- 1 Logistic Regression Models
- 1.1 Importing Data

```
In [1]: import pandas as pd
        import numpy as np
        import pandas as pd
        import os
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.preprocessing import MinMaxScaler
        from sklearn.linear_model import LogisticRegression
        from sklearn.model selection import train test split
        from sklearn.metrics import plot_confusion_matrix
        from sklearn.metrics import confusion_matrix, classification_report
        from sklearn.metrics import roc curve, auc
        from sklearn.metrics import precision score, recall score, accuracy score, f1 sco
        from sklearn.preprocessing import StandardScaler
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.tree import plot tree
        from sklearn.utils import resample
        from imblearn.over sampling import SMOTE
        from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
        from sklearn.model_selection import GridSearchCV, cross_val_score
        from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier
        from xgboost import XGBClassifier
        from sklearn import tree
        import xgboost as xgb
        from numpy import loadtxt
        from xgboost import XGBClassifier
        from xgboost import plot tree
        import gc
        from tqdm import tqdm
        from sklearn.preprocessing import StandardScaler, OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.metrics import mean squared error, recall score
        from sklearn.model_selection import cross_val_predict
        from keras import models
        from keras import layers
        from keras import regularizers
        from keras.wrappers.scikit learn import KerasRegressor
        from keras.models import load model
        from scipy import stats
        import statsmodels.api as sm
        executed in 7.17s, finished 03:59:56 2021-04-22
```

```
In [2]: column_defs = pd.read_excel('data\LCDataDictionary.xlsx',index_col='LoanStatNew')
    column_defs.columns
    executed in 47ms, finished 03:59:56 2021-04-22
```

Out[2]: Index(['Description'], dtype='object')

```
In [3]: def column_info(col_name):
    return column_defs.loc[col_name]['Description']
    executed in 14ms, finished 03:59:56 2021-04-22

In [4]: def na_check(data):
    check = np.round(data.isna().sum().sort_values(ascending=False),2)
    return check
    executed in 14ms, finished 03:59:56 2021-04-22
```

```
In [5]: def reduce_mem_usage(df, int_cast=True, obj_to_category=False, subset=None):
            Iterate through all the columns of a dataframe and modify the data type to re
            :param df: dataframe to reduce (pd.DataFrame)
            :param int cast: indicate if columns should be tried to be casted to int (bod
            :param obj_to_category: convert non-datetime related objects to category dtyp
            :param subset: subset of columns to analyse (list)
            :return: dataset with the column dtypes adjusted (pd.DataFrame)
            start_mem = df.memory_usage().sum() / 1024 ** 2;
            gc.collect()
            print('Memory usage of dataframe is {:.2f} MB'.format(start_mem))
            cols = subset if subset is not None else df.columns.tolist()
            for col in tqdm(cols):
                col type = df[col].dtype
                if col_type != object and col_type.name != 'category' and 'datetime' not
                     c_min = df[col].min()
                     c max = df[col].max()
                    # test if column can be converted to an integer
                     treat_as_int = str(col_type)[:3] == 'int'
                     if int_cast and not treat_as_int:
                         treat as int = check if integer(df[col])
                     if treat as int:
                         if c min > np.iinfo(np.int8).min and c max < np.iinfo(np.int8).ma
                             df[col] = df[col].astype(np.int8)
                         elif c min > np.iinfo(np.uint8).min and c max < np.iinfo(np.uint8
                             df[col] = df[col].astype(np.uint8)
                         elif c min > np.iinfo(np.int16).min and c max < np.iinfo(np.int16)</pre>
                             df[col] = df[col].astype(np.int16)
                         elif c_min > np.iinfo(np.uint16).min and c_max < np.iinfo(np.uint</pre>
                             df[col] = df[col].astype(np.uint16)
                         elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.int31</pre>
                             df[col] = df[col].astype(np.int32)
                         elif c min > np.iinfo(np.uint32).min and c max < np.iinfo(np.uint
                             df[col] = df[col].astype(np.uint32)
                         elif c_min > np.iinfo(np.int64).min and c_max < np.iinfo(np.int64)</pre>
                             df[col] = df[col].astype(np.int64)
                         elif c min > np.iinfo(np.uint64).min and c max < np.iinfo(np.uint
                             df[col] = df[col].astype(np.uint64)
                     else:
                         if c min > np.finfo(np.float32).min and c max < np.finfo(np.float
                             df[col] = df[col].astype(np.float32)
                         else:
                             df[col] = df[col].astype(np.float64)
                elif 'datetime' not in col_type.name and obj_to_category:
                     df[col] = df[col].astype('category')
            gc.collect()
            end_mem = df.memory_usage().sum() / 1024 ** 2
            print('Memory usage after optimization is: {:.3f} MB'.format(end_mem))
            print('Decreased by {:.1f}%'.format(100 * (start_mem - end_mem) / start_mem))
```

```
executed in 27ms, finished 03:59:56 2021-04-22
 In [6]: | df = pd.read csv('data/preprocessed.csv')
           df.head()
           executed in 9.99s, finished 03:22:00 2021-04-14
 Out[6]:
               Unnamed:
                            Unnamed:
                       0
                                   0.1
                                             id
                                                   loan_amnt
                                                                term
                                                                        int_rate
                                                                                   installment
                                                                                                grade
                          0
                                   42536 10129454
                                                        12000.0
                                                                           10.99%
                                                                                          392.8
                                                                                                       В
                                                                     36
             0
                                                                 months
                          1
                                   42537 10149488
                                                         4800.0
                                                                     36
                                                                           10.99%
                                                                                          157.1
                                                                                                       В
             1
                                                                 months
                          2
                                   42538 10149342
                                                        27060.0
                                                                     36
                                                                           10.99%
                                                                                          885.5
                                                                                                       В
             2
                                                                 months
                                   42539 10148122
                                                        12000.0
                                                                            7.62%
                                                                                          374.0
                          3
                                                                     36
                                                                                                       Α
             3
                                                                 months
                                   42540 10129477
                                                        14000.0
                                                                           12.85%
                                                                                          470.8
                                                                                                       В
                                                                     36
             4
                                                                 months
           5 rows × 75 columns
 In [7]: df.drop(columns=['pymnt_plan','out_prncp','Unnamed: 0','Unnamed: 0.1','id'],axis=
           executed in 398ms, finished 03:22:01 2021-04-14
 In [8]: | df.drop(columns=["debt_settlement_flag", "hardship_flag",],axis=1,inplace=True
           executed in 462ms, finished 03:22:03 2021-04-14
           # making average fico score and dropping the fico range high and low
 In [9]:
           df['average fico'] = (df['fico range high'] + df['fico range low'])/2
           df.drop(columns=['fico_range_high','fico_range_low'],axis=1,inplace=True)
           executed in 1.08s, finished 03:22:05 2021-04-14
In [10]: | df.drop('initial_list_status',axis=1,inplace=True)
           executed in 511ms, finished 03:22:07 2021-04-14
In [11]: | df.drop('title',axis=1,inplace=True)
           executed in 429ms, finished 03:22:08 2021-04-14
In [12]: | df.drop(columns=['zip_code'],axis=1,inplace=True)
           executed in 393ms, finished 03:22:10 2021-04-14
In [13]: | df.int_rate = df.int_rate.map(lambda x: float(x.replace('%','')))
           executed in 892ms, finished 03:22:12 2021-04-14
In [14]: regions = pd.read_excel('data/state_regions.xlsx')
           executed in 28ms, finished 03:22:13 2021-04-14
```

return df

In [15]: df['region'] = df.addr_state.apply(lambda x: regions.loc[regions['State Code']] ==
executed in 7m 8s, finished 03:29:22 2021-04-14

In [16]: df.drop(columns = ['addr_state'],axis=1,inplace=True)
 executed in 1.08s, finished 03:29:24 2021-04-14

In [17]: reduce_mem_usage(df,int_cast=False)

executed in 7.78s, finished 03:29:33 2021-04-14

0% | 0/64 [00:00<?, ?it/s]

Memory usage of dataframe is 848.11 MB

100%| 64/64 [00:06<00:00, 9.26it/s]

Memory usage after optimization is: 511.850 MB Decreased by 39.6%

Out[17]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_length	hom
0	12000.0	36 months	10.99	392.799988	В	B2	4	
1	4800.0	36 months	10.99	157.100006	В	B2	2	
2	27060.0	36 months	10.99	885.500000	В	B2	10	
3	12000.0	36 months	7.62	374.000000	А	А3	3	
4	14000.0	36 months	12.85	470.799988	В	B4	4	
1736932	24000.0	60 months	23.99	690.500000	E	E2	1	
1736933	10000.0	36 months	7.99	313.200012	А	A5	10	
1736934	10050.0	36 months	16.99	358.200012	D	D1	8	
1736935	6000.0	36 months	11.44	197.800003	В	B4	5	
1736936	30000.0	60 months	25.49	889.000000	E	E4	4	

1736937 rows × 64 columns

```
In [19]: post_app_drops = ['total_bal_ex_mort', 'pct_tl_nvr_dlq', 'num_tl_op_past_12m', 'num
          ,'num_tl_120dpd_2m','num_bc_sats','num_accts_ever_120_pd','mths_since_recent_bc'
          ,'chargeoff_within_12_mths','bc_util','avg_cur_bal','tot_cur_bal','tot_coll_amt',
          , 'last_pymnt_amnt', 'recoveries', 'total_rec_late_fee'
          ,'total_rec_int','total_rec_prncp','total_pymnt','revol_util','revol_bal']
          executed in 14ms, finished 21:49:47 2021-04-12
In [18]: |df.drop(columns=['issue_d','earliest_cr_line','last_pymnt_d','last_credit_pullid
          executed in 484ms, finished 03:29:35 2021-04-14
In [19]: df.term = df.term.map(lambda x: np.int8(x.replace(' months','')))
          executed in 1.94s, finished 03:29:37 2021-04-14
In [20]: | df.revol_util = df.revol_util.map(lambda x: float(x.replace('%','')))
          executed in 837ms, finished 03:29:39 2021-04-14
 In [ ]: | ## from model testing these features are not relevant and total pymnt,prncp, and
          df.drop(columns=['total_rec_int','total_rec_prncp','total_pymnt',
                             'tot coll amt', 'num il tl', 'deling amnt', 'tax liens', 'last pymnt
In [47]: | df.to_csv('data/full_clean_pre_z')
          executed in 53.2s, finished 03:49:40 2021-04-14
 In [ ]:
          Start Here loading DF
 In [6]: | df = pd.read_csv('data/full_clean_pre_z')
          df.head()
          executed in 6.52s, finished 04:00:06 2021-04-22
 Out[6]:
               Unnamed:
```

	0	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_length
0	0	12000.0	36	10.99	392.8	В	B2	
1	1	4800.0	36	10.99	157.1	В	B2	
2	2	27060.0	36	10.99	885.5	В	B2	
3	3	12000.0	36	7.62	374.0	А	A3	
4	4	14000.0	36	12.85	470.8	В	B4	

5 rows × 51 columns

```
In [7]: df.drop('Unnamed: 0',axis=1,inplace=True)
executed in 266ms, finished 04:00:07 2021-04-22
```

In [8]: reduce_mem_usage(df,int_cast=False)

executed in 6.25s, finished 04:00:14 2021-04-22

0% | 0/50 [00:00<?, ?it/s]

Memory usage of dataframe is 662.59 MB

100%| 50/50 [00:05<00:00, 9.16it/s]

Memory usage after optimization is: 374.363 MB Decreased by 43.5%

Out[8]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_length	hom
0	12000.0	36	10.99	392.799988	В	B2	4	
1	4800.0	36	10.99	157.100006	В	B2	2	
2	27060.0	36	10.99	885.500000	В	B2	10	
3	12000.0	36	7.62	374.000000	Α	A3	3	
4	14000.0	36	12.85	470.799988	В	B4	4	
1736932	24000.0	60	23.99	690.500000	E	E2	1	
1736933	10000.0	36	7.99	313.200012	Α	A5	10	
1736934	10050.0	36	16.99	358.200012	D	D1	8	
1736935	6000.0	36	11.44	197.800003	В	B4	5	
1736936	30000.0	60	25.49	889.000000	Е	E4	4	

1736937 rows × 50 columns

```
In [9]: df.info()
          executed in 14ms, finished 04:00:14 2021-04-22
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 1736937 entries, 0 to 1736936
          Data columns (total 50 columns):
               Column
                                              Dtype
                                               _ _ _ _ _
           0
                                              float32
               loan_amnt
               term
                                               int8
           1
           2
               int_rate
                                              float32
           3
                                              float32
               installment
           4
               grade
                                              object
           5
               sub_grade
                                              object
           6
               emp_length
                                              int8
           7
               home_ownership
                                              object
           8
               annual inc
                                              float32
           9
               verification_status
                                              object
           10 loan_status
                                              object
           11 purpose
                                              object
           12 dti
                                              float32
           13 delinq_2yrs
                                              float32
In [10]: objects = list(df.loc[:,df.dtypes == 'object'].columns)
          executed in 273ms, finished 04:00:17 2021-04-22
In [11]: | objects
          executed in 12ms, finished 04:00:17 2021-04-22
Out[11]: ['grade',
            'sub_grade',
           'home_ownership',
           'verification_status',
            'loan_status',
           'purpose',
            'application_type',
           'region']
In [12]: | categorical = ['sub_grade',
           'grade',
           'home_ownership',
           'verification_status',
           'purpose',
           'application_type',
           'region']
          cat_drop = ['sub_grade',
           'grade',
           'home_ownership',
           'verification_status',
           'purpose',
           'application_type',
           'region','loan_status']
          executed in 13ms, finished 04:00:18 2021-04-22
```

```
In [13]: onehot = pd.get dummies(df[categorical],drop first=True)
          executed in 1.14s, finished 04:00:21 2021-04-22
In [14]: | cont columns = df.drop(columns=cat drop).columns
          executed in 156ms, finished 04:00:22 2021-04-22
In [15]: df_cont_z = df[(np.abs(stats.zscore(df[cont_columns]))<4).all(axis=1)]</pre>
          executed in 1.31s, finished 04:00:24 2021-04-22
In [16]: | z_score_df = df.loc[df_cont_z.index]
          executed in 330ms, finished 04:00:25 2021-04-22
In [17]: onehot_z = pd.get_dummies(z_score_df[categorical],drop_first=True)
          executed in 1.11s, finished 04:00:28 2021-04-22
In [18]: | cont_z = z_score_df.drop(columns=cat_drop)
          executed in 111ms, finished 04:00:30 2021-04-22
In [19]: | xz= pd.concat([cont_z,onehot_z],axis=1)
          yz= z_score_df['loan_status'].map(lambda x: 1 if x== "Charged Off" else 0)
          executed in 595ms, finished 04:00:32 2021-04-22
In [20]: |x_train_z, x_test_z, y_train_z, y_test_z = train_test_split(xz, yz, test_size=0.3
          executed in 951ms, finished 04:00:35 2021-04-22
In [21]: cat index = np.linspace(50,113,num=(113-50)).astype(np.int)
          cat index
          executed in 16ms, finished 04:00:37 2021-04-22
Out[21]: array([ 50, 51,
                                  53, 54, 55, 56,
                                                       57, 58, 59, 60,
                             52,
                                                                             61, 62,
                       64,
                             65,
                                       67, 68,
                                                  69,
                                                       70,
                                                             71, 72,
                                                                       73,
                  63,
                                  66,
                       77,
                            78,
                                 79, 80, 81, 82,
                                                       83, 84, 85, 86,
                  76,
                                                                            87, 88,
                  89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101,
                 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 113])
          2 Using Smote to Oversample Minority Class (do
          not run)
In [42]: | from imblearn.over_sampling import SMOTENC
```

```
In [ ]:
In [22]: | x_smote_z = pd.read_csv('data/x_smote_z')
          y_smote_z = pd.read_csv('data/y_smote_z')
          executed in 21.2s, finished 04:01:01 2021-04-22
In [23]: # as we dropped columns after testing to our original df need to drop from smote
          # at end will need to re run smote
          x_smote_z.drop(columns=['total_rec_int','total_rec_prncp','total_pymnt',
                              'tot_coll_amt', 'num_il_tl', 'delinq_amnt', 'tax_liens', 'last_pymnt
          executed in 505ms, finished 04:01:04 2021-04-22
In [24]: reduce mem usage(x smote z,int cast=False)
          executed in 16.1s, finished 04:01:23 2021-04-22
                           | 0/107 [00:00<?, ?it/s]
             0%|
          Memory usage of dataframe is 1327.29 MB
                 107/107 [00:15<00:00, 7.00it/s]
          Memory usage after optimization is: 356.632 MB
          Decreased by 73.1%
Out[24]:
                    Unnamed:
                                loan_amnt
                                                     int_rate
                                                               installment
                                                                            emp_length
                                                                                          annual_inc
                                             term
                 0
                                7750.000000
                                                 36 10.990000
                                                                 253.800003
                                                                                       3
                                                                                          29000.000000
                 1
                             1 10000.000000
                                                 36 22.910000
                                                                                          72000.000000
                                                                 386.799988
                 2
                             2 10000.000000
                                                 36 12.990000
                                                                 337.000000
                                                                                          40000.000000
                 3
                                 5500.000000
                                                 36 16.549999
                                                                 194.899994
                                                                                          54224.000000
                             4 25000.000000
                                                                 861.000000
                                                                                          75000.000000
                 4
                                                 36 14.520000
           1625891
                        1625891 24366.757812
                                                 51 17.206345
                                                                 707.872986
                                                                                       4 117479.695312
           1625892
                        1625892 19482.703125
                                                 50 15.419235
                                                                 542.377869
                                                                                          51204.097656
           1625893
                        1625893 13179.145508
                                                 36 14.562667
                                                                 461.734833
                                                                                          55000.000000
           1625894
                        1625894 17840.857422
                                                 45 21.473141
                                                                 597.083801
                                                                                          54589.417969
           1625895
                        1625895 20000.000000
                                                 60 22.391314
                                                                 557.422424
                                                                                          62470.488281
```

1625896 rows × 107 columns

In [25]: x_smote_z.drop('Unnamed: 0',axis=1,inplace=True)
executed in 564ms, finished 04:01:26 2021-04-22

```
In [26]: y_smote_z.drop('Unnamed: 0',axis=1,inplace=True)
executed in 15ms, finished 04:01:28 2021-04-22
```

In [27]: reduce_mem_usage(y_smote_z,int_cast=False)
 executed in 251ms, finished 04:01:30 2021-04-22

100%| 1/1 [00:00<00:00, 62.50it/s]

Memory usage of dataframe is 12.40 MB Memory usage after optimization is: 1.551 MB Decreased by 87.5%

Out[27]:

	loan_status
0	0
1	1
2	0
3	1
4	1
1625891	1
1625892	1
1625893	1
1625894	1
1625895	1

1625896 rows × 1 columns

- In [28]: scaler = MinMaxScaler()
 executed in 16ms, finished 04:01:33 2021-04-22
- In [29]: x_smote_cont_z = pd.DataFrame(scaler.fit_transform(x_smote_z[cont_columns]),columns
 x_smote_scaled_z = pd.concat([x_smote_cont_z,x_smote_z[onehot.columns]],axis=1)
 executed in 889ms, finished 04:01:36 2021-04-22
- In [30]: x_test_z= x_test_z.reset_index().drop('index',axis=1)
 x_test_cont_scaled_z = pd.DataFrame(scaler.transform(x_test_z[cont_columns]),columnty
 x_test_scaled_z = pd.concat([x_test_cont_scaled_z,x_test_z[onehot.columns]],axis=
 executed in 284ms, finished 04:01:39 2021-04-22
- In [31]: x_train_final_z, x_val_z, y_train_final_z, y_val_z = train_test_split(x_smote_scale)
 executed in 964ms, finished 04:01:43 2021-04-22

```
In [32]: x_train_z = x_train_z.reset_index().drop('index',axis=1)
    x_cont_z = pd.DataFrame(scaler.fit_transform(x_train_z[cont_columns]),columns=cd
    x_train_scaled_z = pd.concat([x_cont_z,x_train_z[onehot.columns]],axis=1)
    executed in 748ms, finished 04:01:46 2021-04-22
In [33]: y_train_z = y_train_z.reset_index().drop('index',axis=1)
```

2.1 Logistic Regression Models

In [34]: z_score_df[z_score_df.tot_cur_bal ==0]['loan_status'].value_counts(normalize=True executed in 35ms, finished 04:01:56 2021-04-22

Out[34]: Fully Paid 0.743649 Charged Off 0.256351

Name: loan_status, dtype: float64

executed in 47ms, finished 04:01:49 2021-04-22

```
In [35]: | r = ['loan_amnt',
          'term',
          'int_rate',
          'annual_inc',
          'emp_length',
          'dti',
          'total_acc',
           'tot_cur_bal',
            'pct_tl_nvr_dlq',
           'total_rec_late_fee',
           'mort_acc',
           'mths_since_recent_inq',
           'num_tl_90g_dpd_24m',
           'pub_rec_bankruptcies',
           'total_bc_limit',
           'total_il_high_credit_limit',
           'average_fico',
          'bc_util',
               'num_tl_120dpd_2m',
           'num tl 30dpd',
           'num_tl_90g_dpd_24m',
               'tot_coll_amt',
               'grade_B',
           'grade_C',
           'grade_D',
           'grade_E',
           'grade_F',
           'grade_G',
           'home_ownership_MORTGAGE',
           'home_ownership_OWN',
           'home_ownership_RENT',
           'verification_status_Source Verified',
           'verification_status_Verified',
           'purpose_credit_card',
           'purpose_debt_consolidation',
           'purpose_home_improvement',
           'purpose_house',
           'purpose_major_purchase',
           'purpose medical',
           'purpose_moving',
           'purpose_other',
           'purpose_renewable_energy',
           'purpose_small_business',
           'purpose_vacation',
           'purpose_wedding',
           'application_type_Joint App',
           'region_Northeast',
           'region_South',
           'region West']
          executed in 8ms, finished 04:02:05 2021-04-22
```

```
In [36]: balanced_og=['loan_amnt','term','int_rate','installment','emp_length','annual_inc'
    'revol_bal','average_fico','total_acc','total_rec_late_fee','tot_cur_bal','bc_ut'
    'mort_acc','mths_since_recent_bc','mths_since_recent_inq',
    'num_accts_ever_120_pd','num_bc_sats','num_bc_tl','num_op_rev_tl','num_tl_90g_dr'
    'num_tl_op_past_12m','pct_tl_nvr_dlq','pub_rec_bankruptcies','total_bal_ex_mort',
    'grade_B','grade_C','grade_D','grade_E','grade_F','grade_G','home_ownership_MORTC
    'verification_status_Source Verified','verification_status_Verified','purpose_cree'
    'purpose_home_improvement','purpose_house','purpose_major_purchase','purpose_othete'
    'purpose_small_business','purpose_vacation','purpose_wedding','application_type_I
    executed in 15ms, finished 04:02:08 2021-04-22
```

2.1.1 Logistic Regression unsmoted without recoveries

C:\Users\sergi\anaconda3\envs\learn-env\lib\site-packages\sklearn\utils\validat
ion.py:72: DataConversionWarning: A column-vector y was passed when a 1d array
was expected. Please change the shape of y to (n_samples,), for example using
ravel().

return f(**kwargs)

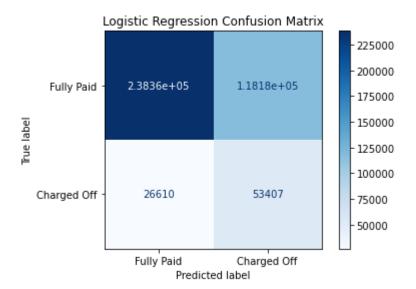
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent worker s.

[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 28.0s finished

AUC: 0.7325226073180483

[[238365 118181] [26610 53407]]

[20010	551	precision	recall	f1-score	support
	0	0.90	0.67	0.77	356546
	1	0.31	0.67	0.42	80017
accur	racy			0.67	436563
macro	avg	0.61	0.67	0.60	436563
weighted	avg	0.79	0.67	0.70	436563



Out[38]:

	0
loan_amnt	-0.358589
term	0.682327
int_rate	1.357631
installment	1.091914
emp_length	-0.061001
annual_inc	-0.428104
dti	1.613735
delinq_2yrs	0.139126
inq_last_6mths	0.188970
revol_bal	-0.875154
average_fico	-0.628713
total_acc	-0.642437
total_rec_late_fee	4.061917
tot_cur_bal	-0.411654
bc_util	-0.022456
mo_sin_rcnt_tl	-0.050420
mort_acc	-0.249371
mths_since_recent_bc	-0.444761
mths_since_recent_inq	-0.143758
num_accts_ever_120_pd	0.156580
num_bc_sats	0.630037
num_bc_tl	-0.167006
num_op_rev_tl	0.413646
num_tl_90g_dpd_24m	0.014719
num_tl_op_past_12m	0.459333
pct_tl_nvr_dlq	0.299752
pub_rec_bankruptcies	0.061015
total_bal_ex_mort	1.105648
total_bc_limit	-0.793603
total_il_high_credit_limit	-1.273516
grade_B	0.262358

	0
grade_C	0.420945
grade_D	0.417083
grade_E	0.345584
grade_F	0.223280
grade_G	0.116112
home_ownership_MORTGAGE	-0.322275
home_ownership_OWN	-0.201177
home_ownership_RENT	-0.077707
verification_status_Source Verified	0.049142
verification_status_Verified	0.035676
purpose_credit_card	-0.102147
purpose_debt_consolidation	-0.088981
purpose_home_improvement	-0.002114
purpose_house	-0.028096
purpose_major_purchase	-0.039484
purpose_other	-0.013780
purpose_renewable_energy	-0.115257
purpose_small_business	0.372360
purpose_vacation	0.030356
purpose_wedding	-0.534285
application_type_Joint App	0.058284
region_South	0.027277
region_West	-0.081059

In [39]: logit_model=sm.Logit(y_train_z,x_train_scaled_z[balanced_og])
 result=logit_model.fit(method='bfgs',maxiter=750)
 print(result.summary())
 executed in 4m 58s, finished 04:09:31 2021-04-22

Optimization terminated successfully.

Current function value: 0.424408

Iterations: 309

Function evaluations: 310 Gradient evaluations: 310

Logit Regression Results

			LOGIC NEGLE				
Dep. Variab Model: Method: Date: Time: converged: Covariance	le: Type:	Thu,	loan_status Logit MLE 22 Apr 2021 04:09:31 True nonrobust	Df Residuals: Df Model: Pseudo R-squ.: Log-Likelihood:		-4.3 -4.8	1018645 1018591 53 0.1087 232e+05 503e+05 0.000
			=======	=======	:=======	:=======	======
[0.025	0.975]				std err		
loan_amnt -0.548	-0.199			-0.3736	0.089		0.000
term	0.705			0.6956	0.015	46.802	0.000
0.666 int_rate	0.725			1.1774	0.046	25.769	0.000
1.088 installment				1.0529	0.107	9.817	0.000
0.843 emp_length -0.076	1.263 -0.048			-0.0620	0.007	-8.662	0.000
-0.076 annual_inc -0.689	-0.442			-0.5654	0.063	-8.949	0.000
dti 1.455	1.581			1.5180	0.032	47.414	0.000
delinq_2yrs 0.035				0.0713	0.019	3.838	0.000
inq_last_6m 0.121				0.1511	0.015	9.960	0.000
revol_bal	-0.748			-0.8498	0.052	-16.326	0.000
average_fic				-0.6585	0.023	-28.369	0.000
total_acc -0.673	-0.545			-0.6092	0.033	-18.737	0.000
total_rec_l 3.467				3.5151	0.025	142.867	0.000
tot_cur_bal				-0.4237	0.029	-14.795	0.000
bc_util -0.118	-0.024			-0.0713	0.024	-2.985	0.003
mo_sin_rcnt -0.149				-0.1019	0.024	-4.263	0.000

mort_acc -0.312 -0.232	-0.2721	0.020	-13.446	0.000
-0.312 -0.232 mths_since_recent_bc	-0.4713	0.021	-22.069	0.000
-0.513 -0.429				
<pre>mths_since_recent_inq -0.196 -0.140</pre>	-0.1679	0.014	-11.673	0.000
num_accts_ever_120_pd	0.0910	0.020	4.586	0.000
0.052 0.130				
num_bc_sats	0.6179	0.034	18.302	0.000
0.552 0.684	-0.2429	0.031	-7.920	0.000
num_bc_tl -0.303 -0.183	-0.2429	0.031	-7.920	0.000
num_op_rev_tl	0.3984	0.030	13.249	0.000
0.339 0.457				
num_tl_90g_dpd_24m -0.004	0.0507	0.028	1.808	0.071
	0 4101	0.010	24 256	0.000
<pre>num_tl_op_past_12m 0.372 0.448</pre>	0.4101	0.019	21.256	0.000
pct_tl_nvr_dlq	0.1721	0.020	8.500	0.000
0.132 0.212				
<pre>pub_rec_bankruptcies</pre>	0.0587	0.008	6.995	0.000
0.042 0.075	1 0020	0 074	14 707	0 000
total_bal_ex_mort 0.946 1.238	1.0920	0.074	14.707	0.000
total_bc_limit	-0.7929	0.034	-22.992	0.000
-0.860 -0.725				
total_il_high_credit_limit	-1.2391	0.067	-18.440	0.000
-1.371 -1.107				
grade_B	0.2443	0.013	18.726	0.000
0.219 0.270 grade_C	0.4207	0.017	25.182	0.000
0.388 0.453	01.207	0.027	23,102	0.000
grade_D	0.4364	0.023	19.348	0.000
0.392 0.481	0 2070		12 510	
<pre>grade_E 0.331 0.443</pre>	0.3872	0.029	13.548	0.000
0.331 0.443 grade_F	0.2887	0.037	7.884	0.000
0.217 0.360	0.2007	0.037	7.00-	0.000
grade_G	0.1983	0.048	4.153	0.000
0.105 0.292				
home_ownership_MORTGAGE	-2.6434	0.030	-88.138	0.000
-2.702 -2.585				
home_ownership_OWN -2.595 -2.476	-2.5357	0.030	-83.206	0.000
home_ownership_RENT	-2.4039	0.030	-81.391	0.000
-2.462 -2.346	_, _,			
verification_status_Source Verified	0.0348	0.007	5.056	0.000
0.021 0.048	0.0050	0.000	2 550	
<pre>verification_status_Verified 0.012 0.042</pre>	0.0268	0.008	3.558	0.000
purpose_credit_card	-0.1892	0.017	-11.181	0.000
-0.222 -0.156				
purpose_debt_consolidation	-0.1723	0.016	-10.687	0.000
-0.204 -0.141	0 00			
purpose_home_improvement	-0.0968	0.020	-4.957	0.000
-0.135 -0.059 purpose_house	-0.1444	0.039	-3.725	0.000
P. P	J. 2111	0.000	J•/ 2J	3.000

-0.220 -0.068				
purpose_major_purchase	-0.1229	0.025	-4.976	0.000
-0.171 -0.074				
purpose_other	-0.1050	0.019	-5.538	0.000
-0.142 -0.068				
purpose_renewable_energy	-0.2122	0.110	-1.925	0.054
-0.428 0.004				
purpose_small_business	0.2552	0.029	8.650	0.000
0.197 0.313				
purpose_vacation	-0.0637	0.036	-1.776	0.076
-0.134 0.007				
purpose_wedding	-0.6412	0.126	-5.084	0.000
-0.888 -0.394				
application_type_Joint App	0.0306	0.015	2.075	0.038
0.002 0.059				
region_South	0.0210	0.006	3.307	0.001
0.009 0.034				
region_West	-0.0868	0.007	-12.327	0.000
-0.101 -0.073				
	=======================================		========	======

2.1.2 Logistic Regression with Recoveries Unsmoted

```
In [42]: balanced_og_recoveries =['recoveries',
    'loan_amnt','term','int_rate','installment','emp_length','annual_inc','dti','deli
    'revol_bal','average_fico','total_acc','total_rec_late_fee','tot_cur_bal','bc_ut
    'mort_acc','mths_since_recent_bc','mths_since_recent_inq',
    'num_bc_sats','num_bc_tl','num_op_rev_tl','num_tl_90g_dpd_24m',
    'num_tl_op_past_12m','pct_tl_nvr_dlq','pub_rec_bankruptcies','total_bal_ex_mort',
    'grade_B','grade_C','grade_D','grade_E','grade_F','grade_G','home_ownership_MORTC
    'verification_status_Source Verified','verification_status_Verified','purpose_krecent_ball','purpose_ball','purpose_ball','purpose_ball','purpose_ball','purpose_major_purchase','purpose_othecent_ball','purpose_wedding','application_type_Joint_App', 'region_South'
```

```
In [43]: #best log reg using balanced on original data using test features 4std z score dr
         logreg = LogisticRegression(C=1e7,fit intercept=False,solver='lbfgs',penalty='12'
                                      class weight='balanced')
         log model = logreg.fit(x train scaled z[balanced og recoveries], y train z)
         y_hat_log = logreg.predict(x_test_scaled_z[balanced_og_recoveries])
         y score log = log model.decision function(x test scaled z[balanced og recoveries]
         fpr,tpr,thresholds = roc_curve(y_test_z,y_score_log)
         print('AUC: {}'.format(auc(fpr, tpr)))
         cf = confusion_matrix(y_test_z,y_hat_log)
         plot_confusion_matrix(log_model,x_test_scaled_z[balanced_og_recoveries],y_test_z,
                               display_labels=["Fully Paid", "Charged Off"].
                               values format=".5g")
         plt.title("Logistic Regression Confusion Matrix")
         print(confusion_matrix(y_test_z, y_hat_log))
         print(classification_report(y_test_z, y_hat_log))
         executed in 28.3s, finished 04:13:09 2021-04-22
         C:\Users\sergi\anaconda3\envs\learn-env\lib\site-packages\sklearn\utils\valid
         ation.py:72: DataConversionWarning: A column-vector y was passed when a 1d ar
         ray was expected. Please change the shape of y to (n samples, ), for example
         using ravel().
           return f(**kwargs)
         [Parallel(n jobs=1)]: Using backend SequentialBackend with 1 concurrent worke
         C:\Users\sergi\anaconda3\envs\learn-env\lib\site-packages\sklearn\linear mode
         1\ logistic.py:762: ConvergenceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html (https://sciki
         t-learn.org/stable/modules/preprocessing.html)
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear model.html#logistic-regres
         sion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regr
         ession)
           n_iter_i = _check_optimize_result(
```

In [44]: # Feature Coefficients for sklearn Log reg model
pd.DataFrame(index =x_train_scaled_z[balanced_og_recoveries].columns,data=log_mod
executed in 104ms, finished 04:13:28 2021-04-22

Out[44]:

	U
recoveries	656.337877
loan_amnt	0.747454
term	0.649438
int_rate	2.783838
installment	-0.199924
emp_length	-0.061298
annual_inc	-1.545751
dti	1.537363
delinq_2yrs	-0.155089
revol_bal	-0.209696

In [45]: # Our smoted model has different pvalues for various features, so we will drop fe
#confidence level
 result.pvalues.sort_values(ascending=False).head(10)
 executed in 16ms, finished 04:13:31 2021-04-22

dtype: float64

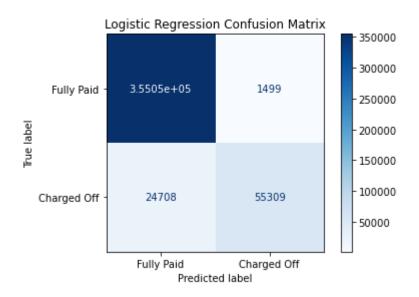
```
In [46]: logit_model=sm.Logit(y_train_z,x_train_scaled_z[balanced_og_recoveries])
    result=logit_model.fit(method='lbfgs',maxiter=750)
    print(result.summary())
    executed in 11m 46s, finished 04:25:21 2021-04-22

C:\Users\sergi\anaconda3\envs\learn-env\lib\site-packages\statsmodels\base\mo
    del.py:566: ConvergenceWarning: Maximum Likelihood optimization failed to con
    verge. Check mle_retvals
    warnings.warn("Maximum Likelihood optimization failed to "
```

2.1.3 Logistic Regression Model for Smoted values with recoveries

```
recover = ['recoveries',
In [47]:
          'loan_amnt','term','int_rate','installment','emp_length','annual_inc','dti','deli
          'pub_rec', 'revol_bal','total_acc','total_rec_late_fee','tot_cur_bal','bc_util¦',
          'mths_since_recent_bc', 'num_accts_ever_120_pd',
          'num_bc_sats', 'num_bc_tl',
          'num_op_rev_tl',
           'num_tl_op_past_12m', 'pct_tl_nvr_dlq',
          'total_bal_ex_mort', 'total_bc_limit',
          'total_il_high_credit_limit', 'average_fico',
           'sub_grade_A2',
          'sub grade A3','sub grade A4','sub grade A5','sub grade B1','sub grade B2','sub
          'sub_grade_C1','sub_grade_C2','sub_grade_C3','sub_grade_C4','sub_grade_C5','sub_grade_C5'
          'sub_grade_D3','sub_grade_D4','sub_grade_D5','sub_grade_E1'
          ,'sub_grade_E2','sub_grade_E3','sub_grade_E4','sub_grade_E5','sub_grade_F1','sub_
          'sub_grade_F5','sub_grade_G1','sub_grade_G2','sub_grade_G3','sub_grade_G4','sub_
          'home_ownership_MORTGAGE','home_ownership_OWN','home_ownership_RENT',
          'verification_status_Source Verified','verification_status_Verified',
          'purpose_credit_card','purpose_debt_consolidation','purpose_home_improvement';''
          purpose_other','purpose_renewable_energy','purpose_small_business','purpose_vac',
          'purpose_moving',
          'application_type_Joint App',
          'region_South','region_West','region_Northeast']
         executed in 49ms, finished 04:26:32 2021-04-22
```

```
In [48]: #log reg model including recoveries
         logreg = LogisticRegression(C=10,fit_intercept=False,solver='lbfgs',penalty='l2'
         log model = logreg.fit(x train final z[recover], y train final z.loan status)
         y hat log = logreg.predict(x test scaled z[recover])
         y score log = log model.decision function(x test scaled z[recover])
         fpr,tpr,thresholds = roc_curve(y_test_z,y_score_log)
         print('AUC: {}'.format(auc(fpr, tpr)))
         cf = confusion_matrix(y_test_z,y_hat_log)
         plot confusion matrix(log model,x test scaled z[recover],y test z,cmap=plt.cm.Bld
                               display_labels=["Fully Paid", "Charged Off"],
                                values_format=".5g")
         plt.title("Logistic Regression Confusion Matrix")
         print(confusion_matrix(y_test_z, y_hat_log))
         print(classification_report(y_test_z, y_hat_log))
         executed in 1m 12.7s, finished 04:27:48 2021-04-22
         [Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent worker
         s.
         C:\Users\sergi\anaconda3\envs\learn-env\lib\site-packages\sklearn\linear model
         \ logistic.py:762: ConvergenceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
         learn.org/stable/modules/preprocessing.html)
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear model.html#logistic-regressi
         on (https://scikit-learn.org/stable/modules/linear model.html#logistic-regressi
         on)
           n iter i = check optimize result(
         [Parallel(n jobs=1)]: Done
                                       1 out of 1 | elapsed: 1.1min finished
         AUC: 0.9009224782285918
         [[355047
                    1499]
          [ 24708
                   55309]]
                        precision
                                     recall f1-score
                                                        support
                    0
                             0.93
                                                 0.96
                                       1.00
                                                         356546
                    1
                             0.97
                                       0.69
                                                 0.81
                                                          80017
             accuracy
                                                 0.94
                                                         436563
                             0.95
                                                 0.89
                                                         436563
            macro avg
                                       0.84
                                                 0.94
         weighted avg
                             0.94
                                       0.94
                                                         436563
```



In [49]: pd.options.display.max_rows = 85
executed in 13ms, finished 04:28:45 2021-04-22

Out[50]:

	0
recoveries	224.589283
loan_amnt	2.907924
term	0.547196
int_rate	8.724993
installment	-2.477596
emp_length	-0.110124
annual_inc	-1.144473
dti	2.570675
delinq_2yrs	0.210603
inq_last_6mths	0.294931

```
In [51]: logit_model=sm.Logit(y_train_final_z,x_train_final_z[recover])
    result=logit_model.fit(method='lbfgs',maxiter=250)
    print(result.summary())
    executed in 7m 32s, finished 04:36:28 2021-04-22

C:\Users\sergi\anaconda3\envs\learn-env\lib\site-packages\statsmodels\base\mo
    del.py:566: ConvergenceWarning: Maximum Likelihood optimization failed to con
    verge. Check mle_retvals
        warnings.warn("Maximum Likelihood optimization failed to "
```

2.1.4 Logistic Regression Model Smoted values, without Recoveries

```
resamp =['loan_amnt','term','int_rate','installment','emp_length','annual_inc';
In [52]:
                          'pub_rec', 'revol_bal','total_acc','total_rec_late_fee','tot_cur_bal','bc_util¦',
                            'mths_since_recent_bc', 'num_accts_ever_120_pd',
                           'num_bc_sats', 'num_bc_tl',
                            'num_op_rev_tl', 'num_tl_90g_dpd_24m',
                            'num_tl_op_past_12m', 'pct_tl_nvr_dlq',
                           'total_bal_ex_mort', 'total_bc_limit',
                            'total_il_high_credit_limit','average_fico',
                           'sub grade A2',
                            'sub_grade_A3','sub_grade_A4','sub_grade_A5','sub_grade_B1','sub_grade_B2','sub_
                           'sub grade C1', 'sub grade C2', 'sub grade C3', 'sub grade C4', 'sub grade C5', 'sub
                            'sub_grade_D3','sub_grade_D4','sub_grade_D5','sub_grade_E1'
                         ,'sub_grade_E2','sub_grade_E3','sub_grade_E4','sub_grade_E5','sub_grade_F1','sub_
                           'sub_grade_F5','sub_grade_G1','sub_grade_G2','sub_grade_G3','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','sub_grade_G4','
                           'home_ownership_MORTGAGE','home_ownership_OWN','home_ownership_RENT',
                          'verification_status_Source Verified','verification_status_Verified',
                            'purpose_credit_card', 'purpose_debt_consolidation', 'purpose_home_improvement', 'r
                          purpose_other','purpose_renewable_energy','purpose_small_business','purpose_vac',
                          'purpose_moving',
                          'application_type_Joint App',
                           'region South','region West','region Northeast']
                         executed in 16ms, finished 04:44:48 2021-04-22
```

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent worker s.

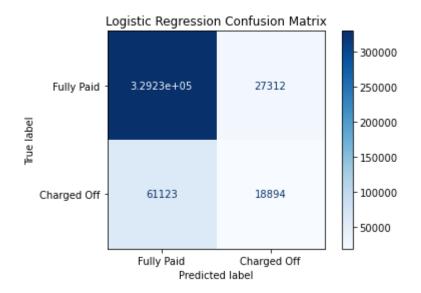
convergence after 18 epochs took 28 seconds

[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 28.1s finished

AUC: 0.6900494207748351

[[329234 27312] [61123 18894]]

0 0.84 0.92 0.88 3	56546
1 0.41 0.24 0.30	80017
accuracy 0.80 4	36563
macro avg 0.63 0.58 0.59 4	36563
weighted avg 0.76 0.80 0.77 4	36563



In [262]: pd.options.display.max_rows= 85 executed in 14ms, finished 05:46:55 2021-04-13

Out[263]:

	0
loan_amnt	1.891263
term	0.535819
int_rate	6.995911
installment	-1.193287
emp_length	-0.136702
annual_inc	0.313413
dti	2.583270
delinq_2yrs	0.644501
inq_last_6mths	0.344524
revol_bal	-1.567845
	4 400045

In [55]: logit_model=sm.Logit(y_train_final_z,x_train_final_z[resamp])
 result=logit_model.fit(method='lbfgs',maxiter=750)
 print(result.summary())

executed in 4m 52s, finished 04:52:33 2021-04-22

Logit Regression Results

========						=======	=======
Dep. Variab	ole:		loan_status	No. Obse	ervations:		1138127
Model:			Logit	Df Resid	duals:		1138044
Method:			MLE				82
Date:		Thu,	22 Apr 2021	Pseudo F	R-squ.:		0.4873
Time:			04:52:33		elihood:	-4.0445e+05	
converged:			True	_		-7	.8889e+05
Covariance	Type:		nonrobust	LLR p-va	alue:		0.000
========			========			=======	======
========	:======	====		coef	c+d onn	_	n. l=1
[0.025	0.975]				std err	Z 	P> z
				2.1560	0.098	21.990	0.000
loan_amnt 1.964	2.348			2.1500	0.030	21.990	0.000
term	2.540			0.5027	0.016	30.586	0.000
0.470	0.535			0.3027	0.010	30.360	0.000
int rate	0.555			7.2072	0.040	179.262	0.000
7.128	7.286			7.2072	0.040	175.202	0.000
installment				-1.5100	0.118	-12.783	0.000
-1.742	-1.279			1.5100	0.110	12.703	0.000
emp_length	1.2/3			-0.1368	0.007	-18.259	0.000
-0.151	-0.122			0.1500	0.007	10.233	0.000
annual_inc	0.122			0.3920	0.062	6.343	0.000
0.271	0.513			0.3320	0.002	0.5.5	0.000
dti	0.525			2.6434	0.034	78.646	0.000
2.578	2.709			_,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,		7000.0	0,000
delinq_2yrs				0.6637	0.019	34.573	0.000
0.626	0.701						
inq_last_6m				0.3508	0.014	24.671	0.000
0.323	0.379						
pub_rec				0.1738	0.015	11.632	0.000
0.144	0.203						
revol_bal				-1.6832	0.053	-31.759	0.000
-1.787	-1.579						
total_acc				-1.2758	0.034	-37.459	0.000
-1.343	-1.209						
total_rec_l	Late_fee			4.4271	0.031	142.461	0.000
4.366	4.488						
tot_cur_bal	L			-0.2271	0.028	-8.237	0.000
-0.281	-0.173						
bc_util				0.6411	0.025	25.833	0.000
0.592	0.690						
mo_sin_rcnt	_t1			0.2385	0.024	9.827	0.000
0.191	0.286						
<pre>mths_since_</pre>		2		-0.3742	0.022	-16.997	0.000
-0.417	-0.331						
num_accts_e		od		0.8164	0.020	40.442	0.000
0.777	0.856				_	_	_
num_bc_sats	5			0.8718	0.035	24.604	0.000

0 902 0 041				
0.802	0.1275	0.032	3.952	0.000
0.064 0.191	0.12/3	0.032	3.332	0.000
num_op_rev_tl	0.5645	0.032	17.836	0.000
0.502 0.627				
num_t1_90g_dpd_24m	-0.1595	0.030	-5.352	0.000
-0.218 -0.101				
num_tl_op_past_12m	1.0435	0.020	51.331	0.000
1.004 1.083 pct_tl_nvr_dlq	1.3804	0.020	69.363	0.000
1.341 1.419	1.5004	0.020	09.303	0.000
total_bal_ex_mort	1.9785	0.077	25.700	0.000
1.828 2.129				
total_bc_limit	-1.3348	0.034	-38.920	0.000
-1.402 -1.268				
total_il_high_credit_limit	-2.3481	0.069	-33.868	0.000
-2.484 -2.212	0.0264	0.004	25 520	0.000
average_fico -0.882 -0.790	-0.8361	0.024	-35.528	0.000
-0.002 -0.790 sub_grade_A2	-3.1012	0.032	-97.733	0.000
-3.163 -3.039	3.1012	0.032	37.733	0.000
sub_grade_A3	-3.2481	0.029	-110.253	0.000
-3.306 -3.190				
sub_grade_A4	-3.2478	0.023	-138.280	0.000
-3.294 -3.202				
sub_grade_A5	-3.2969	0.020	-165.388	0.000
-3.336 -3.258	2 4000	0 010	104 202	0 000
sub_grade_B1 -3.435 -3.367	-3.4009	0.018	-194.203	0.000
sub_grade_B2	-3.6234	0.017	-214.474	0.000
-3.657 -3.590				
sub_grade_B3	-3.7443	0.016	-235.099	0.000
-3.776 -3.713				
sub_grade_B4	-3.8306	0.015	-253.739	0.000
-3.860 -3.801	2 0670	0.015	260 400	0.000
sub_grade_B5 -3.897 -3.839	-3.8679	0.015	-260.100	0.000
sub_grade_C1	-3.9714	0.015	-271.353	0.000
-4.000 -3.943	3,3,1	0.023	2,2,333	0.000
sub_grade_C2	-4.1335	0.015	-271.097	0.000
-4.163 -4.104				
sub_grade_C3	-4.1899	0.015	-271.874	0.000
-4.220 -4.160	4 2454	0.016	274 440	0.000
sub_grade_C4 -4.346 -4.284	-4.3151	0.016	-274.140	0.000
-4.346 -4.284 sub_grade_C5	-4.5168	0.017	-271.297	0.000
-4.549 -4.484	4.5100	0.017	271.237	0.000
sub_grade_D1	-4.8100	0.019	-256.753	0.000
-4.847 -4.773				
sub_grade_D2	-5.0447	0.020	-252.285	0.000
-5.084 -5.006	F 2200	0.004	245 462	
sub_grade_D3	-5.2398	0.021	-245.163	0.000
-5.282 -5.198 sub_grade_D4	-5.4344	0.023	-238.138	0.000
-5.479 -5.390	J. 1 J 11	0.025	250.150	0.000
sub_grade_D5	-5.6902	0.025	-229.391	0.000
-5.739 -5.642				

sub_grade_E1 -5.884 -5.775	-5.8298	0.028	-209.966	0.000
sub_grade_E2	-5.9535	0.029	-205.485	0.000
-6.010 -5.897 sub_grade_E3	-6.1471	0.031	-197.510	0.000
-6.208 -6.086 sub_grade_E4	-6.4066	0.034	-190.412	0.000
-6.473 -6.341 sub_grade_E5	-6.6574	0.035	-189.973	0.000
-6.726 -6.589				
sub_grade_F1 -7.041 -6.875	-6.9581	0.042	-164.210	0.000
sub_grade_F2 -7.106 -6.913	-7.0097	0.049	-142.765	0.000
sub_grade_F3 -7.411 -7.201	-7.3057	0.054	-136.395	0.000
sub_grade_F4	-7.4520	0.060	-123.521	0.000
-7.570 -7.334 sub_grade_F5	-7.5491	0.065	-115.945	0.000
-7.677 -7.422 sub_grade_G1	-7.9231	0.074	-106.914	0.000
-8.068 -7.778 sub_grade_G2	-7.8289	0.090	-87.322	0.000
-8.005 -7.653 sub_grade_G3	-8.0357	0.099	-80.933	0.000
-8.230 -7.841				
sub_grade_G4 -8.475 -8.042	-8.2587	0.110	-74.748	0.000
sub_grade_G5 -8.246 -7.779	-8.0126	0.119	-67.185	0.000
home_ownership_MORTGAGE -0.281 -0.210	-0.2456	0.018	-13.527	0.000
home_ownership_OWN -0.332 -0.256	-0.2941	0.019	-15.174	0.000
home_ownership_RENT	0.2025	0.018	11.450	0.000
<pre>0.168 0.237 verification_status_Source Verified</pre>	0.0042	0.007	0.631	0.528
-0.009 0.017 verification_status_Verified	-0.0982	0.008	-13.036	0.000
-0.113 -0.083 purpose_credit_card	-1.2692	0.013	-95.255	0.000
-1.295 -1.243				
purpose_debt_consolidation -0.997 -0.948	-0.9722	0.013	-77.556	0.000
<pre>purpose_home_improvement -1.285 -1.214</pre>	-1.2495	0.018	-68.874	0.000
purpose_house -1.408 -1.227	-1.3176	0.046	-28.556	0.000
purpose_major_purchase -1.425 -1.322	-1.3732	0.026	-52.343	0.000
purpose_other	-1.2017	0.018	-68.096	0.000
-1.236 -1.167 purpose_renewable_energy	-1.3684	0.139	-9.843	0.000
-1.641 -1.096 purpose_small_business	-0.8205	0.033	-24.652	0.000
-0.886 -0.755 purpose_vacation	-1.3081	0.042	-31.443	0.000
· · · · · · · · · · · · · · · · · · ·			==	

-1.390	-1.227						
purpose_wed	lding	-2.1062	0.169	-12.492	0.000		
-2.437	-1.776						
purpose_med	lical	-1.1888	0.032	-36.988	0.000		
-1.252	-1.126						
purpose_mov	ring	-1.2438	0.040	-30.796	0.000		
-1.323	-1.165						
application	_type_Joint App	-0.5429	0.018	-30.922	0.000		
-0.577	-0.509						
region_Sout	:h	-0.7420	0.007	-101.132	0.000		
-0.756	-0.728						
region_West	:	-0.7465	0.008	-94.987	0.000		
-0.762	-0.731						
region_Nort	heast	-0.6726	0.008	-79.360	0.000		
-0.689	-0.656						

```
In [73]:
```

```
plt.rc('figure', figsize=(12, 25))
#plt.text(0.01, 0.05, str(model.summary()), {'fontsize': 12}) old approach
plt.text(0.01, 0.05, str(result.summary()), {'fontsize': 12}, fontproperties = 'n
plt.axis('off')
plt.savefig('log_test.png')

executed in 2.24s, finished 06:44:14 2021-04-22
```

Logit Regression Results

Dep. Variable:	loan_status	No. Observations:	1138127
Model:	Logit	_ Logit Df Residuals:	
Method:	MLE	Df Model:	82
Date:	Thu, 22 Apr 2021	Pseudo R-squ.:	0.4873
Time:	06:44:12	Log-Likelihood:	-4.0445e+05
converged:	True	LL-Null:	-7.8889e+05
Covariance Type:	nonrobust	LLR p-value:	0.000
		coef std err	z P> z

Covariance Type:	nonrobust	LLR p-va	lue:		0.000		
		coef	std err	Z	P> z	[0.025	0.975]
loan amnt		2.1560	0.098	21.990	0.000	1.964	2.348
term _		0.5027	0.016	30.586	0.000	0.470	0.535
int rate		7.2072	0.040	179.262	0.000	7.128	7.286
installment		-1.5100	0.118	-12.783	0.000	-1.742	-1.279
emp_length		-0.1368	0.007	-18.259	0.000	-0.151	-0.122
annual_inc		0.3920	0.062	6.343	0.000	0.271	0.513
dti		2.6434	0.034	78.646	0.000	2.578	2.709
delinq_2yrs		0.6637	0.019	34.573	0.000	0.626	0.701
inq_last_6mths		0.3508	0.014	24.671	0.000	0.323	0.379
pub_rec		0.1738	0.015	11.632	0.000	0.144	0.203
revol_bal		-1.6832	0.053	-31.759	0.000	-1.787	-1.579
total_acc		-1.2758	0.034	-37.459	0.000	-1.343	-1.209
total_rec_late_fee		4.4271	0.031	142.461	0.000	4.366	4.488
tot_cur_bal		-0.2271	0.028	-8.237	0.000	-0.281	-0.173
bc_util		0.6411	0.025	25.833	0.000	0.592	0.690
mo_sin_rcnt_tl		0.2385	0.024	9.827	0.000	0.191	0.286
mths_since_recent_bc		-0.3742	0.022	-16.997	0.000	-0.417	-0.331
num_accts_ever_120_pd		0.8164	0.020	40.442	0.000	0.777	0.856
num_bc_sats		0.8718	0.035	24.604	0.000	0.802	0.941
num_bc_tl		0.1275	0.032	3.952	0.000	0.064	0.191
num_op_rev_tl		0.5645	0.032	17.836	0.000	0.502	0.627
num_tl_90g_dpd_24m		-0.1595	0.030	-5.352	0.000	-0.218	-0.101
num_tl_op_past_12m		1.0435	0.020	51.331	0.000	1.004	1.083
pct_tl_nvr_dlq total bal ex mort		1.3804 1.9785	0.020	69.363	0.000	1.341	1.419
total_bat_ex_mort		-1.3348	0.077 0.034	25.700 -38.920	0.000	1.828 -1.402	2.129 -1.268
total_bc_timit total_il_high_credit_limit		-2.3481	0.054	-33.868	0.000	-2.484	-2.212
average_fico		-0.8361	0.003	-35.528	0.000	-0.882	-0.790
sub grade A2		-3.1012	0.024	-97.733	0.000	-3.163	-3.039
sub grade A3		-3.2481	0.029	-110.253	0.000	-3.306	-3.190
sub grade A4		-3.2478	0.023	-138.280	0.000	-3.294	-3.202
sub grade A5		-3.2969	0.020	-165.388	0.000	-3.336	-3.258
sub grade B1		-3.4009	0.018	-194.203	0.000	-3.435	-3.367
sub grade B2		-3.6234	0.017	-214.474	0.000	-3.657	-3.590
sub grade B3		-3.7443	0.016	-235.099	0.000	-3.776	-3.713
sub grade B4		-3.8306	0.015	-253.739	0.000	-3.860	-3.801
sub grade B5		-3.8679	0.015	-260.100	0.000	-3.897	-3.839
sub grade C1		-3.9714	0.015	-271.353	0.000	-4.000	-3.943
sub_grade_C2		-4.1335	0.015	-271.097	0.000	-4.163	-4.104
sub_grade_C3		-4.1899	0.015	-271.874	0.000	-4.220	-4.160
sub_grade_C4		-4.3151	0.016	-274.140	0.000	-4.346	-4.284
sub_grade_C5		-4.5168	0.017	-271.297	0.000	-4.549	-4.484
sub_grade_D1		-4.8100	0.019	-256.753	0.000	-4.847	-4.773
sub_grade_D2		-5.0447	0.020	-252.285	0.000	-5.084	-5.006
sub_grade_D3		-5.2398	0.021	-245.163	0.000	-5.282	-5.198
sub_grade_D4		-5.4344		-238.138	0.000	-5.479	-5.390
sub_grade_D5		-5.6902	0.025	-229.391	0.000	-5.739	-5.642
sub_grade_E1		-5.8298	0.028	-209.966	0.000	-5.884	-5.775
sub_grade_E2		-5.9535	0.029	-205.485	0.000	-6.010	-5.897
sub_grade_E3		-6.1471	0.031	-197.510	0.000	-6.208	-6.086
sub_grade_E4		-6.4066	0.034	-190.412	0.000	-6.473	-6.341
sub_grade_E5		-6.6574	0.035	-189.973	0.000	-6.726	-6.589
sub_grade_F1		-6.9581	0.042	-164.210	0.000	-7.041	-6.875
sub_grade_F2		-7.0097	0.049	-142.765	0.000	-7.106	-6.913
sub_grade_F3		-7.3057	0.054	-136.395	0.000	-7.411	-7.201
sub grade F4		-7.4520	0.060	-123.521	0.000	-7.570	-7.334

```
sub_grade_F5
                                         -7.5491
                                                                                          -7.677
                                                       0.065
                                                               -115.945
                                                                               0.000
                                                                                                       -7.422
sub_grade_G1
                                          -7.9231
                                                       0.074
                                                                -106.914
                                                                               0.000
                                                                                          -8.068
                                                                                                       -7.778
                                                                                          -8.005
sub_grade_G2
                                          -7.8289
                                                       0.090
                                                                 -87.322
                                                                               0.000
                                                                                                       -7.653
sub_grade_G3
                                         -8.0357
                                                       0.099
                                                                 -80.933
                                                                               0.000
                                                                                          -8.230
                                                                                                       -7.841
sub_grade_G4
                                         -8.2587
                                                       0.110
                                                                 -74.748
                                                                               0.000
                                                                                          -8.475
                                                                                                       -8.042
                                                                              0.000
                                                                                          -8.246
                                                                                                       -7.779
sub_grade_G5
                                         -8.0126
                                                       0.119
                                                                 -67.185
home_ownership_MORTGAGE
                                         -0.2456
                                                       0.018
                                                                 -13.527
                                                                               0.000
                                                                                          -0.281
                                                                                                       -0.210
                                         -0.2941
                                                                 -15.174
                                                                                          -0.332
                                                                                                       -0.256
home_ownership_OWN
                                                       0.019
                                                                               0.000
home_ownership_RENT
                                          0.2025
                                                       0.018
                                                                  11.450
                                                                               0.000
                                                                                           0.168
                                                                                                        0.237
verification_status_Source Verified
                                          0.0042
                                                       0.007
                                                                   0.631
                                                                               0.528
                                                                                          -0.009
                                                                                                        0.017
verification_status_Verified
                                         -0.0982
                                                       0.008
                                                                 -13.036
                                                                               0.000
                                                                                          -0.113
                                                                                                       -0.083
purpose credit card
                                         -1.2692
                                                       0.013
                                                                 -95.255
                                                                               0.000
                                                                                          -1.295
                                                                                                       -1.243
                                                                 -77.556
purpose_debt_consolidation
                                         -0.9722
                                                       0.013
                                                                              0.000
                                                                                          -0.997
                                                                                                       -0.948
purpose_home_improvement
                                         -1.2495
                                                       0.018
                                                                 -68.874
                                                                              0.000
                                                                                          -1.285
                                                                                                       -1.214
purpose_house
                                         -1.3176
                                                       0.046
                                                                 -28.556
                                                                               0.000
                                                                                          -1.408
                                                                                                       -1.227
purpose_major_purchase
                                         -1.3732
                                                       0.026
                                                                 -52.343
                                                                               0.000
                                                                                          -1.425
                                                                                                       -1.322
purpose other
                                         -1.2017
                                                       0.018
                                                                 -68.096
                                                                               0.000
                                                                                          -1.236
                                                                                                       -1.167
                                                                               0.000
purpose_renewable_energy
                                         -1.3684
                                                       0.139
                                                                 -9.843
                                                                                          -1.641
                                                                                                       -1.096
purpose_small_business
                                         -0.8205
                                                       0.033
                                                                 -24.652
                                                                               0.000
                                                                                          -0.886
                                                                                                       -0.755
purpose_vacation
                                                                                          -1.390
                                         -1.3081
                                                       0.042
                                                                 -31.443
                                                                              0.000
                                                                                                       -1.227
purpose_wedding
                                         -2.1062
                                                       0.169
                                                                 -12.492
                                                                              0.000
                                                                                          -2.437
                                                                                                       -1.776
purpose medical
                                         -1.1888
                                                       0.032
                                                                 -36.988
                                                                               0.000
                                                                                          -1.252
                                                                                                       -1.126
                                         -1.2438
                                                                               0.000
                                                                                          -1.323
purpose_moving
                                                       0.040
                                                                 -30.796
                                                                                                       -1.165
application_type_Joint App
                                          -0.5429
                                                       0.018
                                                                 -30.922
                                                                               0.000
                                                                                          -0.577
                                                                                                       -0.509
                                                                               0.000
                                                                                          -0.756
                                                                                                       -0.728
                                         -0.7420
                                                       0.007
                                                                -101.132
region South
region West
                                         -0.7465
                                                       0.008
                                                                 -94.987
                                                                               0.000
                                                                                          -0.762
                                                                                                       -0.731
                                                       0.008
                                                                 -79.360
                                                                               0.000
                                                                                          -0.689
                                                                                                       -0.656
region_Northeast
                                         -0.6726
```

In [67]: log_summary = model_scores(y_test_z,y_hat_log,"Logistic Regression")
log_summary
executed in 403ms, finished 05:11:37 2021-04-22

Out[67]:

Model	precision_score	recall_score	accuracy_score	f1_score
Logistic Regression	0.408908	0.236125	0.797429	0.299375

```
In [68]: log_summary.to_csv('data/log_scores')
executed in 31ms, finished 05:12:12 2021-04-22
```