Credit_Risk_Modeling

May 26, 2018

0.0.1 Invoke Packages

```
In [148]: import numpy as np
          import pandas as pd
          import seaborn as sns
          import matplotlib.pyplot as plt
          from sklearn.model_selection import GridSearchCV
          from mlxtend.plotting import plot_confusion_matrix
          from sklearn.linear_model import LogisticRegression
          from sklearn.model_selection import cross_val_predict
          from sklearn.metrics import confusion_matrix, mean_squared_error, classification_repo
          %matplotlib inline
```

0.0.2 Reading dataframe and clearning the noise

```
In [149]: loans_2007 = pd.read_csv(r"./databank/loans_2007.csv", low_memory = False)

          # Removing rows with duplicate data
          loans_2007 = loans_2007.drop_duplicates()
          # Display first row of  the dataframe
          print(loans_2007.info())
          # Display dataframe size
          print("\nTotal number of features : ",  loans_2007.shape[1])
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 42538 entries, 0 to 42537
Data columns (total 52 columns):
id                            42538 non-null object
member_id                     42535 non-null float64
loan_amnt                     42535 non-null float64
funded_amnt                   42535 non-null float64
funded_amnt_inv               42535 non-null float64
term                          42535 non-null object
int_rate                      42535 non-null object
installment                   42535 non-null float64
grade                         42535 non-null object
sub_grade                     42535 non-null object
emp_title                     39909 non-null object
```

```
emp_length                    41423 non-null object
home_ownership                42535 non-null object
annual_inc                    42531 non-null float64
verification_status           42535 non-null object
issue_d                       42535 non-null object
loan_status                   42535 non-null object
pymnt_plan                    42535 non-null object
purpose                       42535 non-null object
title                         42522 non-null object
zip_code                      42535 non-null object
addr_state                    42535 non-null object
dti                           42535 non-null float64
delinq_2yrs                   42506 non-null float64
earliest_cr_line              42506 non-null object
inq_last_6mths                42506 non-null float64
open_acc                      42506 non-null float64
pub_rec                       42506 non-null float64
revol_bal                     42535 non-null float64
revol_util                    42445 non-null object
total_acc                     42506 non-null float64
initial_list_status           42535 non-null object
out_prncp                     42535 non-null float64
out_prncp_inv                 42535 non-null float64
total_pymnt                   42535 non-null float64
total_pymnt_inv               42535 non-null float64
total_rec_prncp               42535 non-null float64
total_rec_int                 42535 non-null float64
total_rec_late_fee            42535 non-null float64
recoveries                    42535 non-null float64
collection_recovery_fee       42535 non-null float64
last_pymnt_d                  42452 non-null object
last_pymnt_amnt               42535 non-null float64
last_credit_pull_d            42531 non-null object
collections_12_mths_ex_med    42390 non-null float64
policy_code                   42535 non-null float64
application_type              42535 non-null object
acc_now_delinq                42506 non-null float64
chargeoff_within_12_mths      42390 non-null float64
delinq_amnt                   42506 non-null float64
pub_rec_bankruptcies          41170 non-null float64
tax_liens                     42430 non-null float64
dtypes: float64(30), object(22)
memory usage: 17.2+ MB
None

Total number of features :  52
```

0.0.3 Cleaning dataframe by columns carrying irrelevant information

```
In [150]: cols = ["id", "member_id", "funded_amnt", "funded_amnt_inv", "grade", "sub_grade", "e
                  "issue_d", "zip_code", "out_prncp", "out_prncp_inv", "total_pymnt", "total_py
                  "total_rec_prncp", "total_rec_int", "total_rec_late_fee", "recoveries", "coll
                  "last_pymnt_d", "last_pymnt_amnt"]
          loans_2007 = loans_2007.drop(cols, axis=1)
          loans_2007.shape[1]
```

```
Out[150]: 32
```

0.0.4 Selecting Target Column

```
In [151]: # Selecting "loan_status" as a target column
          loans_2007["loan_status"].value_counts()
```

```
Out[151]: Fully Paid                                             33136
          Charged Off                                             5634
          Does not meet the credit policy. Status:Fully Paid      1988
          Current                                                  961
          Does not meet the credit policy. Status:Charged Off      761
          Late (31-120 days)                                        24
          In Grace Period                                           20
          Late (16-30 days)                                          8
          Default                                                    3
          Name: loan_status, dtype: int64
```

0.0.5 Cleaning the target column

```
In [152]: # Only first two values above in "Load_Status" are found to be useful for our modeli
          keep = ["Fully Paid", "Charged Off"]
          map_dict = {"Fully Paid": 1, "Charged Off": 0}

          loans_2007 = loans_2007[(loans_2007["loan_status"] == keep[0]) | (loans_2007["loan_st
                                                                             == keep[1])]
          loans_2007["loan_status"] = loans_2007["loan_status"].map(map_dict)
          loans_2007["loan_status"].unique()
```

```
Out[152]: array([1, 0], dtype=int64)
```

0.0.6 Removing the columns with single value

```
In [153]: # Since single valued columns carry no useful information for credibility evaluation
          drop_columns = []

          for col in loans_2007.columns:
              current = loans_2007[col].dropna()
              if len(current.unique()) == 1:
                  drop_columns.append(col)
```

```
loans_2007 = loans_2007.drop(drop_columns, axis=1)
loans_2007.columns
```

```
Out[153]: Index(['loan_amnt', 'term', 'int_rate', 'installment', 'emp_length',
               'home_ownership', 'annual_inc', 'verification_status', 'loan_status',
               'purpose', 'title', 'addr_state', 'dti', 'delinq_2yrs',
               'earliest_cr_line', 'inq_last_6mths', 'open_acc', 'pub_rec',
               'revol_bal', 'revol_util', 'total_acc', 'last_credit_pull_d',
               'pub_rec_bankruptcies'],
              dtype='object')
```

0.0.7 Checking the dataframe for null values

```
In [154]: # Display list of columns carrying null values (in descending order)
          null_counts = loans_2007.isnull().sum().sort_values(ascending=False)
          null_counts[0:10]
```

```
Out[154]: emp_length              1036
          pub_rec_bankruptcies     697
          revol_util                50
          title                     11
          last_credit_pull_d         2
          purpose                    0
          term                       0
          int_rate                   0
          installment                0
          home_ownership             0
          dtype: int64
```

0.0.8 Verifying the null values proportion

```
In [155]: # Show columns with number of null values as percentage of total training examples
          # (in descending order)
          null_percent = (loans_2007.isnull().sum()/loans_2007.shape[0]).sort_values(ascending=
          null_percent[0:5]
```

```
Out[155]: emp_length              2.672169
          pub_rec_bankruptcies    1.797782
          revol_util              0.128966
          title                   0.028372
          last_credit_pull_d      0.005159
          dtype: float64
```

Consider clearning columns with more less 1% NULL value while removing the columns with above 1% NULL values.

0.0.9 Further Cleaning/Removing the dataframe

```
In [156]: loans_2007 = loans_2007.drop('pub_rec_bankruptcies', axis=1)
          loans_2007 = loans_2007.dropna(subset=['title', 'revol_util', 'last_credit_pull_d'],
                                         axis=0, how='any')
          print("Total NaN values in the dataframe: ", loans_2007.isnull().sum().sum())
          print('pub_rec_bankruptcies' in loans_2007)
```

```
Total NaN values in the dataframe:  1032
False
```

0.0.10 Review the columns that carry object type data

```
In [157]: object_columns_df = loans_2007.select_dtypes(include=["object"])
          object_columns_df.iloc[0]
```

```
Out[157]: term                      36 months
          int_rate                     10.65%
          emp_length                10+ years
          home_ownership                 RENT
          verification_status        Verified
          purpose                 credit_card
          title                      Computer
          addr_state                       AZ
          earliest_cr_line           Jan-1985
          revol_util                    83.7%
          last_credit_pull_d         Jun-2016
          Name: 0, dtype: object
```

The following columns seem to carry categorical data that could be helpful for our regression analysis later:

- term
- emp_length
- home_ownership
- verification_status
- purpose
- title

The above results show that the following columns carry type of information that we can convert into numerical type for further analysis:

- int_rate
- revol_util

The remaining table seem to be not much useful and should be drop for our data frame. They are:

- addr_state
- earliest_cr_line
- last_credit_pull_d

0.0.11 Verify the columns with categorical data

```
In [158]: cols = ['term', 'emp_length', 'home_ownership', 'verification_status', 'purpose', 't

          for i in cols:
              print("\nUnique Counts for " + i + " :\n", object_columns_df[i].value_counts())
```

```
Unique Counts for term :
  36 months    29040
 60 months     9667
Name: term, dtype: int64

Unique Counts for emp_length :
 10+ years    8545
< 1 year     4513
2 years      4303
3 years      4022
4 years      3353
5 years      3202
1 year       3176
6 years      2177
7 years      1714
8 years      1442
9 years      1228
Name: emp_length, dtype: int64

Unique Counts for home_ownership :
 RENT        18513
MORTGAGE    17111
OWN          2984
OTHER          96
NONE            3
Name: home_ownership, dtype: int64

Unique Counts for verification_status :
 Not Verified       16696
Verified           12289
Source Verified     9722
Name: verification_status, dtype: int64

Unique Counts for purpose :
 debt_consolidation    18130
credit_card            5039
other                  3864
home_improvement       2897
major_purchase         2154
small_business         1762
car                    1510
```

```
wedding                 929
medical                 680
moving                  576
vacation                375
house                   369
educational             320
renewable_energy        102
Name: purpose, dtype: int64

Unique Counts for title :
 Debt Consolidation                                                  2104
Debt Consolidation Loan                                             1632
Personal Loan                                                        642
Consolidation                                                        494
debt consolidation                                                   485
Credit Card Consolidation                                            353
Home Improvement                                                     346
Debt consolidation                                                   324
Small Business Loan                                                  310
Credit Card Loan                                                     305
Personal                                                             302
Consolidation Loan                                                   251
Home Improvement Loan                                                234
personal loan                                                        227
personal                                                             211
Loan                                                                 208
Wedding Loan                                                         201
Car Loan                                                             195
consolidation                                                        193
Other Loan                                                           181
Credit Card Payoff                                                   150
Wedding                                                              149
Credit Card Refinance                                                143
Major Purchase Loan                                                  139
Consolidate                                                          125
Medical                                                              118
Credit Card                                                          115
home improvement                                                     107
My Loan                                                               92
Credit Cards                                                          91
                                                                    ...
money honey                                                            1
Working capital business loan                                          1
Graduation/Travel Expenses                                             1
Home Improvements                                                      1
Making ends meet                                                       1
amexloan                                                               1
HudsonKK                                                               1
```

```
New kitchen                                                     1
Small business loan                                             1
COSMETIC                                                        1
Dept Consolidation Loan Success                                 1
Freash Start!                                                   1
Triathlete                                                      1
Hearing Aids                                                    1
business plan debt consultation                                 1
Condo Renovation Loan                                           1
pay off high interest debt                                      1
CREATING FINACIAL INDEPENDENCE FOR MY CHILDREN AND ME           1
Home sale buyout                                                1
KDC_Loan123                                                     1
Car loan and pay off my family                                  1
Credit Card Relieve                                             1
Family Support                                                  1
Catrin's wish                                                   1
Furniture                                                       1
Monty                                                           1
Discover payoff                                                 1
New Job Relocate Debt Until IL Home Sell                        1
missvi1                                                         1
The consolidator                                                1
Name: title, Length: 19331, dtype: int64
```

It appears that column 'purpose' and 'title' carry overlapping information. However, considering the duplication of loan categories under the 'title' column, let's keep the 'purpose' column and drop the 'title' one.

Column 'emp_length' carries multiple category data.

0.0.12 Drop less useful columns with duplicate/overlapping data

```
In [159]: cols = ['addr_state', 'earliest_cr_line', 'last_credit_pull_d', 'title']
          loans_2007 = loans_2007.drop(cols, axis=1)
```

0.0.13 Assign data variables to columns

```
In [160]: cat_columns = ['home_ownership', 'verification_status', 'purpose', 'term']
          loans_2007_dummies = pd.get_dummies(loans_2007[cat_columns])
          loans_2007 = pd.concat([loans_2007, loans_2007_dummies], axis=1)

          # Removinng the original non-dummy columns
          loans_2007 = loans_2007.drop(cat_columns, axis=1)
          loans_2007.columns
```

```
Out[160]: Index(['loan_amnt', 'int_rate', 'installment', 'emp_length', 'annual_inc',
                 'loan_status', 'dti', 'delinq_2yrs', 'inq_last_6mths', 'open_acc',
                 'pub_rec', 'revol_bal', 'revol_util', 'total_acc',
```

```
                 'home_ownership_MORTGAGE', 'home_ownership_NONE',
                 'home_ownership_OTHER', 'home_ownership_OWN', 'home_ownership_RENT',
                 'verification_status_Not Verified',
                 'verification_status_Source Verified', 'verification_status_Verified',
                 'purpose_car', 'purpose_credit_card', 'purpose_debt_consolidation',
                 'purpose_educational', 'purpose_home_improvement', 'purpose_house',
                 'purpose_major_purchase', 'purpose_medical', 'purpose_moving',
                 'purpose_other', 'purpose_renewable_energy', 'purpose_small_business',
                 'purpose_vacation', 'purpose_wedding', 'term_ 36 months',
                 'term_ 60 months'],
                dtype='object')
```

0.0.14 Mapping column with multiple category data

```
In [161]: mapping_dict = {
              "emp_length": {
                  "10+ years": 10,
                  "9 years": 9,
                  "8 years": 8,
                  "7 years": 7,
                  "6 years": 6,
                  "5 years": 5,
                  "4 years": 4,
                  "3 years": 3,
                  "2 years": 2,
                  "1 year": 1,
                  "< 1 year": 0,
                  np.nan: 0
              }
          }

          loans_2007 = loans_2007.replace(mapping_dict)
          np.sort(loans_2007['emp_length'].unique().astype('int64'))
```

```
Out[161]: array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10], dtype=int64)
```

0.0.15 Convert Columns String type Numeric Data to Real Numbers

```
In [162]: loans_2007['int_rate'] = loans_2007['int_rate'].str.rstrip('%').astype('float')
          loans_2007['revol_util'] = loans_2007['revol_util'].str.rstrip('%').astype('float')
```

0.0.16 Preserving completely cleansed dataframe in .csv format

```
In [163]: loans_2007.to_csv("cleaned_loans_2007.csv", index=False)
          loans_2007.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 38707 entries, 0 to 39785
Data columns (total 38 columns):
```

```
loan_amnt                              38707 non-null float64
int_rate                               38707 non-null float64
installment                            38707 non-null float64
emp_length                             38707 non-null int64
annual_inc                             38707 non-null float64
loan_status                            38707 non-null int64
dti                                    38707 non-null float64
delinq_2yrs                            38707 non-null float64
inq_last_6mths                         38707 non-null float64
open_acc                               38707 non-null float64
pub_rec                                38707 non-null float64
revol_bal                              38707 non-null float64
revol_util                             38707 non-null float64
total_acc                              38707 non-null float64
home_ownership_MORTGAGE                38707 non-null uint8
home_ownership_NONE                    38707 non-null uint8
home_ownership_OTHER                   38707 non-null uint8
home_ownership_OWN                     38707 non-null uint8
home_ownership_RENT                    38707 non-null uint8
verification_status_Not Verified       38707 non-null uint8
verification_status_Source Verified    38707 non-null uint8
verification_status_Verified           38707 non-null uint8
purpose_car                            38707 non-null uint8
purpose_credit_card                    38707 non-null uint8
purpose_debt_consolidation             38707 non-null uint8
purpose_educational                    38707 non-null uint8
purpose_home_improvement               38707 non-null uint8
purpose_house                          38707 non-null uint8
purpose_major_purchase                 38707 non-null uint8
purpose_medical                        38707 non-null uint8
purpose_moving                         38707 non-null uint8
purpose_other                          38707 non-null uint8
purpose_renewable_energy               38707 non-null uint8
purpose_small_business                 38707 non-null uint8
purpose_vacation                       38707 non-null uint8
purpose_wedding                        38707 non-null uint8
term_ 36 months                        38707 non-null uint8
term_ 60 months                        38707 non-null uint8
dtypes: float64(12), int64(2), uint8(24)
memory usage: 5.3 MB
```

0.0.17 Finalizing the feature columns

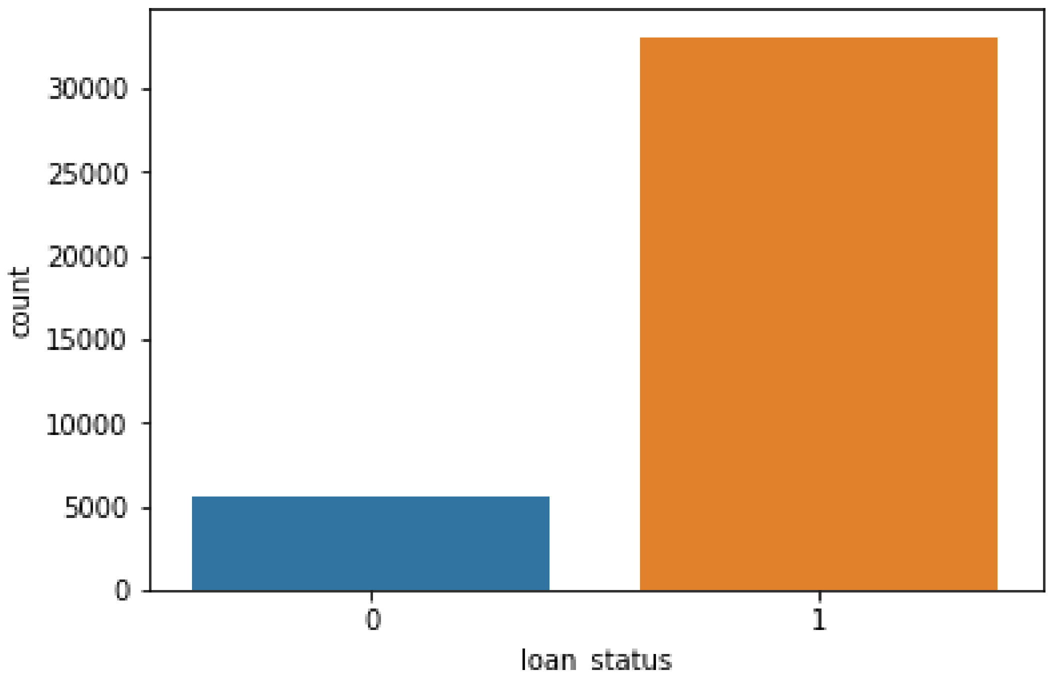
```
In [164]: features = loans_2007.columns.values
```

0.0.18 Evaluating the data skewness

```
In [165]: target_vals = loans_2007["loan_status"].value_counts()
          print(target_vals)

          print("The binary data ratio = 1 :", target_vals[1] / target_vals[0])
          sns.countplot(x="loan_status", data=loans_2007)
```

```
1    33092
0     5615
Name: loan_status, dtype: int64
The binary data ratio = 1 : 5.893499554764025
```

```
Out[165]: <matplotlib.axes._subplots.AxesSubplot at 0xce180b8>
```



This clearly indicates that our data is skewed.

Let's consider a logistic regression model that predict "1" as loan would be pay-off on time and "0" as loan would not be pay-off on time.

Considering the conservative investors approach:

* We must emphasize an algorithm that can avoid predicting "False Positive" which can suggest them any risky investment as a safe option. This may, otherwise, cause severe business losses.

* Similarly, it is acceptable that the algorithm is little lenient with predicting "False Negative" so that some safe investments could end up with wrong rejections. This may cause slip of some safe business opportunity.

0.0.19 Develop Logistic Regression Model and Fit Verification

In [166]:
```
# split train/test/cv as 60/20/20
train_set = loans_2007.iloc[:23224]
test_set = loans_2007.iloc[23225:30966]
cross_val = loans_2007.iloc[30967:]

# Find the logistic regression model using sklearn
logistic_model = LogisticRegression()
logistic_model.fit(train_set[features], train_set["loan_status"])
predictions_test = logistic_model.predict(test_set[features])
mse_vals_test = mean_squared_error(predictions_test, test_set["loan_status"])

mse_vals_test
```

Out[166]: 0.1331869267536494

0.0.20 Verifying the Logistic Reg Model over CV Set

In [167]:
```
# Find the MSE for CV

logistic_model = LogisticRegression()
logistic_model.fit(train_set[features], train_set["loan_status"])
predictions_cv = logistic_model.predict(cross_val[features])
mse_vals_cv = mean_squared_error(predictions_cv, cross_val["loan_status"])

mse_vals_cv
```

Out[167]: 0.13217054263565892

0.0.21 Checking the Model Generalization using Another Classifier

In [168]:
```
# Check for model generalization using scikit-learn package and carry out K-Fold
# Cross Validation

logistic_model = LogisticRegression()
predictions_tot = pd.Series(cross_val_predict(logistic_model, X=loans_2007[features]
                                              y=loans_2007["loan_status"], cv=11))
mse_vals_tot = mean_squared_error(predictions_tot, loans_2007["loan_status"])

mse_vals_tot
```

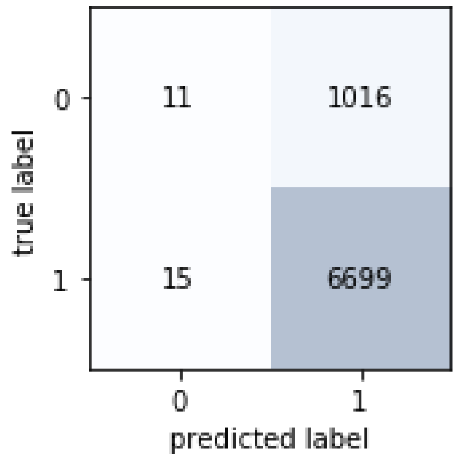
Out[168]: 0.14573591340067688

The error results for model predictibility over test set and cross-validation set using two different classifier. This shows a better model generalization for predictibility over outside data.

0.0.22 Check Prediction Integrity using Evaluation Matrix

```
In [169]: # Calc for TP/FP/TN/FN

          # For Logistic Reg Classifier over Test Set

          tp = len(predictions_test[(predictions_test == 1) & (test_set["loan_status"] == 1)])
          tn = len(predictions_test[(predictions_test == 0) & (test_set["loan_status"] == 0)])
          fp = len(predictions_test[(predictions_test == 1) & (test_set["loan_status"] == 0)])
          fn = len(predictions_test[(predictions_test == 0) & (test_set["loan_status"] == 1)])

          precision_test = tp / (tp + fp)
          recall_test = tp / (tp + fn)
          accuracy_test = (tp + tn) / len(test_set['loan_status'])
          fpr_test = fp / (fp + tn)
          tpr_test = tp / (tp + fn)
          F1_score_test = 2 * precision_test * recall_test / (precision_test + recall_test)

          print("Precision over Test Set:", precision_test)
          print("Recall over Test Set:", recall_test)
          print("Accuracy over Test Set:", accuracy_test)
          print("FPR over Test Set:", fpr_test)
          print("TPR over Test Set:", tpr_test)
          print("F1 Score over Test Set:", F1_score_test)

          # Verify the calc using sklearn function
          plot_confusion_matrix(confusion_matrix(test_set["loan_status"], predictions_test))
          print(classification_report(test_set['loan_status'], predictions_test))
```

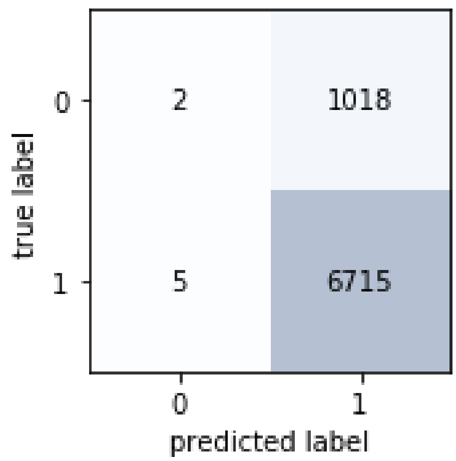
```
Precision over Test Set: 0.8683084899546338
Recall over Test Set: 0.9977658623771224
Accuracy over Test Set: 0.8668130732463506
FPR over Test Set: 0.9892891918208374
TPR over Test Set: 0.9977658623771224
F1 Score over Test Set: 0.9285466768313811
             precision    recall  f1-score   support

          0       0.42      0.01      0.02      1027
          1       0.87      1.00      0.93      6714

avg / total       0.81      0.87      0.81      7741
```



In [170]:
```
# Calc for TP/FP/TN/FN

# For Logistic Reg Classifier over Cross Validation Set

tp = len(predictions_cv[(predictions_cv == 1) & (cross_val["loan_status"] == 1)])
tn = len(predictions_cv[(predictions_cv == 0) & (cross_val["loan_status"] == 0)])
fp = len(predictions_cv[(predictions_cv == 1) & (cross_val["loan_status"] == 0)])
fn = len(predictions_cv[(predictions_cv == 0) & (cross_val["loan_status"] == 1)])

precision_cv = tp / (tp + fp)
recall_cv = tp / (tp + fn)
accuracy_cv = (tp + tn) / len(cross_val['loan_status'])
fpr_cv = fp / (fp + tn)
tpr_cv = tp / (tp + fn)
F1_score_cv = 2 * precision_cv * recall_cv / (precision_cv + recall_cv)

print("Precision over Cross Validation Set:", precision_cv)
print("Recall over Cross Validation Set:", recall_cv)
print("Accuracy over Cross Validation Set:", accuracy_cv)
print("FPR over Cross Validation Set:", fpr_cv)
print("TPR over Cross Validation Set:", tpr_cv)
print("F1 Score over Cross Validation Set:", F1_score_cv)

# Verify the calc using sklearn function
plot_confusion_matrix(confusion_matrix(cross_val["loan_status"], predictions_cv))
print(classification_report(cross_val['loan_status'], predictions_cv))
```

```
Precision over Cross Validation Set: 0.8683563946721842
Recall over Cross Validation Set: 0.9992559523809523
Accuracy over Cross Validation Set: 0.8678294573643411
FPR over Cross Validation Set: 0.9980392156862745
```

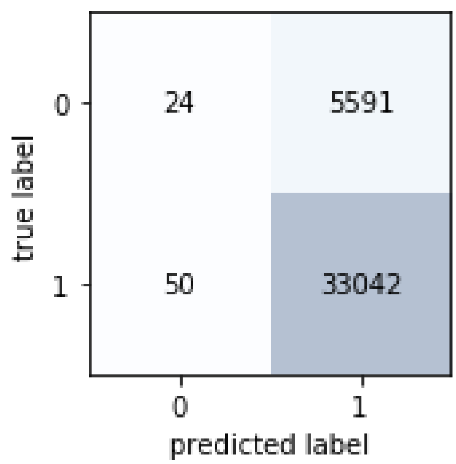
```
TPR over Cross Validation Set: 0.9992559523809523
F1 Score over Cross Validation Set: 0.9292188472981389
             precision    recall  f1-score   support

          0       0.29      0.00      0.00      1020
          1       0.87      1.00      0.93      6720

avg / total       0.79      0.87      0.81      7740
```



In [171]:
```
# Calc for TP/FP/TN/FN

# For K-Fold Cross Validation Classifier over entire data set

tp = len(predictions_tot[(predictions_tot == 1) & (loans_2007["loan_status"] == 1)])
tn = len(predictions_tot[(predictions_tot == 0) & (loans_2007["loan_status"] == 0)])
fp = len(predictions_tot[(predictions_tot == 1) & (loans_2007["loan_status"] == 0)])
fn = len(predictions_tot[(predictions_tot == 0) & (loans_2007["loan_status"] == 1)])

precision_tot = tp / (tp + fp)
recall_tot = tp / (tp + fn)
accuracy_tot = (tp + tn) / len(loans_2007['loan_status'])
fpr_tot = fp / (fp + tn)
tpr_tot = tp / (tp + fn)
F1_score_tot = 2 * precision_tot * recall_tot / (precision_tot + recall_tot)

print("Precision by K-Fold Classify:", precision_tot)
print("Recall by K-Fold Classify:", recall_tot)
print("Accuracy by K-Fold Classify:", accuracy_tot)
print("FPR by K-Fold Classify:", fpr_tot)
```

```
print("TPR by K-Fold Classify:", tpr_tot)
print("F1 Score by K-Fold Classify:", F1_score_tot)

# Verify the calc using sklearn function
plot_confusion_matrix(confusion_matrix(loans_2007["loan_status"], predictions_tot))
print(classification_report(loans_2007['loan_status'], predictions_tot))
```

```
Precision by K-Fold Classify: 0.8556253660614451
Recall by K-Fold Classify: 0.9982295937383526
Accuracy by K-Fold Classify: 0.8306766217996745
FPR by K-Fold Classify: 0.9974250505793636
TPR by K-Fold Classify: 0.9982295937383526
F1 Score by K-Fold Classify: 0.9214427019123255
             precision    recall  f1-score   support

          0       0.32      0.00      0.01      5615
          1       0.86      1.00      0.92     33092

avg / total       0.78      0.85      0.79     38707
```



0.0.23 Results

```
In [172]: output_cols = ["Test Set", "Cross Validation Set", "K-Fold Classify"]
          output_index = ["precision", "recall", "accuracy", "fpr", "tpr", "F1_score", "MSE"]
          output = pd.DataFrame(index = output_index, columns = output_cols)

          output['Test Set'] = [precision_test, recall_test, accuracy_test, fpr_test, tpr_test
                                F1_score_test, mse_vals_test]
          output['Cross Validation Set'] = [precision_cv, recall_cv, accuracy_cv, fpr_cv, tpr_
```

```
                                  F1_score_cv, mse_vals_cv]
output['K-Fold Classify'] = [precision_tot, recall_tot, accuracy_tot, fpr_tot, tpr_to
                             F1_score_tot, mse_vals_tot]
output
```

Out[172]:

	Test Set	Cross Validation Set	K-Fold Classify
precision	0.868308	0.868356	0.855625
recall	0.997766	0.999256	0.998230
accuracy	0.866813	0.867829	0.830677
fpr	0.989289	0.998039	0.997425
tpr	0.997766	0.999256	0.998230
F1_score	0.928547	0.929219	0.921443
MSE	0.133187	0.132171	0.145736

0.0.24 Results Review

* The precision of 0.5 indicates that only 50
* The prediction algorithm seems to be biased towards the positive outcome. This also gets reflected in the high recall value. This could not gain confident to make business/investment decision by the conservative investors.
* High value of FPR shows the positive bias of the predictive algorithm. The 99

0.0.25 Revise Model

In [173]:
```
# Need to reduce "False Positive" to improve predictive reliability
# To enhance conservative predictive outcome, let's set-up penalty for wrongly label
penalty = {0:6, 1:1}
# Set up Logistic regression model
logistic_model = LogisticRegression(class_weight = penalty)
logistic_model.fit(train_set[features], train_set["loan_status"])
predictions_test_rev = logistic_model.predict(test_set[features])
mse_vals_test_rev = mean_squared_error(predictions_test_rev, test_set["loan_status"]

mse_vals_test_rev
```

Out[173]: 0.0

0.0.26 Re-verify the Logistic Reg Revised Model

In [174]:
```
# Find the MSE for CV

logistic_model.fit(train_set[features], train_set["loan_status"])
predictions_cv_rev = logistic_model.predict(cross_val[features])
mse_vals_cv_rev = mean_squared_error(predictions_cv_rev, cross_val["loan_status"])

mse_vals_cv_rev
```

Out[174]: 0.0

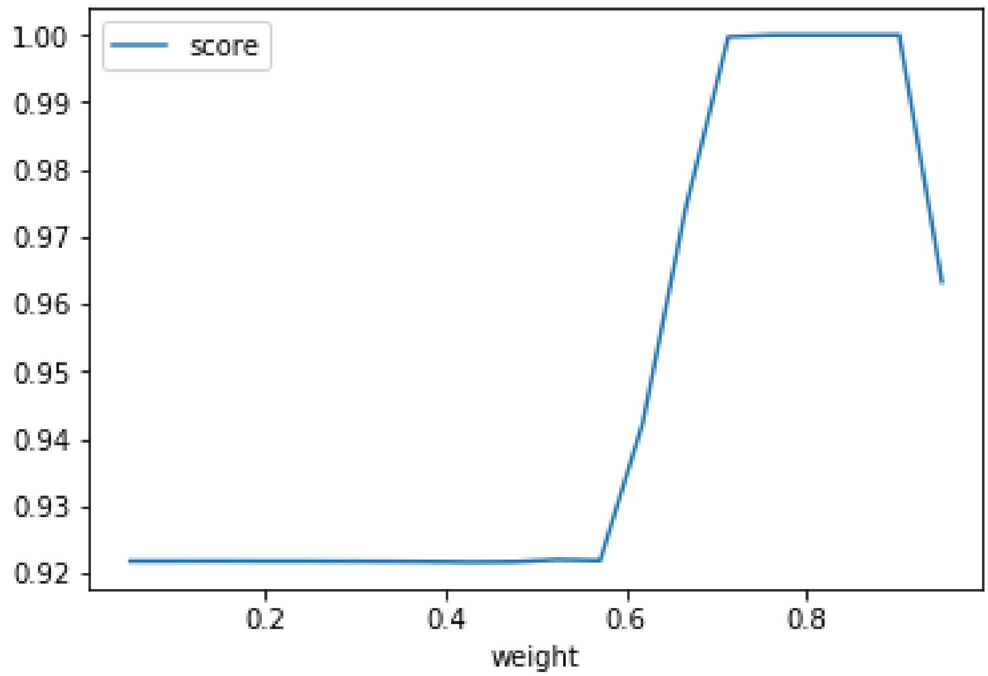
0.0.27 Re-Check (Manually) the Revised Model Generalization using Class Weights Classifier

In order to accomplish splitting the skewed data appropriately into partitions, every class should be applied with different weight so that all partitions are eventually left out for testing. We have data skewed in the order of 1:5.89. It should be noted that RandomForestClassifier suites to allow for class weighting.

We should manage the class weights manually to find a better balance between the "False Positives" and "False Negatives". The F1 score is a good indicator of tradeoff between the precision and recall.

In [175]:
```
# Check for model generalization using scikit-learn GridSearchCV classifier

wts = np.linspace(0.05, 0.95, 20)

# Initialize the classifier (presumming 3-Folds will provide a reasonable balance be
# the accuracy and computation time)
grdcv = GridSearchCV(
    estimator=LogisticRegression(),
    param_grid={
                'class_weight': [{0: x, 1: 1.0-x} for x in wts]
                },
    scoring='f1',
    cv=3)

grd_rslt = grdcv.fit(loans_2007[features], loans_2007['loan_status'])
print("Best parameters : %s" % grd_rslt.best_params_)

# Plot the weights vs F1_score
df_wt = pd.DataFrame({ 'score': grd_rslt.cv_results_['mean_test_score'],
                       'weight': wts })
df_wt.plot(x='weight')

# Initializing the Logistic Regression Cross Validation
logistic_model_rev = LogisticRegression(**grd_rslt.best_params_)
logistic_model_rev.fit(train_set[features], train_set['loan_status'])
predictions_tot_rev = logistic_model_rev.predict(cross_val[features])
mse_vals_tot_rev = mean_squared_error(predictions_tot_rev, cross_val["loan_status"])

print("MSE for GridSearchCV Cross-Validation Check =", mse_vals_tot_rev)
```

```
Best parameters : {'class_weight': {0: 0.7605263157894736, 1: 0.2394736842105264}}
MSE for GridSearchCV Cross-Validation Check = 0.0
```

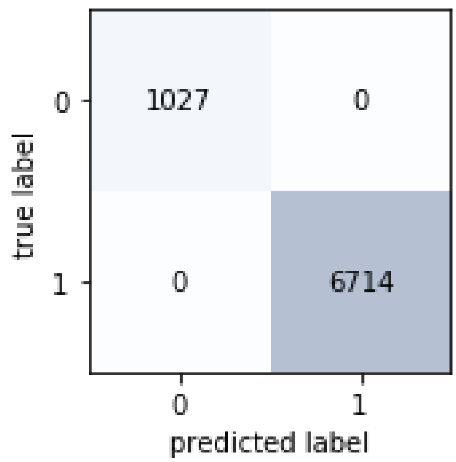


0.0.28 Re-Check Prediction Integrity using Evaluation Matrix

```
In [176]: # Calc for TP/FP/TN/FN
          # For Logistic Reg Classifier over Test Set

          tp = len(predictions_test_rev[(predictions_test_rev == 1) & (test_set["loan_status"]
          tn = len(predictions_test_rev[(predictions_test_rev == 0) & (test_set["loan_status"]
          fp = len(predictions_test_rev[(predictions_test_rev == 1) & (test_set["loan_status"]
          fn = len(predictions_test_rev[(predictions_test_rev == 0) & (test_set["loan_status"]

          precision_test_rev = tp / (tp + fp)
          recall_test_rev = tp / (tp + fn)
          accuracy_test_rev = (tp + tn) / len(test_set['loan_status'])
          fpr_test_rev = fp / (fp + tn)
          tpr_test_rev = tp / (tp + fn)
          F1_score_test_rev = 2 * precision_test_rev * recall_test_rev / (precision_test_rev +
                                                                          recall_test_rev)

          print("Precision over Test Set:", precision_test_rev)
          print("Recall over Test Set:", recall_test_rev)
          print("Accuracy over Test Set:", accuracy_test_rev)
          print("FPR over Test Set:", fpr_test_rev)
          print("TPR over Test Set:", tpr_test_rev)
          print("F1 Score over Test Set:", F1_score_test_rev)
```

```
# Verify the calc using sklearn function
plot_confusion_matrix(confusion_matrix(test_set["loan_status"], predictions_test_rev
print(classification_report(test_set['loan_status'], predictions_test_rev))
```

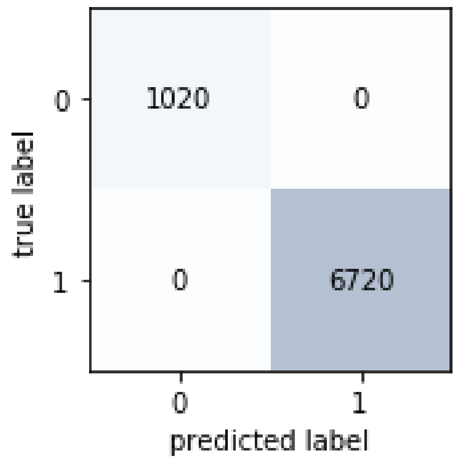
```
Precision over Test Set: 1.0
Recall over Test Set: 1.0
Accuracy over Test Set: 1.0
FPR over Test Set: 0.0
TPR over Test Set: 1.0
F1 Score over Test Set: 1.0
             precision    recall  f1-score   support

          0       1.00      1.00      1.00      1027
          1       1.00      1.00      1.00      6714

avg / total       1.00      1.00      1.00      7741
```




```
In [177]: # Calc for TP/FP/TN/FN
          # For Logistic Reg Classifier over Cross Validation Set

          tp = len(predictions_cv_rev[(predictions_cv_rev == 1) & (cross_val["loan_status"] ==
          tn = len(predictions_cv_rev[(predictions_cv_rev == 0) & (cross_val["loan_status"] ==
          fp = len(predictions_cv_rev[(predictions_cv_rev == 1) & (cross_val["loan_status"] ==
          fn = len(predictions_cv_rev[(predictions_cv_rev == 0) & (cross_val["loan_status"] ==

          precision_cv_rev = tp / (tp + fp)
          recall_cv_rev = tp / (tp + fn)
          accuracy_cv_rev = (tp + tn) / len(cross_val['loan_status'])
```

```
fpr_cv_rev = fp / (fp + tn)
tpr_cv_rev = tp / (tp + fn)
F1_score_cv_rev = 2 * precision_cv_rev * recall_cv_rev / (precision_cv_rev + recall_c

print("Precision over Cross Validation Set:", precision_cv_rev)
print("Recall over Cross Validation Set:", recall_cv_rev)
print("Accuracy over Cross Validation Set:", accuracy_cv_rev)
print("FPR over Cross Validation Set:", fpr_cv_rev)
print("TPR over Cross Validation Set:", tpr_cv_rev)
print("F1 Score over Cross Validation Set:", F1_score_cv_rev)

# Verify the calc using sklearn function
plot_confusion_matrix(confusion_matrix(cross_val["loan_status"], predictions_cv_rev))
print(classification_report(cross_val['loan_status'], predictions_cv_rev))
```

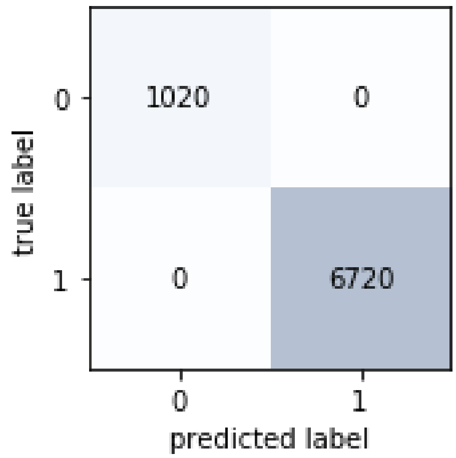
```
Precision over Cross Validation Set: 1.0
Recall over Cross Validation Set: 1.0
Accuracy over Cross Validation Set: 1.0
FPR over Cross Validation Set: 0.0
TPR over Cross Validation Set: 1.0
F1 Score over Cross Validation Set: 1.0
             precision    recall  f1-score   support

          0       1.00      1.00      1.00      1020
          1       1.00      1.00      1.00      6720

avg / total       1.00      1.00      1.00      7740
```



In [178]:
```
# Calc for TP/FP/TN/FN
# For GridSearchCV Classifier with Logistic Reg over the cross validation data set
```

```
    tp = len(predictions_tot_rev[(predictions_tot_rev == 1) & (cross_val["loan_status"] =
    tn = len(predictions_tot_rev[(predictions_tot_rev == 0) & (cross_val["loan_status"] =
    fp = len(predictions_tot_rev[(predictions_tot_rev == 1) & (cross_val["loan_status"] =
    fn = len(predictions_tot_rev[(predictions_tot_rev == 0) & (cross_val["loan_status"] =

    precision_tot_rev = tp / (tp + fp)
    recall_tot_rev = tp / (tp + fn)
    accuracy_tot_rev = (tp + tn) / len(cross_val['loan_status'])
    fpr_tot_rev = fp / (fp + tn)
    tpr_tot_rev = tp / (tp + fn)
    F1_score_tot_rev = 2 * precision_tot_rev * recall_tot_rev / (precision_tot_rev +
                                                                  recall_tot_rev)

    print("Precision by GridSearchCV Classifier:", precision_tot_rev)
    print("Recall by GridSearchCV Classifier:", recall_tot_rev)
    print("Accuracy by GridSearchCVClassifier:", accuracy_tot_rev)
    print("FPR by GridSearchCV Classifier:", fpr_tot_rev)
    print("TPR by GridSearchCV Classifier:", tpr_tot_rev)
    print("F1 Score by GridSearchCV Classifier:", F1_score_tot_rev)

    # Verify the calc using sklearn function
    plot_confusion_matrix(confusion_matrix(cross_val["loan_status"], predictions_tot_rev)
    print(classification_report(cross_val['loan_status'], predictions_tot_rev))
```

```
Precision by GridSearchCV Classifier: 1.0
Recall by GridSearchCV Classifier: 1.0
Accuracy by GridSearchCVClassifier: 1.0
FPR by GridSearchCV Classifier: 0.0
TPR by GridSearchCV Classifier: 1.0
F1 Score by GridSearchCV Classifier: 1.0
             precision    recall  f1-score   support

          0       1.00      1.00      1.00      1020
          1       1.00      1.00      1.00      6720

avg / total       1.00      1.00      1.00      7740
```



0.0.29 Revised Model Results Summary

In [179]:
```
output_cols = ["Test Set", "Cross Validation Set", "GridSearch CV"]
output_rev = pd.DataFrame(index = output_index, columns = output_cols)

output_rev['Test Set'] = [precision_test_rev, recall_test_rev, accuracy_test_rev, fp
                          tpr_test_rev, F1_score_test_rev, mse_vals_test_rev]
output_rev['Cross Validation Set'] = [precision_cv_rev, recall_cv_rev, accuracy_cv_r
                                      tpr_cv_rev, F1_score_cv_rev, mse_vals_cv_rev]
output_rev["GridSearch CV"] = [precision_tot_rev, recall_tot_rev, accuracy_tot_rev, 
                               tpr_tot_rev, F1_score_tot_rev, mse_vals_tot_rev]
output_rev
```

Out[179]:

	Test Set	Cross Validation Set	GridSearch CV
precision	1.0	1.0	1.0
recall	1.0	1.0	1.0
accuracy	1.0	1.0	1.0
fpr	0.0	0.0	0.0
tpr	1.0	1.0	1.0
F1_score	1.0	1.0	1.0
MSE	0.0	0.0	0.0

0.0.30 Conclusion

* The results above show generalization of the revised model over the unknown data set.
    * Precision value of 1.0 indicates that this model predicts ONLY actual positive examples as positive outcome.
    * Recall value of 1.0 is an indication that this model captures ALL positive examples correctly.
    * F1-Score is an indicative of perfect 'Precision' and 'Recall' scores.

* The zero value of fpr confirms that the model is absolutely not predicting "False Positive". This confirm the reliability of the algorithm and its alignment with our need for conservative business proposition to avoid any risky investment option. The checks for model predictive behavior above assure this model would recommend only loan options that are safe and will be paid off on time.

* The TPR value of 1.0 is an indicative that this model will show ALL of the safe loan opportunities that will be paid off on time. This will give an utmost confidence to the conservative investors and encourage them to treat any/all of the recommended business opportunity as risk free to do business.