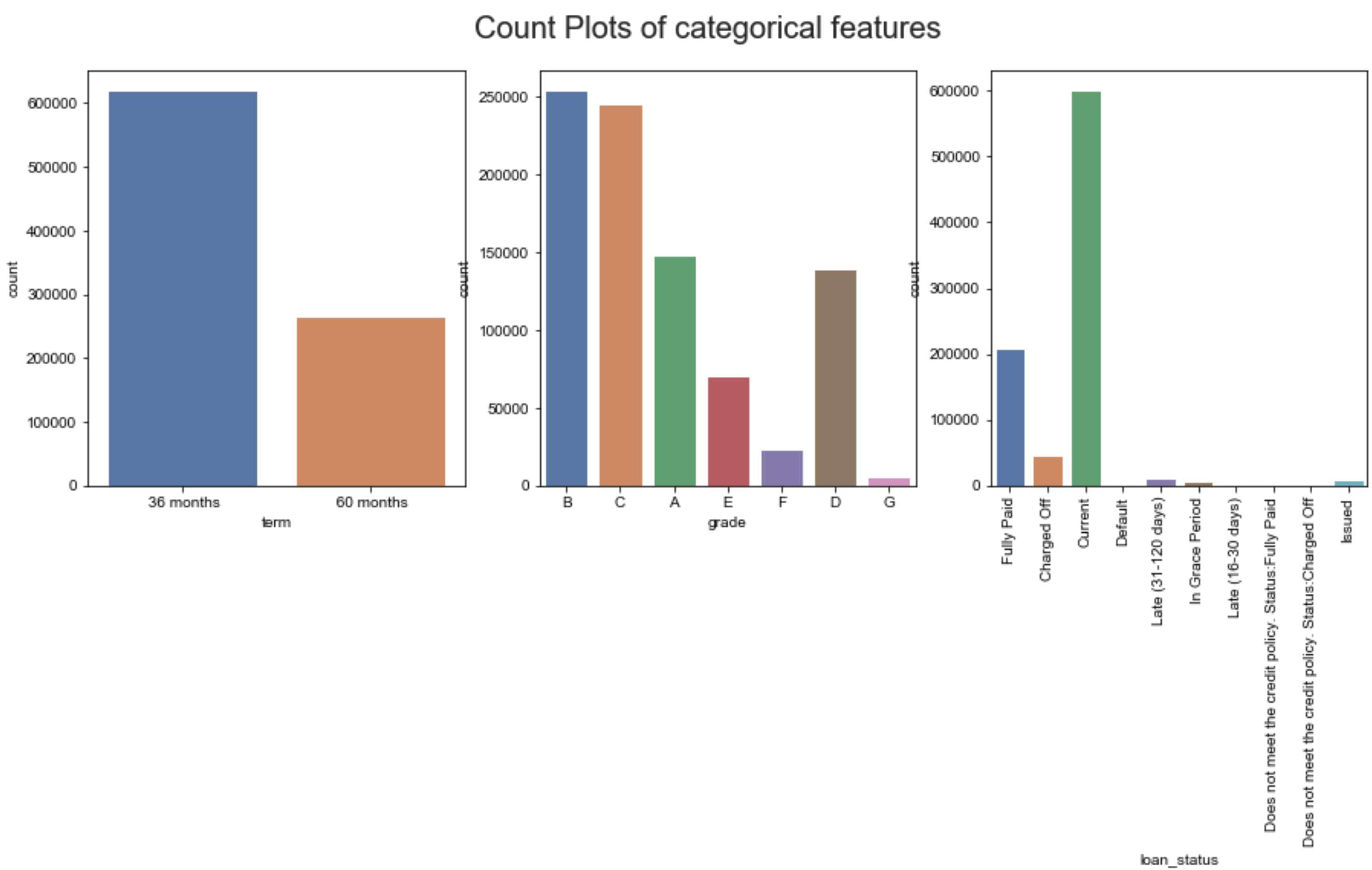
fig, ax = plt.subplots(nrows = 1, ncols = 3, figsize = (15, 5))
sns.set(style="darkgrid")


sns.countplot(x="term", data = df_cat, ax=ax[0])
sns.countplot(x="grade", data = df_cat, ax=ax[1])

# Set tick labels for loan status separartely since they don't fit
labels = df_cat['loan_status'].unique()
ax[2].set_xticklabels(labels = labels, rotation=90)

sns.countplot(x="loan_status", data = df_cat, ax=ax[2])


fig.suptitle('Count Plots of categorical features', fontsize=20)
plt.show()
```



Comment

- We see that most of the loand are 36 month loans
- Grade B and C are the most common grades among the loans
- Similarly, for *loan status*, current is the most common status while the next common category is Fully paid followed by charged off. The rest of the categories are quite insignificant compared to these

- **Check out the date variable**

In [31]:

```
print("Min Date: ", df_no_na['issue_d'].min())
print("Min Date: ", df_no_na['issue_d'].max())
```

```
Min Date:  2007-06-01 00:00:00
Min Date:  2015-12-01 00:00:00
```

Outliers in the dataset

Given the skews in most of our continuous features, there exist sets of outliers; however, there is no point in removing them since I will be using an L2 penalty which reduces their effect on the model.

It is possible to understand outlier behaviour in this dataset using many approaches such as:

- IsolationForest
- OneClassSVM
- Elliptic Envelope

All of these are offered in sklearn and can be used to study these outliers; however, this is not the focus of this case study so will not be covered.

Part 2: Business Analysis

We are interested in evaluating whether the 36 month term loans would make for a good investment. Please investigate the following. Assume a 36 month investment period for each loan, and exclude loans with less than 36 months of data available.

In [32]:

```
# Subet datframe
df_36_only = df_no_na[df_no_na['term'] == ' 36 months']
```

1) What percentage of loans has been fully paid?

In [33]:

```
perc_fully_paid = len(df_36_only[df_36_only['loan_status'] == 'Fully Paid']) / len(df_36_only)
print("Percentage of loans Fully Paid: {:.2f}%".format(perc_fully_paid*100))
```

```
Percentage of loans Fully Paid: 26.98%
```

2) When bucketed by year of origination and grade, which cohort has the highest rate of defaults? Here you may assume that any loan which was not fully paid had “defaulted”.

- **If 'Defaulted' = 1** i.e. anywhere loan not fully paid
- **If 'Fully Paid' = 0**

In [34]:

```
df_36_only['loan_status'] = np.where(df_36_only['loan_status'] == 'Fully Paid'
, 0, 1)
```

```
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/ipykerne
l_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pan
das-docs/stable/indexing.html#indexing-view-versus-copy
  """Entry point for launching an IPython kernel.
```

In [35]:

```
# Check if the above code caused no errors
perc_fully_paid = len(df_36_only[df_36_only['loan_status'] == 0]) / len(df_36_
only)
print("Percentage of loans Fully Paid {:.2f}%".format(perc_fully_paid*100))
```

```
Percentage of loans Fully Paid 26.98%
```

In [36]:

```
# Group by YEAR and grade
grouped = df_36_only.groupby([df_36_only['issue_d'].dt.year, 'grade'])
```

Rate of Default = Default / Total (In group)

In [37]:

```
# Apply function to get Default Rate

cohorts = grouped['loan_status'].agg([('perc_default',
                              lambda x: ((x == 1).sum() / ((x == 0).sum() + (x
== 1).sum())))])
```

As is clear from the Dataframe below, *2007 G* is the cohort with the highest default rate of basically 100%

In [38]:

```
# Sort values
cohorts.sort_values(by = ['perc_default'], ascending = False).head()
```

Out[38]:

issue_d	grade	perc_default
2007	G	1.000000
2008	G	0.976744
2015	A	0.955312
	B	0.948912
	C	0.931936

3) When bucketed by year of origination and grade, what annualized rate of return have these loans generated on average?

- For simplicity, use the following approximation:
    - Annualized rate of return = (total_pymnt / funded_amnt) ^ (1/3) - 1

In [39]:

```
averages = grouped.agg({'funded_amnt': 'mean', 'total_pymnt': 'mean'})
```

In [40]:

```
# define annualized rate of return
averages['Annualized_Rate_of_Returns'] = ((averages['total_pymnt'] / averages[
'funded_amnt'])**(1/3))-1
```

In [41]:

```
averages.head()
```

Out[41]:

issue_d	grade	funded_amnt	total_pymnt	Annualized_Rate_of_Returns
2007	A	4945.945946	5396.874459	0.029511
	B	8184.693878	8323.797551	0.005633
	C	8132.978723	8245.527730	0.004592
	D	7654.040404	7540.993273	-0.004948
	E	7817.750000	7633.371200	-0.007924

Part 3: Modeling

Assumptions:

1. You are given the ability to invest in each loan independently; **i.e. IID Assumption**
2. You invest immediately following loan origination and hold to maturity (36 months); and
3. All loan fields that would be known upon origination are made available to you. **i.e. No missing data**

Discussion

- Class 1 = Default
- Class 0 = No Default

Task: Predict Loan Default

- As a risk-averse investor, I would like to ensure that those loans that I predict to be safe (i.e. will not default) **will actually not default** since I would like to ensure that my investment is safe
- Hence, we cannot afford **False Negatives**
- However, as an investor, I would like to be very sure of those I predict to default since I would not like to loose out on a perfectly good opportunity. Hence, **False Positives** are also costly.
- Hence, we would like to ensure that both false positives and false negatives are minimized
- The choice of metric will depend on the imbalance of the classes, which we know from part 2 is already imbalanced towards the "will default" class.
    - In this case metrics that are robust to class imbalance such as:
        - AUC
        - F1 Score: 2 *(precision* recall) / (precision + recall)

Precision = True / Predicted to be True

- tp / (tp + fp)

Recall = True / Actual Truth

- tp / (tp + fn)

Data preparation for modelling

In [42]:

```
# Libraries for preprocessing
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder

# Modelling
from sklearn.linear_model import LogisticRegression

# Splitting and Cross-validation
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.model_selection import StratifiedKFold

# Metrics
from sklearn.metrics import accuracy_score, roc_auc_score, f1_score
from sklearn.metrics import confusion_matrix, classification_report
```

1. Drop missing data: Already dropped in the first part of this study

2. Separate Features and Target

In [43]:

```
y = df_36_only['loan_status']
X = df_36_only.drop(['loan_status'], axis = 1)
```

In [44]:

```
print("Default% = {:.2f}%".format((len(y[y==1]) / len(y))*100))
```

```
Default% = 73.02%
```

3. Drop columns that clearly don't add any value

In [45]:

```
X.shape
```

Out[45]:

```
(621121, 10)
```

In [46]:

```
X.sample(5)
```

Out[46]:

	loan_amnt	funded_amnt	term	int_rate	grade	annual_inc	issue_d	dti	revo
710884	6000.0	6000.0	36 months	12.69	C	99650.0	2015-06-01	30.96	70!
703362	16000.0	16000.0	36 months	7.89	A	37500.0	2015-07-01	38.50	16!
705666	10000.0	10000.0	36 months	12.69	C	43000.0	2015-07-01	13.90	11:
84676	8000.0	8000.0	36 months	19.20	D	50000.0	2013-10-01	8.45	7!
408645	16000.0	16000.0	36 months	12.49	B	104000.0	2014-04-01	13.44	19:

In [47]:

```
X.drop(['term', 'issue_d'], axis = 1, inplace =True)
```

In [48]:

```
X.sample(5)
```

Out[48]:

	loan_amnt	funded_amnt	int_rate	grade	annual_inc	dti	revol_bal	total_pymı
64084	6000.0	6000.0	8.90	A	60000.0	6.64	8691.0	6763.5100(
226286	30000.0	30000.0	7.62	A	90000.0	0.66	4536.0	33201.8836ε
477501	24000.0	24000.0	6.89	A	120000.0	22.67	38405.0	0.0000(
397187	18000.0	18000.0	8.90	A	64000.0	16.18	20886.0	19391.4700(
312054	24925.0	24925.0	26.06	G	60000.0	33.72	56586.0	31888.3300(

In [49]:

```
X.shape
```

Out[49]:

```
(621121, 8)
```

4. OneHotEncoding Categorical Variables

In [50]:

```
X_one_hot = pd.get_dummies(X)
```

5. Test Train Split: IID assumption

In [51]:

```
X_train, X_test, y_train, y_test = train_test_split(X_one_hot, y, test_size =
0.33)
```

6. Fit Logistic Regression Mode

- *penalty* = *l2* is default, it makes logistic less prone to overfitting (It's basically the ridge penalty)
- *C* = *1* is the default hyperparameter value which is used to tune Logistic Regression
- *class_weight* = *balanced* mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as n_samples / (n_classes * np.bincount(y)). **(We use this is because we have an imbalanced dataset)**
- *max_iter* used with solver == 'sag' (we need to vary the number of iterations to allow the to function to converge
- *solver* = '*sag*' corresponds to Stochastic Average Gradient and makes computation faster for large datasets such as this one
- *random_state* used with solver == 'sag' (since we're doing stochastic optimization)

Source: [https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html (https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)](https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)

In [52]:

```
lr = LogisticRegression(penalty = 'l2',
                        C = 1,
                        class_weight = 'balanced',
                        solver = 'sag',
                        max_iter = 100,
                        random_state = 4896)
lr.fit(X_train, y_train)
```

```
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
```

Out[52]:

```
LogisticRegression(C=1, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_st
ate=4896,
          solver='sag', tol=0.0001, verbose=0, warm_start=False)
```

In [53]:

```
y_pred = lr.predict(X_train)
```

In [54]:

```
# Evaluate model performance over these three metrics
print("Score on Train set (only)")
print("Accuracy score: {:.2f}".format(accuracy_score(y_train, y_pred)))
print("F1 score: {:.2f}".format(f1_score(y_train, y_pred)))
print("ROC AUC score: {:.2f}".format(roc_auc_score(y_train, y_pred)))
```

```
Score on Train set (only)
Accuracy score: 0.93
F1 score: 0.95
ROC AUC score: 0.95
```

In [55]:

```
cm = confusion_matrix(y_train, y_pred)
print("True Negatives:", cm[0][0])
print("False Negatives:", cm[1][0])
print("True Positives:", cm[1][1])
print("False Positives:", cm[0][1])
```

```
True Negatives: 111952
False Negatives: 28934
True Positives: 274892
False Positives: 373
```

- Our False Positive rare seems fine.
- However, we seem to have quite a bit of False nagatives in our case, which is **NOT GOOD**

- **Try scaling the numerical data to see if scores improve**

In [56]:

```
# Save continuous columns separately
X_train_cont = X_train.select_dtypes(include = ["float64"]).reset_index(drop =
True)
X_test_cont = X_test.select_dtypes(include = ["float64"]).reset_index(drop = T
rue)
```

In [57]:

```
# Save continuous column names
train_cont = list(X_train_cont)
test_cont = list(X_test_cont)
```

In [58]:

```
# Fit on X_train
scale = StandardScaler()
scale.fit(X_train_cont)
```

Out[58]:

```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

In [59]:

```
# Save categorical columns separately
X_train_cat = X_train.select_dtypes(exclude = ["float64"]).reset_index(drop =
True)
X_test_cat = X_test.select_dtypes(exclude = ["float64"]).reset_index(drop = Tr
ue)
```

In [60]:

```
# Transform using X_train
X_train_scaled = scale.transform(X_train_cont)

# Transform using X_train to avoid information leakage
X_test_scaled = scale.transform(X_test_cont)
```

In [61]:

```
# Convert to Pandas Dataframe
X_train_scaled = pd.DataFrame(X_train_scaled, columns = train_cont).reset_inde
x(drop = True)
X_test_scaled = pd.DataFrame(X_test_scaled, columns = test_cont).reset_index(d
rop = True)
```

In [62]:

```
# Check
X_train_scaled.head()
```

Out[62]:

	loan_amnt	funded_amnt	int_rate	annual_inc	dti	revol_bal	total_pymnt
0	1.610232	1.611412	0.301029	-0.194231	-0.079529	-0.146563	-0.977086
1	-0.318240	-0.317454	1.616361	-0.318910	0.156310	-0.167930	0.341735
2	-1.089629	-1.089000	0.070133	-0.537097	0.254576	-0.373046	-0.922579
3	-0.832499	-0.831818	-0.267132	0.012097	0.533993	0.776527	-0.708784
4	1.555591	1.556761	-0.809350	-0.272155	-0.427732	0.142902	2.124878

In [63]:

```
# Check
print(X_test_scaled.shape)
# Check
print(X_train_scaled.shape)
```

```
(204970, 7)
(416151, 7)
```

In [64]:

```
X_train_scaled = pd.concat([X_train_scaled, X_train_cat], axis = 1, join = "in
ner").reset_index(drop = True)
```

In [65]:

```
X_test_scaled = pd.concat([X_test_scaled, X_test_cat], axis = 1, join = "inner
").reset_index(drop = True)
```

In [66]:

```
# Check
print(X_test_scaled.shape)
# Check
print(X_train_scaled.shape)
```

```
(204970, 14)
(416151, 14)
```

In [67]:

```
# Check
X_train_cat.head()
```

Out[67]:

	grade_A	grade_B	grade_C	grade_D	grade_E	grade_F	grade_G
0	0	0	1	0	0	0	0
1	0	0	0	1	0	0	0
2	0	0	1	0	0	0	0
3	0	1	0	0	0	0	0
4	1	0	0	0	0	0	0

In [68]:

```
# Check
X_train_scaled.head()
```

Out[68]:

	loan_amnt	funded_amnt	int_rate	annual_inc	dti	revol_bal	total_pymnt	grad
0	1.610232	1.611412	0.301029	-0.194231	-0.079529	-0.146563	-0.977086	
1	-0.318240	-0.317454	1.616361	-0.318910	0.156310	-0.167930	0.341735	
2	-1.089629	-1.089000	0.070133	-0.537097	0.254576	-0.373046	-0.922579	
3	-0.832499	-0.831818	-0.267132	0.012097	0.533993	0.776527	-0.708784	
4	1.555591	1.556761	-0.809350	-0.272155	-0.427732	0.142902	2.124878	

- **Fit model on scaled Training Data**

In [69]:

```
lr.fit(X_train_scaled, y_train)
```

```
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
```

Out[69]:

```
LogisticRegression(C=1, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_st
ate=4896,
          solver='sag', tol=0.0001, verbose=0, warm_start=False)
```

In [70]:

```
y_pred = lr.predict(X_train_scaled)
```

In [71]:

```
# Evaluate model performance over these three metrics
print("Score on Train set (only)")
print("Accuracy score: {:.2f}".format(accuracy_score(y_train, y_pred)))
print("F1 score: {:.2f}".format(f1_score(y_train, y_pred)))
print("ROC AUC score: {:.2f}".format(roc_auc_score(y_train, y_pred)))
```

```
Score on Train set (only)
Accuracy score: 0.94
F1 score: 0.96
ROC AUC score: 0.96
```

In [72]:

```
cm = confusion_matrix(y_train, y_pred)
print("True Negatives:", cm[0][0])
print("False Negatives:", cm[1][0])
print("True Positives:", cm[1][1])
print("False Positives:", cm[0][1])
```

```
True Negatives: 111903
False Negatives: 24096
True Positives: 279730
False Positives: 422
```

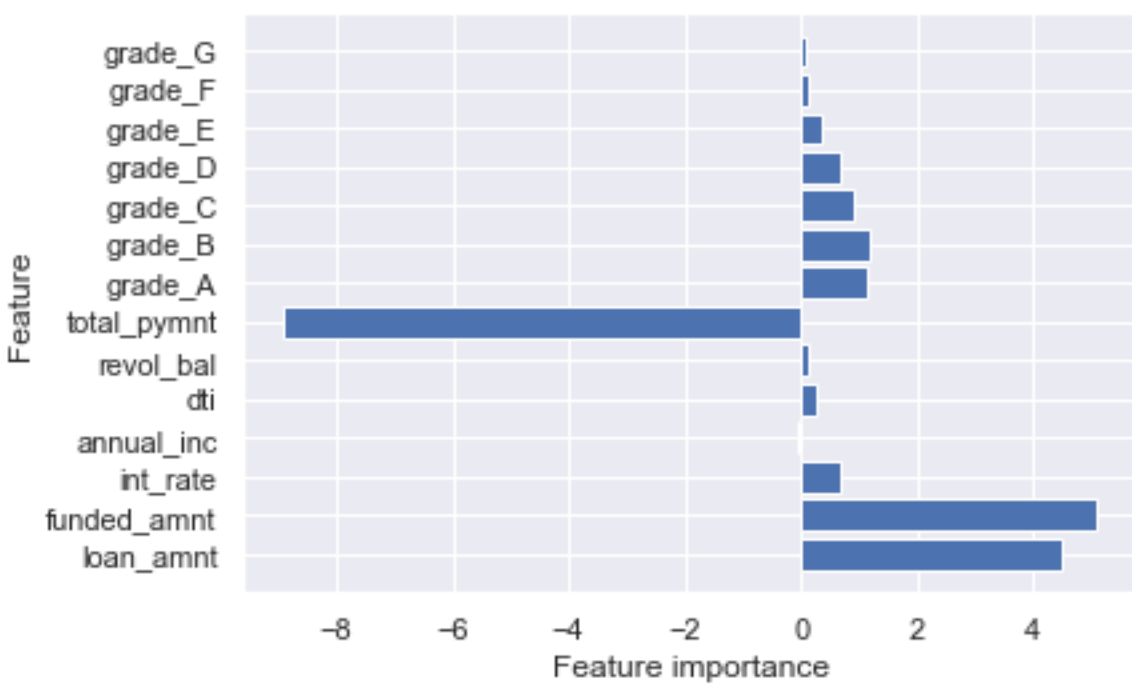
Scaling significantly improved performance

- Number of False Negatives fell by roughly 7000
- However, the Number for False Positives rose by 300

- **Look at feature importances**

In [73]:

```
n_features =  X_train_scaled.shape[1]
coefs_lr = lr.coef_[0]
plt.barh(range(n_features), coefs_lr, align='center')
plt.yticks(np.arange(n_features), list(X_train_scaled.columns.values))
plt.xlabel("Feature importance")
plt.ylabel("Feature")
plt.ylim(-1, n_features)
plt.show()
```



7. Tune Parameters to optimize model performance: On Scaled Data

- Perform Grid-search on Sampled data to save time

In [74]:

```
# Cross-validation strategy: shuffles the date
cv = StratifiedShuffleSplit(n_splits = 5, random_state= 4896)
```

In [77]:

```
pipe_lr = make_pipeline(LogisticRegression(penalty = 'l2', class_weight = 'bal
anced', solver = 'sag', max_iter = 100,
                        random_state = 4896))
param_grid_lr = [{'logisticregression__C':np.logspace(-3, 0, 5)}]
grid_lr = GridSearchCV(pipe_lr, param_grid_lr, scoring = 'roc_auc', cv = cv)
```

In [78]:

```
grid_lr.fit(X_train_scaled, y_train)
```

```
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
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hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
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hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
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hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
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hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
```

```
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
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hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
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  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
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hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
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hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
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hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
```

```
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
```

Out[78]:

```
GridSearchCV(cv=StratifiedShuffleSplit(n_splits=5, random_state=48
96, test_size='default',
            train_size=None),
       error_score='raise-deprecating',
       estimator=Pipeline(memory=None,
     steps=[('logisticregression', LogisticRegression(C=1.0, class
_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_st
ate=4896,
          solver='sag', tol=0.0001, verbose=0, warm_start=False))]
),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'logisticregression__C': array([0.001  , 0.005
62, 0.03162, 0.17783, 1.     ])}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='wa
rn',
       scoring='roc_auc', verbose=0)
```

In [79]:

```
print("Best Score %s" % grid_lr.best_score_)
print("Best Parameters %s" % grid_lr.best_params_)
```

```
Best Score 0.9811531963960071
Best Parameters {'logisticregression__C': 1.0}
```

In [80]:

```
best_param = grid_lr.best_params_.get('logisticregression__C')
```

Fit Best Parameter value

In [81]:

```
lr = LogisticRegression(penalty = 'l2',
                        C = best_param,
                        class_weight = 'balanced',
                        solver = 'sag',
                        max_iter = 100,
                        random_state = 4896)
lr.fit(X_train_scaled, y_train)
```

```
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
```

Out[81]:

```
LogisticRegression(C=1.0, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_st
ate=4896,
          solver='sag', tol=0.0001, verbose=0, warm_start=False)
```

In [82]:

```
y_pred = lr.predict(X_train_scaled)
```

In [83]:

```
# Evaluate model performance over these three metrics
print("Score on Train set (only)")
print("Accuracy score: {:.2f}".format(accuracy_score(y_train, y_pred)))
print("F1 score: {:.2f}".format(f1_score(y_train, y_pred)))
print("ROC AUC score: {:.2f}".format(roc_auc_score(y_train, y_pred)))
```

```
Score on Train set (only)
Accuracy score: 0.94
F1 score: 0.96
ROC AUC score: 0.96
```

In [84]:

```
cm = confusion_matrix(y_train, y_pred)
print("True Negatives:", cm[0][0])
print("False Negatives:", cm[1][0])
print("True Positives:", cm[1][1])
print("False Positives:", cm[0][1])
```

```
True Negatives: 111903
False Negatives: 24096
True Positives: 279730
False Positives: 422
```

8. Evaluating on Test Set and Check for overfitting

In [85]:

```
y_pred = lr.predict(X_test_scaled)
```

In [86]:

```
# Evaluate model performance over these three metrics
print("Score on Test set")
print("Accuracy score: {:.2f}".format(accuracy_score(y_test, y_pred)))
print("F1 score: {:.2f}".format(f1_score(y_test, y_pred)))
print("ROC AUC score: {:.2f}".format(roc_auc_score(y_test, y_pred)))
```

```
Score on Test set
Accuracy score: 0.94
F1 score: 0.96
ROC AUC score: 0.96
```

In [87]:

```
cm = confusion_matrix(y_test, y_pred)
print("True Negatives:", cm[0][0])
print("False Negatives:", cm[1][0])
print("True Positives:", cm[1][1])
print("False Positives:", cm[0][1])
```

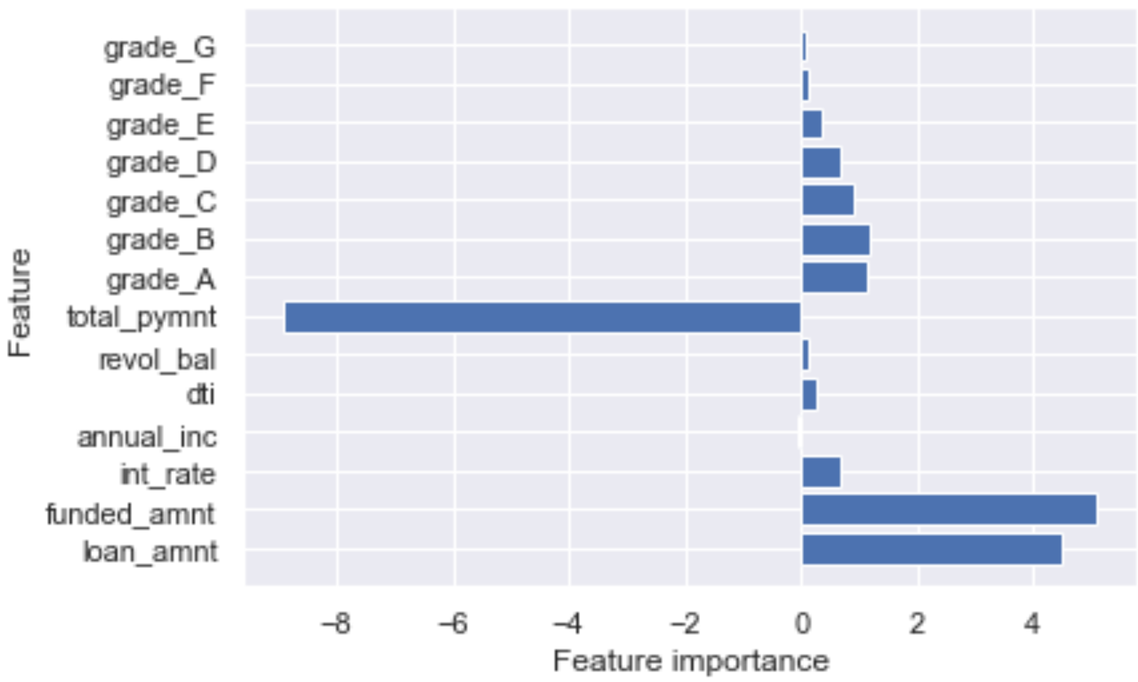
```
True Negatives: 55057
False Negatives: 11900
True Positives: 137820
False Positives: 193
```

There seems to be no overfitting since train and test scores seem to be the similar.

9. Look at feature importances

In [88]:

```
n_features =  X_train.shape[1]
coefs_lr = grid_lr.best_estimator_.named_steps["logisticregression"].coef_[0]
plt.barh(range(n_features), coefs_lr, align='center')
plt.yticks(np.arange(n_features), list(X_train.columns.values))
plt.xlabel("Feature importance")
plt.ylabel("Feature")
plt.ylim(-1, n_features)
plt.show()
```



10. Put everything in a Pipeline (To prevent any kind of data leakage)

In [89]:

```
# Scale Numeric Features

numeric_features = list(X.select_dtypes(include = ["float64"]))
numeric_transformer = Pipeline(steps=[
    ('scaler', StandardScaler())])
```

In [90]:

```
# OneHotEncode Categorical Features

categorical_features = list(X.select_dtypes(exclude = ["float64"]))
categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))])
```

In [91]:

```
# Add in preprocessor
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)])
```

In [92]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33)
```

In [93]:

```
# Define steps in Pipe
pipe = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', LogisticRegression(penalty = 'l2',
                                                         C = best_param,
                                                         class_weight = 'balanc
ed',
                                                         solver = 'sag',
                                                         max_iter = 100,
                                                         random_state = 4896))]
) # solver='lbfgs'
```

Tune Parameters

In [98]:

```
param_grid = {
    'classifier__C': np.logspace(-3, 0, 5)
}

grid_search = GridSearchCV(pipe, param_grid, cv = cv)
grid_search.fit(X_train, y_train)
```

```
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/pranjalbajaj/anaconda3/lib/python3.7/site-packages/sklearn/
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```
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linear_model/sag.py:334: ConvergenceWarning: The max_iter was reac
hed which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
```

Out[98]:

```
GridSearchCV(cv=StratifiedShuffleSplit(n_splits=5, random_state=48
96, test_size='default',
            train_size=None),
       error_score='raise-deprecating',
       estimator=Pipeline(memory=None,
     steps=[('preprocessor', ColumnTransformer(n_jobs=None, remain
der='drop', sparse_threshold=0.3,
         transformer_weights=None,
         transformers=[('num', Pipeline(memory=None,
     steps=[('scaler', StandardScaler(copy=True, with_mean=True, w
ith_std=True))]), ['loan_amnt', 'funded_amnt', 'int... penalty='l2
', random_state=4896,
          solver='sag', tol=0.0001, verbose=0, warm_start=False))]
),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'classifier__C': array([0.001  , 0.00562, 0.031
62, 0.17783, 1.     ])},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='wa
rn',
       scoring=None, verbose=0)
```

In [117]:

```
y_pred = pipe.predict(X_test)
```

In [118]:

```
# Evaluate model performance over these three metrics
print("Score on Test set")
print("Accuracy score: {:.2f}".format(accuracy_score(y_test, y_pred)))
print("F1 score: {:.2f}".format(f1_score(y_test, y_pred)))
print("ROC AUC score: {:.2f}".format(roc_auc_score(y_test, y_pred)))
```

```
Score on Test set
Accuracy score: 0.94
F1 score: 0.96
ROC AUC score: 0.96
```

In [119]:

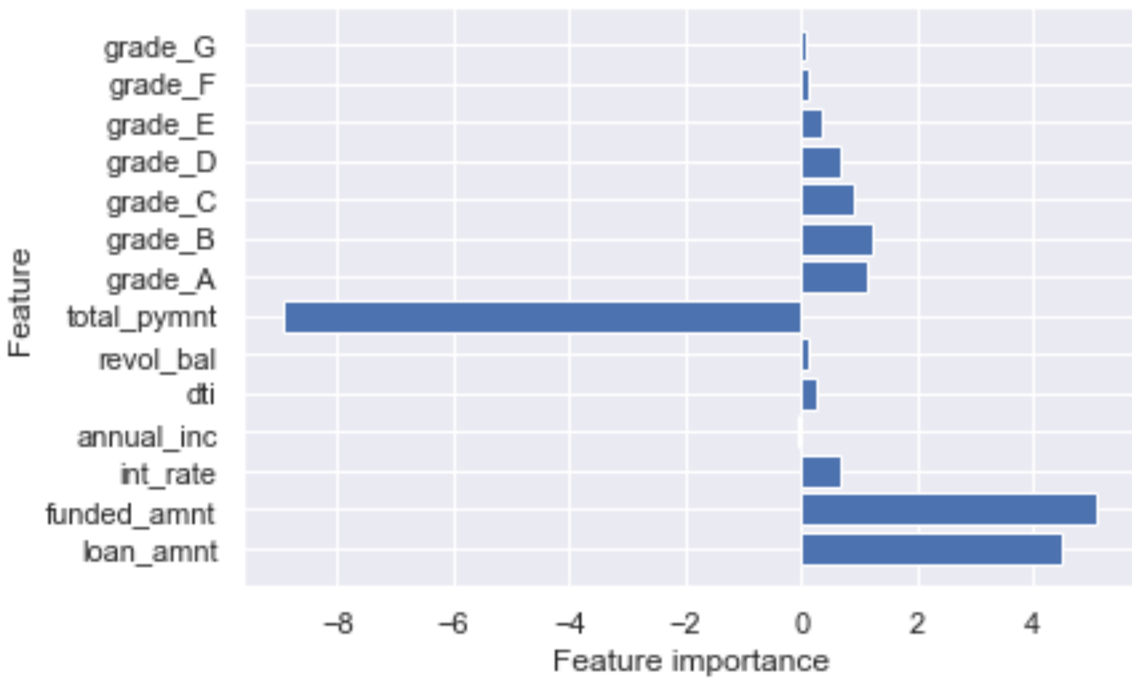
```
cm = confusion_matrix(y_test, y_pred)
print("True Negatives:", cm[0][0])
print("False Negatives:", cm[1][0])
print("True Positives:", cm[1][1])
print("False Positives:", cm[0][1])
```

```
True Negatives: 54957
False Negatives: 11808
True Positives: 138004
False Positives: 201
```

Feature Importances

In [110]:

```
n_features =  X_train_scaled.shape[1]
coefs_lr = grid_search.best_estimator_.named_steps['classifier'].coef_[0]
plt.barh(range(n_features), coefs_lr, align='center')
plt.yticks(np.arange(n_features), list(X_train_scaled))
plt.xlabel("Feature importance")
plt.ylabel("Feature")
plt.ylim(-1, n_features)
plt.show()
```



Was the model effective? Explain how you validated your model and describe how you measure the performance of the model.

Metrics

For this study, I chose two metrics to optimize performance:

- AUC
- F1 Score: 2 *(precision* recall) / (precision + recall)

Both of these metrics are fairly robust to class imbalance and capture our need to minimize:

- False Negatives
- False Positives

Since both these scenarios can be costly to an investor and should be minimized.

Model Performance

- The final scores on the test set were:

Metrics

- Score on Test set
- Accuracy score: 0.94
- F1 score: 0.96
- ROC AUC score: 0.96

Confusion Matrix Results

- True Negatives: 54957
- False Negatives: 11808
- True Positives: 138004
- False Positives: 201

After the pipeline, final scores on the test set were:

Overall, the model performs well according to these metrics; however, to truly gauge the performance of a model, it must be compared to a dummy classifier or a random baseline. See results below.

In [111]:

```
from sklearn.dummy import DummyClassifier
```

In [112]:

```
dummy = DummyClassifier(strategy='stratified', random_state=None, constant=Non
e)
dummy.fit(X_train_scaled, y_train)
y_pred = dummy.predict(X_test_scaled)

# Evaluate model performance over these three metrics
print("Score on Test set")
print("Accuracy score: {:.2f}".format(accuracy_score(y_test, y_pred)))
print("F1 score: {:.2f}".format(f1_score(y_test, y_pred)))
print("ROC AUC score: {:.2f}".format(roc_auc_score(y_test, y_pred)))

print("Confusion Matrix Metrics")
cm = confusion_matrix(y_test, y_pred)
print("True Negatives:", cm[0][0])
print("False Negatives:", cm[1][0])
print("True Positives:", cm[1][1])
print("False Positives:", cm[0][1])
```

```
Score on Test set
Accuracy score: 0.61
F1 score: 0.73
ROC AUC score: 0.50
Confusion Matrix Metrics
True Negatives: 14815
False Negatives: 40346
True Positives: 109466
False Positives: 40343
```

In [120]:

```
print("F1 score improvement: {:.2f}%".format((0.96 - 0.73)*100 / 0.73))
print("AUC improvement: {:.2f}%".format((0.96 - 0.5)*100 / 0.5) )
```

```
F1 score improvement: 31.51%
AUC improvement: 92.00%
```

Compared to this dummy classifier, we seem to be doing much better in terms of both F1 Score and AUC score. I do have reason to believe that the model was effective.

Note on Feature Importances:

- It is key in an evaluation to draw upon feature importances and we find consitently that:
  - Total Payment, Funded Amount and Loan Amount in this order are the most important features
  - This makes complete sense since our EDA discussed revealed that these features were the most informative!

Note:

- I made sure to make predicitons on the Test Set ONLY once i.e. after the model tuning stage.
- I created a new test and train split during the pipeline stage, which I used to generate another set of predicitons on the test set once after all parameters were trained. This was done to ensure that the pipeline works.

Further comments

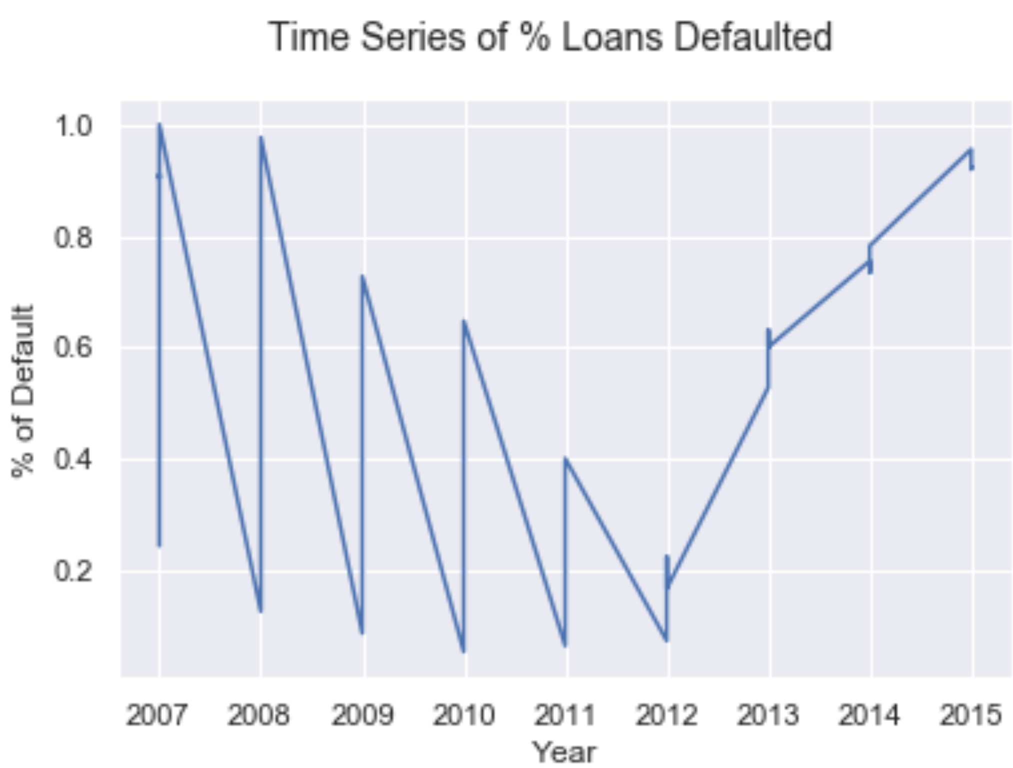
Given the context of this data, using an IID split will mean that we're using future values to present the past values which doesn't seem to make much sense in the real workd. Further, effective EDA should involve looking at the temporal component of the data as well as below.

In [115]:

```
cohorts.reset_index(inplace = True)
```

In [116]:

```
plt.suptitle('Time Series of % Loans Defaulted', fontsize = 14)
plt.xlabel('Year', fontsize = 12)
plt.ylabel('% of Default', fontsize = 12)
plt.plot(cohorts['issue_d'], cohorts['perc_default'])
plt.show()
```



There clearly is a temporal trend in the data which makes it very difficult to assume that observations are IID.

- The recession period from 2007-9 clearly shows very high default deates, with rates slipping as they go down to 2012
- The reates begin to rise again after 2012 in a strange pattern

Next steps and improved modelling approaches:

- The approach should follow using, say 2007-2012 data for the train set and 2013-15 as the test set.
- To tune model parameters, it may be possible to use *TimeSeriesSplit* offered by sklearn
- Given that there were only 4 missing values, we wouldn't have gained much imputing them; however, if there were more missing values then using packages such as *fancyimpute* may make sense which impute continous data by imputing values that of similar rows
- Tree-based models such as Random Forest or XG Boost are often good performers, not prone to overfitting and equally interpretable as Logistic Regression thanks to **shap values** which allow for interpretibility of these complex models