# credit_risk_ensemble

May 30, 2021

# 1 Ensemble Learning

## 1.1 Initial Imports

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
import numpy as np
import pandas as pd
from pathlib import Path
from collections import Counter
from datetime import datetime
```

[34]:
```
from sklearn.metrics import balanced_accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import make_classification

from imblearn.metrics import classification_report_imbalanced
from imblearn.ensemble import BalancedRandomForestClassifier
from imblearn.ensemble import EasyEnsembleClassifier
```

## 1.2 Read the CSV and Perform Basic Data Cleaning

[4]:
```
# Load the data
file_path = Path('Resources/LoanStats_2019Q1.csv')
df = pd.read_csv(file_path)

# Preview the data
df.head()
```

[4]:
```
   loan_amnt  int_rate  installment home_ownership  annual_inc  \
0    10500.0    0.1719       375.35           RENT     66000.0
1    25000.0    0.2000       929.09       MORTGAGE    105000.0
```

```
2    20000.0    0.2000        529.88       MORTGAGE     56000.0
3    10000.0    0.1640        353.55           RENT     92000.0
4    22000.0    0.1474        520.39       MORTGAGE     52000.0

  verification_status   issue_d loan_status pymnt_plan    dti  …  \
0     Source Verified  Mar-2019    low_risk          n  27.24  …
1            Verified  Mar-2019    low_risk          n  20.23  …
2            Verified  Mar-2019    low_risk          n  24.26  …
3            Verified  Mar-2019    low_risk          n  31.44  …
4        Not Verified  Mar-2019    low_risk          n  18.76  …

   pct_tl_nvr_dlq  percent_bc_gt_75  pub_rec_bankruptcies  tax_liens  \
0            85.7             100.0                   0.0        0.0
1            91.2              50.0                   1.0        0.0
2            66.7              50.0                   0.0        0.0
3           100.0              50.0                   1.0        0.0
4           100.0               0.0                   0.0        0.0

   tot_hi_cred_lim  total_bal_ex_mort total_bc_limit  \
0          65687.0            38199.0         2000.0
1         271427.0            60641.0        41200.0
2          60644.0            45684.0         7500.0
3          99506.0            68784.0        19700.0
4         219750.0            25919.0        27600.0

   total_il_high_credit_limit  hardship_flag  debt_settlement_flag
0                     61987.0              N                     N
1                     49197.0              N                     N
2                     43144.0              N                     N
3                     76506.0              N                     N
4                     20000.0              N                     N

[5 rows x 86 columns]
```

[5]:
```
df.columns
```

[5]:
```
Index(['loan_amnt', 'int_rate', 'installment', 'home_ownership', 'annual_inc',
       'verification_status', 'issue_d', 'loan_status', 'pymnt_plan', 'dti',
       'delinq_2yrs', 'inq_last_6mths', 'open_acc', 'pub_rec', 'revol_bal',
       'total_acc', 'initial_list_status', 'out_prncp', 'out_prncp_inv',
       'total_pymnt', 'total_pymnt_inv', 'total_rec_prncp', 'total_rec_int',
       'total_rec_late_fee', 'recoveries', 'collection_recovery_fee',
       'last_pymnt_amnt', 'next_pymnt_d', 'collections_12_mths_ex_med',
       'policy_code', 'application_type', 'acc_now_delinq', 'tot_coll_amt',
       'tot_cur_bal', 'open_acc_6m', 'open_act_il', 'open_il_12m',
       'open_il_24m', 'mths_since_rcnt_il', 'total_bal_il', 'il_util',
       'open_rv_12m', 'open_rv_24m', 'max_bal_bc', 'all_util',
```

```
       'total_rev_hi_lim', 'inq_fi', 'total_cu_tl', 'inq_last_12m',
       'acc_open_past_24mths', 'avg_cur_bal', 'bc_open_to_buy', 'bc_util',
       'chargeoff_within_12_mths', 'delinq_amnt', 'mo_sin_old_il_acct',
       'mo_sin_old_rev_tl_op', 'mo_sin_rcnt_rev_tl_op', 'mo_sin_rcnt_tl',
       'mort_acc', 'mths_since_recent_bc', 'mths_since_recent_inq',
       'num_accts_ever_120_pd', 'num_actv_bc_tl', 'num_actv_rev_tl',
       'num_bc_sats', 'num_bc_tl', 'num_il_tl', 'num_op_rev_tl',
       'num_rev_accts', 'num_rev_tl_bal_gt_0', 'num_sats', 'num_tl_120dpd_2m',
       'num_tl_30dpd', 'num_tl_90g_dpd_24m', 'num_tl_op_past_12m',
       'pct_tl_nvr_dlq', 'percent_bc_gt_75', 'pub_rec_bankruptcies',
       'tax_liens', 'tot_hi_cred_lim', 'total_bal_ex_mort', 'total_bc_limit',
       'total_il_high_credit_limit', 'hardship_flag', 'debt_settlement_flag'],
      dtype='object')
```

[6]:
```python
## Adding month and date columns from dates

# df["month"] = datetime.strptime(df["issue_d"], 'MMM-YYYY').month
# >>> print dt.year, dt.month, dt.day
df['issue_date'] = pd.to_datetime(df['issue_d'])
df['next_pymnt_date'] = pd.to_datetime(df['next_pymnt_d'])

df['issue_month'] = pd.DatetimeIndex(df['issue_date']).month.astype(str)
df["issue_year"] = pd.DatetimeIndex(df['issue_date']).year.astype(str)
df['next_pymnt_d_month'] = pd.DatetimeIndex(df['next_pymnt_date']).month.
 ↪astype(str)
df['next_pymnt_d_year'] = pd.DatetimeIndex(df['next_pymnt_date']).year.
 ↪astype(str)
```

[7]:
```python
df
```

[7]:
```
       loan_amnt  int_rate  installment home_ownership  annual_inc  \
0        10500.0    0.1719       375.35           RENT     66000.0
1        25000.0    0.2000       929.09       MORTGAGE    105000.0
2        20000.0    0.2000       529.88       MORTGAGE     56000.0
3        10000.0    0.1640       353.55           RENT     92000.0
4        22000.0    0.1474       520.39       MORTGAGE     52000.0
…          …         …          …              …           …
68812    10000.0    0.1502       346.76           RENT     26000.0
68813    12000.0    0.2727       368.37           RENT     63000.0
68814     5000.0    0.1992       185.62       MORTGAGE     52000.0
68815    40000.0    0.0646      1225.24       MORTGAGE    520000.0
68816    16000.0    0.1131       350.36       MORTGAGE     72000.0

      verification_status   issue_d loan_status pymnt_plan    dti  …  \
0         Source Verified  Mar-2019    low_risk          n  27.24  …
1                Verified  Mar-2019    low_risk          n  20.23  …
2                Verified  Mar-2019    low_risk          n  24.26  …
```

```
3              Verified  Mar-2019    low_risk          n  31.44  …
4          Not Verified  Mar-2019    low_risk          n  18.76  …
…                   …       …           …          …    …  …
68812   Source Verified  Jan-2019    low_risk          n   9.60  …
68813      Not Verified  Jan-2019    low_risk          n  29.07  …
68814   Source Verified  Jan-2019    low_risk          n  14.86  …
68815          Verified  Jan-2019    low_risk          n   9.96  …
68816          Verified  Jan-2019    low_risk          n   7.02  …

       total_bc_limit  total_il_high_credit_limit  hardship_flag  \
0              2000.0                     61987.0              N
1             41200.0                     49197.0              N
2              7500.0                     43144.0              N
3             19700.0                     76506.0              N
4             27600.0                     20000.0              N
…                 …                          …           …
68812         11300.0                      5425.0              N
68813         13500.0                     62939.0              N
68814          3600.0                     18492.0              N
68815        100800.0                     78634.0              N
68816         23000.0                     63090.0              N

       debt_settlement_flag  issue_date  next_pymnt_date issue_month  \
0                         N  2019-03-01       2019-05-01           3
1                         N  2019-03-01       2019-05-01           3
2                         N  2019-03-01       2019-05-01           3
3                         N  2019-03-01       2019-05-01           3
4                         N  2019-03-01       2019-05-01           3
…                     …          …              …          …
68812                     N  2019-01-01       2019-05-01           1
68813                     N  2019-01-01       2019-05-01           1
68814                     N  2019-01-01       2019-05-01           1
68815                     N  2019-01-01       2019-05-01           1
68816                     N  2019-01-01       2019-05-01           1

       issue_year  next_pymnt_d_month  next_pymnt_d_year
0            2019                   5               2019
1            2019                   5               2019
2            2019                   5               2019
3            2019                   5               2019
4            2019                   5               2019
…           …                 …                 …
68812        2019                   5               2019
68813        2019                   5               2019
68814        2019                   5               2019
68815        2019                   5               2019
68816        2019                   5               2019
```

```
[68817 rows x 92 columns]
```

### 1.3 Split the Data into Training and Testing

[8]:
```
# Create our features
X = df[['loan_amnt', 'int_rate', 'installment', 'home_ownership', 'annual_inc',
       'verification_status', 'issue_d', 'pymnt_plan', 'dti',
       'delinq_2yrs', 'inq_last_6mths', 'open_acc', 'pub_rec', 'revol_bal',
       'total_acc', 'initial_list_status', 'out_prncp', 'out_prncp_inv',
       'total_pymnt', 'total_pymnt_inv', 'total_rec_prncp', 'total_rec_int',
       'total_rec_late_fee', 'recoveries', 'collection_recovery_fee',
       'last_pymnt_amnt', 'next_pymnt_d', 'collections_12_mths_ex_med',
       'policy_code', 'application_type', 'acc_now_delinq', 'tot_coll_amt',
       'tot_cur_bal', 'open_acc_6m', 'open_act_il', 'open_il_12m',
       'open_il_24m', 'mths_since_rcnt_il', 'total_bal_il', 'il_util',
       'open_rv_12m', 'open_rv_24m', 'max_bal_bc', 'all_util',
       'total_rev_hi_lim', 'inq_fi', 'total_cu_tl', 'inq_last_12m',
       'acc_open_past_24mths', 'avg_cur_bal', 'bc_open_to_buy', 'bc_util',
       'chargeoff_within_12_mths', 'delinq_amnt', 'mo_sin_old_il_acct',
       'mo_sin_old_rev_tl_op', 'mo_sin_rcnt_rev_tl_op', 'mo_sin_rcnt_tl',
       'mort_acc', 'mths_since_recent_bc', 'mths_since_recent_inq',
       'num_accts_ever_120_pd', 'num_actv_bc_tl', 'num_actv_rev_tl',
       'num_bc_sats', 'num_bc_tl', 'num_il_tl', 'num_op_rev_tl',
       'num_rev_accts', 'num_rev_tl_bal_gt_0', 'num_sats', 'num_tl_120dpd_2m',
       'num_tl_30dpd', 'num_tl_90g_dpd_24m', 'num_tl_op_past_12m',
       'pct_tl_nvr_dlq', 'percent_bc_gt_75', 'pub_rec_bankruptcies',
       'tax_liens', 'tot_hi_cred_lim', 'total_bal_ex_mort', 'total_bc_limit',
       'total_il_high_credit_limit', 'hardship_flag','issue_month','issue_year',
       'next_pymnt_d_month','next_pymnt_d_year',"debt_settlement_flag"]]

# Create our target
y = df["loan_status"]
```

[9]:
```
y.value_counts()
```

[9]:
```
low_risk     68470
high_risk      347
Name: loan_status, dtype: int64
```

[15]:
```
categorical =␣
 ↪["home_ownership","verification_status","pymnt_plan","application_type",
             ␣
 ↪"hardship_flag","initial_list_status",'issue_month','issue_year','next_pymnt_d_month','next
              "debt_settlement_flag"]
```

[16]:
```
categorical_df = pd.get_dummies(df[categorical], prefix='d_')
categorical_df
```

[16]:
```
       d__ANY  d__MORTGAGE  d__OWN  d__RENT  d__Not Verified  \
0           0            0       0        1                0
1           0            1       0        0                0
2           0            1       0        0                0
3           0            0       0        1                0
4           0            1       0        0                1
…         …          …        …      …               …
68812       0            0       0        1                0
68813       0            0       0        1                1
68814       0            1       0        0                0
68815       0            1       0        0                0
68816       0            1       0        0                0

       d__Source Verified  d__Verified  d__n  d__Individual  d__Joint App  \
0                       1            0     1              1             0
1                       0            1     1              1             0
2                       0            1     1              1             0
3                       0            1     1              1             0
4                       0            0     1              1             0
…                      …           …    …            …            …
68812                   1            0     1              1             0
68813                   0            0     1              1             0
68814                   1            0     1              1             0
68815                   0            1     1              1             0
68816                   0            1     1              1             0

       …  d__f  d__w  d__1  d__2  d__3  d__2019  d__4  d__5  d__2019  d__N
0      …     0     1     0     0     1        1     0     1        1     1
1      …     0     1     0     0     1        1     0     1        1     1
2      …     0     1     0     0     1        1     0     1        1     1
3      …     0     1     0     0     1        1     0     1        1     1
4      …     0     1     0     0     1        1     0     1        1     1
…    …   …   …   …   …   …      …   …   …      …   …
68812  …     0     1     1     0     0        1     0     1        1     1
68813  …     0     1     1     0     0        1     0     1        1     1
68814  …     0     1     1     0     0        1     0     1        1     1
68815  …     1     0     1     0     0        1     0     1        1     1
68816  …     0     1     1     0     0        1     0     1        1     1

[68817 rows x 21 columns]
```

[17]:
```
print(X.shape)
```

```
(68817, 89)
```

[18]:
```python
X_new = pd.concat([X, categorical_df], axis="columns")
X_new.drop(categorical, axis="columns", inplace=True)
X_new.drop('issue_d', axis="columns", inplace=True)
X_new.drop('next_pymnt_d', axis="columns", inplace=True)
X = X_new
```

[19]:
```python
print(X.shape)
```

```
(68817, 97)
```

[20]:
```python
X.describe()
```

[20]:
```
          loan_amnt      int_rate   installment    annual_inc           dti  \
count  68817.000000  68817.000000  68817.000000  6.881700e+04  68817.000000
mean   16677.594562      0.127718    480.652863  8.821371e+04     21.778153
std    10277.348590      0.048130    288.062432  1.155800e+05     20.199244
min     1000.000000      0.060000     30.890000  4.000000e+01      0.000000
25%     9000.000000      0.088100    265.730000  5.000000e+04     13.890000
50%    15000.000000      0.118000    404.560000  7.300000e+04     19.760000
75%    24000.000000      0.155700    648.100000  1.040000e+05     26.660000
max    40000.000000      0.308400   1676.230000  8.797500e+06    999.000000

        delinq_2yrs  inq_last_6mths      open_acc       pub_rec  \
count  68817.000000    68817.000000  68817.000000  68817.000000
mean       0.217766        0.497697     12.587340      0.126030
std        0.718367        0.758122      6.022869      0.336797
min        0.000000        0.000000      2.000000      0.000000
25%        0.000000        0.000000      8.000000      0.000000
50%        0.000000        0.000000     11.000000      0.000000
75%        0.000000        1.000000     16.000000      0.000000
max       18.000000        5.000000     72.000000      4.000000

          revol_bal  …           d__f          d__w          d__1  \
count  68817.000000  …   68817.000000  68817.000000  68817.000000
mean   17604.142828  …       0.123879      0.876121      0.451066
std    21835.880400  …       0.329446      0.329446      0.497603
min        0.000000  …       0.000000      0.000000      0.000000
25%     6293.000000  …       0.000000      1.000000      0.000000
50%    12068.000000  …       0.000000      1.000000      0.000000
75%    21735.000000  …       0.000000      1.000000      1.000000
max   587191.000000  …       1.000000      1.000000      1.000000

               d__2          d__3  d__2019          d__4          d__5  \
count  68817.000000  68817.000000  68817.0  68817.000000  68817.000000
mean       0.371696      0.177238      1.0      0.383161      0.616839
std        0.483261      0.381873      0.0      0.486161      0.486161
min        0.000000      0.000000      1.0      0.000000      0.000000
```

```
25%        0.000000      0.000000      1.0      0.000000      0.000000
50%        0.000000      0.000000      1.0      0.000000      1.000000
75%        1.000000      0.000000      1.0      1.000000      1.000000
max        1.000000      1.000000      1.0      1.000000      1.000000

       d__2019     d__N
count  68817.0  68817.0
mean       1.0      1.0
std        0.0      0.0
min        1.0      1.0
25%        1.0      1.0
50%        1.0      1.0
75%        1.0      1.0
max        1.0      1.0

[8 rows x 97 columns]
```

[21]:
```python
# Check the balance of our target values
print(len(X))
print(len(y))
```

```
68817
68817
```

[22]:
```python
X
```

[22]:
```
       loan_amnt  int_rate  installment  annual_inc    dti  delinq_2yrs  \
0        10500.0    0.1719       375.35     66000.0  27.24          0.0
1        25000.0    0.2000       929.09    105000.0  20.23          0.0
2        20000.0    0.2000       529.88     56000.0  24.26          0.0
3        10000.0    0.1640       353.55     92000.0  31.44          0.0
4        22000.0    0.1474       520.39     52000.0  18.76          0.0
…            …         …           …          …      …            …
68812    10000.0    0.1502       346.76     26000.0   9.60          0.0
68813    12000.0    0.2727       368.37     63000.0  29.07          0.0
68814     5000.0    0.1992       185.62     52000.0  14.86          0.0
68815    40000.0    0.0646      1225.24    520000.0   9.96          0.0
68816    16000.0    0.1131       350.36     72000.0   7.02          2.0

       inq_last_6mths  open_acc  pub_rec  revol_bal  …  d__f  d__w  d__1  \
0                 0.0       8.0      0.0     1609.0  …     0     1     0
1                 0.0      17.0      1.0    18368.0  …     0     1     0
2                 0.0       8.0      0.0    13247.0  …     0     1     0
3                 1.0      10.0      1.0    17996.0  …     0     1     0
4                 1.0      14.0      0.0     9091.0  …     0     1     0
…                 …         …        …          …  …   …     …     …
68812             0.0       9.0      0.0     2684.0  …     0     1     1
```

```
68813                0.0       8.0       0.0     13314.0  ...      0      1      1
68814                0.0       5.0       1.0      3715.0  ...      0      1      1
68815                1.0      21.0       0.0     59529.0  ...      1      0      1
68816                0.0      12.0       1.0     11882.0  ...      0      1      1

       d__2  d__3  d__2019  d__4  d__5  d__2019  d__N
0         0     1        1     0     1        1     1
1         0     1        1     0     1        1     1
2         0     1        1     0     1        1     1
3         0     1        1     0     1        1     1
4         0     1        1     0     1        1     1
...     ...   ...      ...   ...   ...      ...   ...
68812     0     0        1     0     1        1     1
68813     0     0        1     0     1        1     1
68814     0     0        1     0     1        1     1
68815     0     0        1     0     1        1     1
68816     0     0        1     0     1        1     1

[68817 rows x 97 columns]
```

[23]:
```python
X.to_csv("view.csv")
```

[24]:
```python
# Split the X and y into X_train, X_test, y_train, y_test
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=32)
```

### 1.4 Data Pre-Processing

Scale the training and testing data using the `StandardScaler` from `sklearn`. Remember that when scaling the data, you only scale the features data (`X_train` and `X_testing`).

[25]:
```python
# Create the StandardScaler instance
scaler = StandardScaler()
```

[26]:
```python
X_train.head()
```

[26]:
```
       loan_amnt  int_rate  installment  annual_inc    dti  delinq_2yrs  \
63152    15000.0    0.2235       417.28    125000.0  11.06          0.0
2905     40000.0    0.1033       856.40    105000.0  15.02          0.0
27484    12925.0    0.1691       460.24     55000.0  13.81          0.0
12354    10000.0    0.1474       345.39     70000.0   9.19          0.0
4134     15000.0    0.1171       496.14     85000.0  10.29          0.0

       inq_last_6mths  open_acc  pub_rec  revol_bal  ...  d__f  d__w  d__1  \
63152             2.0      10.0      2.0     9550.0  ...     0     1     1
2905              1.0      13.0      0.0    34395.0  ...     0     1     0
27484             2.0       9.0      0.0     8524.0  ...     0     1     0
```

```
12354              1.0       9.0       1.0      2352.0  …      1      0      0
4134               0.0       8.0       0.0      1701.0  …      0      1      0

       d__2  d__3  d__2019  d__4  d__5  d__2019  d__N
63152     0     0        1     0     1        1     1
2905      0     1        1     0     1        1     1
27484     1     0        1     0     1        1     1
12354     1     0        1     0     1        1     1
4134      0     1        1     0     1        1     1

[5 rows x 97 columns]
```

[27]:
```
# Fit the Standard Scaler with the training data
# When fitting scaling functions, only train on the training dataset
X_scaler = scaler.fit(X_train)
# scaler_test = StandardScaler().fit(X_test)
```

[28]:
```
# Scale the training and testing data
X_train_scaled = X_scaler.transform(X_train)
X_test_scaled = X_scaler.transform(X_test)
```

### 1.5 Ensemble Learners

In this section, you will compare two ensemble algorithms to determine which algorithm results in the best performance. You will train a Balanced Random Forest Classifier and an Easy Ensemble classifier . For each algorithm, be sure to complete the folliowing steps:

1. Train the model using the training data.
2. Calculate the balanced accuracy score from sklearn.metrics.
3. Display the confusion matrix from sklearn.metrics.
4. Generate a classication report using the `imbalanced_classification_report` from imbalanced-learn.
5. For the Balanced Random Forest Classifier only, print the feature importance sorted in descending order (most important feature to least important) along with the feature score

Note: Use a random state of 1 for each algorithm to ensure consistency between tests

#### 1.5.1 Balanced Random Forest Classifier

[35]:
```
# Resample the training data with the BalancedRandomForestClassifier
brfc = BalancedRandomForestClassifier(max_depth=2, random_state=1)
brfc.fit(X_train, y_train)
```

[35]:
```
BalancedRandomForestClassifier(max_depth=2, random_state=1)
```

[36]:
```
# Calculated the balanced accuracy score
y_pred = brfc.predict(X_test)
balanced_accuracy_score(y_test, y_pred)
```

[36]:
```
0.7147418320530224
```

[37]:
```
# Display the confusion matrix
confusion_matrix(y_test, y_pred)
```

[37]:
```
array([[   38,    44],
       [  581, 16542]])
```

[38]:
```
# Print the imbalanced classification report
print(classification_report_imbalanced(y_test, y_pred))
```

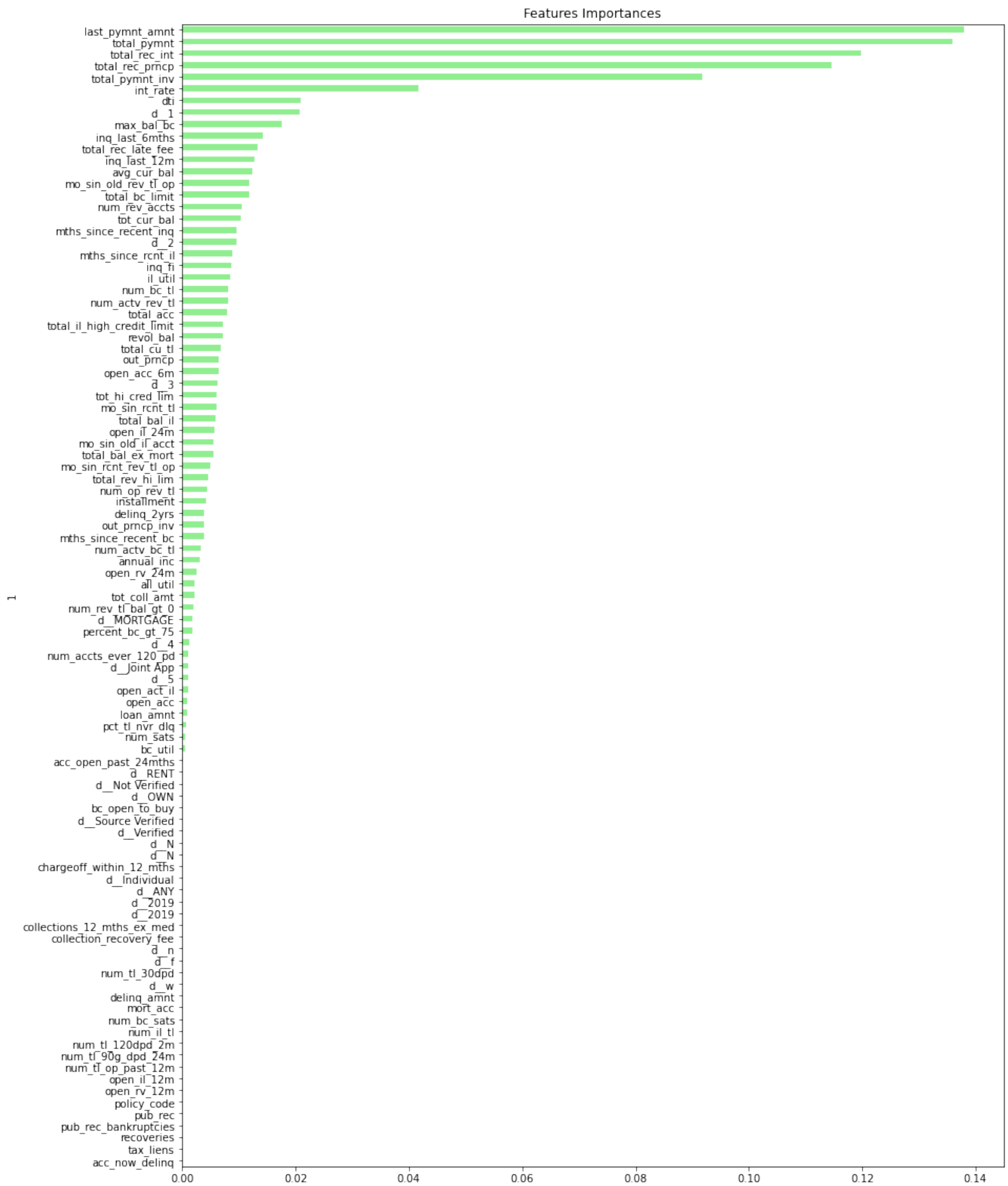
```
                   pre       rec       spe        f1       geo       iba
sup

  high_risk       0.06      0.46      0.97      0.11      0.67      0.43
82
   low_risk       1.00      0.97      0.46      0.98      0.67      0.47
17123

avg / total       0.99      0.96      0.47      0.98      0.67      0.47
17205
```

[39]:
```
# List the features sorted in descending order by feature importance
importances_df = pd.DataFrame(sorted(zip(clf.feature_importances_, X.columns),␣
 ↪reverse=True))
importances_df.set_index(importances_df[1], inplace=True)
importances_df.drop(columns=1, inplace=True)
importances_df.rename(columns={0: 'Feature Importances'}, inplace=True)
importances_sorted = importances_df.sort_values(by='Feature Importances',␣
 ↪ascending=True)
importances_sorted.plot(kind='barh', color='lightgreen', title= 'Features␣
 ↪Importances', legend=False, figsize=(14,20))
```

[39]:
```
<AxesSubplot:title={'center':'Features Importances'}, ylabel='1'>
```




### 1.5.2 Easy Ensemble Classifier

[46]:
```
# Train the Classifier
eec = EasyEnsembleClassifier(random_state=1)
eec.fit(X_train, y_train)
```

[46]: EasyEnsembleClassifier(random_state=1)

```
[47]: # Calculated the balanced accuracy score
y_pred = eec.predict(X_test)
balanced_accuracy_score(y_test, y_pred)
```

[47]: 0.9197705838531258

```
[48]: # Display the confusion matrix
confusion_matrix(y_test, y_pred)
```

```
[48]: array([[   74,     8],
       [ 1077, 16046]])
```

```
[49]: # Print the imbalanced classification report
print(classification_report_imbalanced(y_test, y_pred))
```

```
                   pre       rec       spe        f1       geo       iba
sup

  high_risk       0.06      0.90      0.94      0.12      0.92      0.84
82
   low_risk       1.00      0.94      0.90      0.97      0.92      0.85
17123

avg / total       1.00      0.94      0.90      0.96      0.92      0.85
17205
```

```
[52]: print(np.mean([est.steps[1][1].feature_importances_ for est in eec.
 ↪estimators_], axis=0))
```

```
[0.014 0.068 0.076 0.    0.008 0.002 0.006 0.002 0.    0.002 0.002 0.016
 0.014 0.022 0.026 0.096 0.168 0.018 0.    0.    0.106 0.    0.    0.
 0.004 0.004 0.004 0.002 0.    0.    0.008 0.004 0.    0.    0.    0.012
 0.006 0.002 0.004 0.    0.    0.002 0.006 0.016 0.016 0.    0.    0.002
 0.01  0.    0.004 0.002 0.006 0.002 0.    0.    0.    0.    0.002 0.002
 0.002 0.    0.002 0.004 0.    0.    0.    0.004 0.    0.002 0.    0.
 0.004 0.004 0.008 0.    0.    0.    0.    0.    0.002 0.    0.    0.
 0.    0.    0.    0.    0.    0.078 0.004 0.048 0.    0.034 0.038 0.
 0.   ]
```

### 1.5.3 Final Questions

1. Which model had the best balanced accuracy score?

   Easy Ensemble Classifier with 0.9197

2. Which model had the best recall score?

   Balanced Random Forest Classifier with 0.96 (96%)

3. Which model had the best geometric mean score?

   Easy Ensemble Classifier with 0.92

4. What are the top three features?

   last_paymnt_amt, total_payment, total_rec_int

```
[ ]:
```