Hi, people, and welcome to my project!

Classification with Python

In this notebook I try to practice all the classification algorithms.

- K Nearest Neighbor(KNN)
- Decision Tree
- Support Vector Machine
- Logistic Regression

I have the following:

- pre-processing, feature selection, feature-extraction, and so on, to make a better model.
- using scikit-learn, Scipy or Numpy libraries for developing the classification algorithms.

In [246]:

```
import itertools
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import NullFormatter
import pandas as pd
import numpy as np
import matplotlib.ticker as ticker
from sklearn import preprocessing
%matplotlib inline
```

About dataset

This dataset is about past loans. The **Loan_train.csv** data set includes details of 346 customers whose loan are already paid off or defaulted. It includes following fields:

Field	**Description**
Loan_status	Whether a loan is paid off on in collection
Principal	Basic principal loan amount at the
Terms	Origination terms which can be weekly (7 days), biweekly, and monthly payoff schedule
Effective_date	When the loan got originated and took effects
Due_date	Since it’s one-time payoff schedule, each loan has one single due date
Age	Age of applicant
Education	Education of applicant
Gender	The gender of applicant

Lets download the dataset

In [76]:

```
!wget -O loan_train.csv https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/ML01
01ENv3/labs/loan_train.csv
```

```
--2019-12-24 05:27:35--  https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/ML0
101ENv3/labs/loan_train.csv
Resolving s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.net)... 67.228.25
4.196
Connecting to s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.net)|67.228.25
4.196|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 23101 (23K) [text/csv]
Saving to: ‘loan_train.csv’

100%[======================================>] 23,101      --.-K/s   in 0.001s

2019-12-24 05:27:35 (15.7 MB/s) - ‘loan_train.csv’ saved [23101/23101]
```

Load Data From CSV File

In [247]:
```
df = pd.read_csv('loan_train.csv')
df.head()
```

Out[247]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	education	Gender
0	0	0	PAIDOFF	1000	30	9/8/2016	10/7/2016	45	High School or Below	male
1	2	2	PAIDOFF	1000	30	9/8/2016	10/7/2016	33	Bechalor	female
2	3	3	PAIDOFF	1000	15	9/8/2016	9/22/2016	27	college	male
3	4	4	PAIDOFF	1000	30	9/9/2016	10/8/2016	28	college	female
4	6	6	PAIDOFF	1000	30	9/9/2016	10/8/2016	29	college	male

In [248]:
```
df.shape
```

Out[248]:
```
(346, 10)
```

Convert to date time object

In [249]:
```
df['due_date'] = pd.to_datetime(df['due_date'])
df['effective_date'] = pd.to_datetime(df['effective_date'])
df.head()
```

Out[249]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	education	Gender
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	High School or Below	male
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Bechalor	female
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	college	male
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	college	female
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	college	male

Data visualization and pre-processing

How many of each class is in our data set

In [250]:
```
df['loan_status'].value_counts()
```

Out[250]:
```
PAIDOFF       260
COLLECTION     86
Name: loan_status, dtype: int64
```

260 people have paid off the loan on time while 86 have gone into collection

Plot some columns to underestand data better:

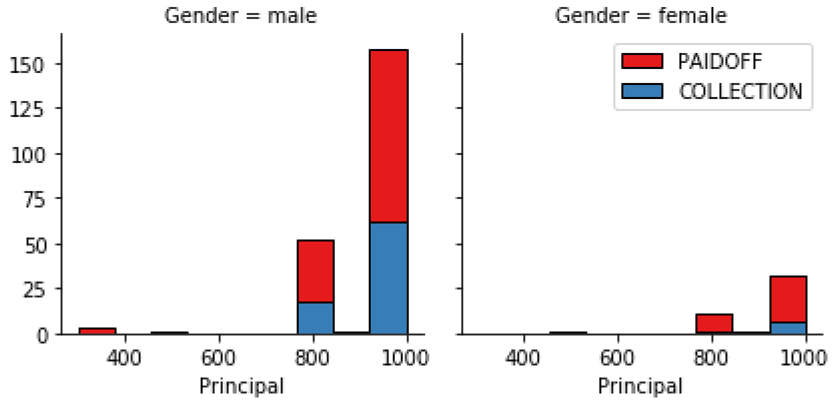
In [198]:

```
!conda install -c anaconda seaborn -y
```

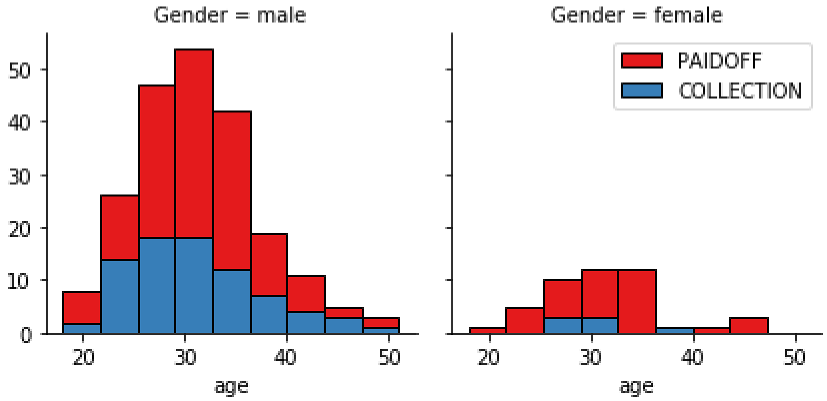
```
Solving environment: done

# All requested packages already installed.
```

In [251]:

```
import seaborn as sns

bins = np.linspace(df.Principal.min(), df.Principal.max(), 10)
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set1", col_wrap=2)
g.map(plt.hist, 'Principal', bins=bins, ec="k")

g.axes[-1].legend()
plt.show()
```



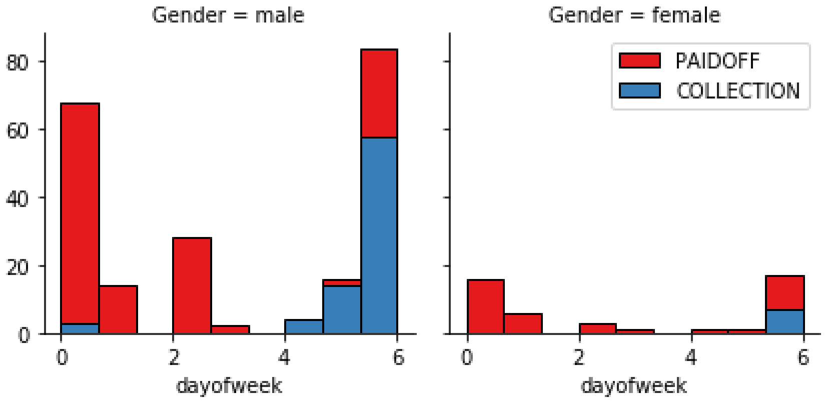
```
In [252]: bins = np.linspace(df.age.min(), df.age.max(), 10)
          g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set1", col_wrap=2)
          g.map(plt.hist, 'age', bins=bins, ec="k")

          g.axes[-1].legend()
          plt.show()
```



Pre-processing: Feature selection/extraction

The day of the week people get the loan

```
In [253]: df['dayofweek'] = df['effective_date'].dt.dayofweek
          bins = np.linspace(df.dayofweek.min(), df.dayofweek.max(), 10)
          g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set1", col_wrap=2)
          g.map(plt.hist, 'dayofweek', bins=bins, ec="k")
          g.axes[-1].legend()
          plt.show()
```



People who get the loan at the end of the week dont pay it off, so use Feature binarization to set a threshold values less then day 4

In [254]:
```
df['weekend'] = df['dayofweek'].apply(lambda x: 1 if (x>3)  else 0)
df.head()
```

Out[254]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	education	Gender	dayofweek	weeke
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	High School or Below	male	3	0
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Bechalor	female	3	0
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	college	male	3	0
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	college	female	4	1
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	college	male	4	1

Convert Categorical features to numerical values

By gender:

In [255]:
```
df.groupby(['Gender'])['loan_status'].value_counts(normalize=True)
```

Out[255]:
```
Gender  loan_status
female  PAIDOFF        0.865385
        COLLECTION     0.134615
male    PAIDOFF        0.731293
        COLLECTION     0.268707
Name: loan_status, dtype: float64
```

86 % of female pay there loans while only 73 % of males pay there loan

Convert male to 0 and female to 1:

In [256]:
```
df['Gender'].replace(to_replace=['male','female'], value=[0,1],inplace=True)
df.head()
```

Out[256]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	education	Gender	dayofweek	weeke
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	High School or Below	0	3	0
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Bechalor	1	3	0
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	college	0	3	0
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	college	1	4	1
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	college	0	4	1

One Hot Encoding

Education?

In [257]:

```
df.groupby(['education'])['loan_status'].value_counts(normalize=True)
```

Out[257]:

```
education             loan_status
Bechalor              PAIDOFF        0.750000
                      COLLECTION     0.250000
High School or Below  PAIDOFF        0.741722
                      COLLECTION     0.258278
Master or Above       COLLECTION     0.500000
                      PAIDOFF        0.500000
college               PAIDOFF        0.765101
                      COLLECTION     0.234899
Name: loan_status, dtype: float64
```

Feature before One Hot Encoding

In [258]:

```
df[['Principal','terms','age','Gender','education']].head()
```

Out[258]:

	Principal	terms	age	Gender	education
0	1000	30	45	0	High School or Below
1	1000	30	33	1	Bechalor
2	1000	15	27	0	college
3	1000	30	28	1	college
4	1000	30	29	0	college

In [259]:

```
Feature = df[['Principal','terms','age','Gender','weekend']]
Feature = pd.concat([Feature,pd.get_dummies(df['education'])], axis=1)
Feature.drop(['Master or Above'], axis = 1,inplace=True)
Feature.head()
```

Out[259]:

	Principal	terms	age	Gender	weekend	Bechalor	High School or Below	college
0	1000	30	45	0	0	0	1	0
1	1000	30	33	1	0	1	0	0
2	1000	15	27	0	0	0	0	1
3	1000	30	28	1	1	0	0	1
4	1000	30	29	0	1	0	0	1

Feature selection

In [260]:

```
X = Feature
X[0:5]
```

Out[260]:

	Principal	terms	age	Gender	weekend	Bechalor	High School or Below	college
0	1000	30	45	0	0	0	1	0
1	1000	30	33	1	0	1	0	0
2	1000	15	27	0	0	0	0	1
3	1000	30	28	1	1	0	0	1
4	1000	30	29	0	1	0	0	1

In [261]:

```
y = df['loan_status'].values
y[0:5]
```

Out[261]:

```
array(['PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'],
      dtype=object)
```

Normalize Data

Data Standardization give data zero mean and unit variance (technically should be done after train test split)

```
In [262]: X= preprocessing.StandardScaler().fit(X).transform(X)
          X[0:5]
```

```
          /opt/conda/envs/Python36/lib/python3.6/site-packages/sklearn/preprocessing/data.py:645: DataConversionWarnin
          g: Data with input dtype uint8, int64 were all converted to float64 by StandardScaler.
            return self.partial_fit(X, y)
          /opt/conda/envs/Python36/lib/python3.6/site-packages/ipykernel/__main__.py:1: DataConversionWarning: Data wit
          h input dtype uint8, int64 were all converted to float64 by StandardScaler.
            if __name__ == '__main__':
```

```
Out[262]: array([[ 0.51578458,  0.92071769,  2.33152555, -0.42056004, -1.20577805,
                  -0.38170062,  1.13639374, -0.86968108],
                 [ 0.51578458,  0.92071769,  0.34170148,  2.37778177, -1.20577805,
                   2.61985426, -0.87997669, -0.86968108],
                 [ 0.51578458, -0.95911111, -0.65321055, -0.42056004, -1.20577805,
                  -0.38170062, -0.87997669,  1.14984679],
                 [ 0.51578458,  0.92071769, -0.48739188,  2.37778177,  0.82934003,
                  -0.38170062, -0.87997669,  1.14984679],
                 [ 0.51578458,  0.92071769, -0.3215732 , -0.42056004,  0.82934003,
                  -0.38170062, -0.87997669,  1.14984679]])
```

Classification

K Nearest Neighbor(KNN)

Finding the best k to build the model with the best accuracy.
Split your train_loan.csv into train and test to find the best **k**.

In [263]:

```
# first of all, I will replace 'loan_status' in df on PAIDOFF -> 0 and COLLECTION -> 1
df['loan_status'].replace(to_replace=['PAIDOFF','COLLECTION'], value=[0,1],inplace=True)
y = df['loan_status'].values
df.head()
```

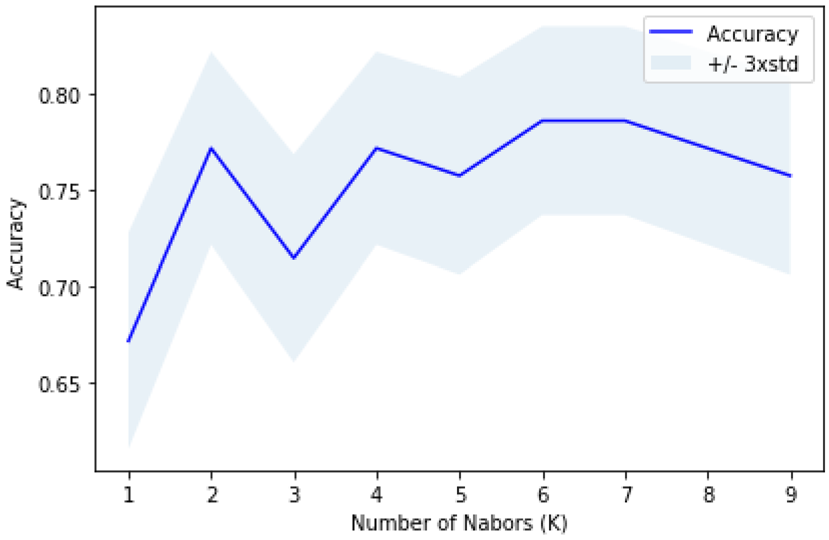
Out[263]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	education	Gender	dayofweek	weeke
0	0	0	0	1000	30	2016-09-08	2016-10-07	45	High School or Below	0	3	0
1	2	2	0	1000	30	2016-09-08	2016-10-07	33	Bechalor	1	3	0
2	3	3	0	1000	15	2016-09-08	2016-09-22	27	college	0	3	0
3	4	4	0	1000	30	2016-09-09	2016-10-08	28	college	1	4	1
4	6	6	0	1000	30	2016-09-09	2016-10-08	29	college	0	4	1

In [264]:

```
# Split our data on test and train
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4)

# import knn & metrics
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics

# Let's try K coefficient up to 10
if True:
    Ks = 10
    mean_acc = np.zeros((Ks - 1))
    std_acc = np.zeros((Ks - 1))

    for n in range(1, Ks):
        # Train Model and Predict
        neigh = KNeighborsClassifier(n_neighbors=n).fit(X_train, y_train)
        yhat = neigh.predict(X_test)
        mean_acc[n - 1] = metrics.accuracy_score(y_test, yhat)

        std_acc[n - 1] = np.std(yhat == y_test) / np.sqrt(yhat.shape[0])

    print(mean_acc)

    plt.plot(range(1, Ks), mean_acc, 'b')
    plt.fill_between(range(1, Ks), mean_acc - 1 * std_acc, mean_acc + 1 * std_acc, alpha=0.10)
    plt.legend(('Accuracy ', '+/- 3xstd'))
    plt.ylabel('Accuracy ')
    plt.xlabel('Number of Nabors (K)')
    plt.tight_layout()
    plt.show()

    print("The best accuracy was with", mean_acc.max(), "with k=", mean_acc.argmax() + 1)
```

```
[0.67142857 0.77142857 0.71428571 0.77142857 0.75714286 0.78571429
 0.78571429 0.77142857 0.75714286]
```



```
The best accuracy was with 0.7857142857142857 with k= 6
```

In [283]:
```
# let's create the best knn with k = 6
knn_6 = KNeighborsClassifier(n_neighbors=6).fit(X_train, y_train)
knn_6_pred = knn_6.predict(X_test)

print("KNN acc by Jaccard is ", jaccard_similarity_score(y_test, knn_6_pred))
print("KNN acc by F1 score is ", f1_score(y_test, knn_6_pred, average='weighted'))
```

```
KNN acc by Jaccard is  0.7857142857142857
KNN acc by F1 score is  0.7334244702665754
```

Decision Tree

In [266]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [289]:

```
# Assuming, that we already have splitted data
LoanTree = DecisionTreeClassifier(criterion="entropy", max_depth=4)
LoanTree.fit(X_train, y_train)

predTree = LoanTree.predict(X_test)

print("DecisionTrees's Accuracy: ", metrics.accuracy_score(y_test, predTree))
print("DecisionTrees's Accuracy by F1 score is ", f1_score(y_test, predTree, average='weighted'))
```

```
DecisionTrees's Accuracy:  0.7857142857142857
DecisionTrees's Accuracy by F1 score is  0.6914285714285714
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
arning: F-score is ill-defined and being set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

Support Vector Machine

In [268]:

```
from sklearn import svm

vector = svm.SVC(kernel='linear', gamma='auto')
vector.fit(X_train, y_train)

y_vector = vector.predict(X_test)
print("SVC Accuracy: ", metrics.accuracy_score(y_test, y_vector))
```

```
SVC Accuracy:  0.7857142857142857
```

Logistic Regression

In [269]:

```
from sklearn.linear_model import LogisticRegression

LR = LogisticRegression(C=0.02, solver='lbfgs').fit(X_train, y_train)

LR_pred = LR.predict(X_test)
print("LR Accuracy: ", metrics.accuracy_score(y_test, LR_pred))

LR_pred_proba = LR.predict_proba(X_test) #probability

#print(LR_pred," ",LR_pred_proba)
```

```
LR Accuracy:  0.7857142857142857
```

Model Evaluation using Test set

In [270]:

```
from sklearn.metrics import jaccard_similarity_score
from sklearn.metrics import f1_score
from sklearn.metrics import log_loss
```

First, download and load the test set:

In [219]:

```
!wget -O loan_test.csv https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/ML010
1ENv3/labs/loan_test.csv
```

```
--2019-12-24 06:01:02--  https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/ML0
101ENv3/labs/loan_test.csv
Resolving s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.net)... 67.228.25
4.196
Connecting to s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.net)|67.228.25
4.196|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 3642 (3.6K) [text/csv]
Saving to: ‘loan_test.csv’

100%[======================================>] 3,642       --.-K/s   in 0s

2019-12-24 06:01:02 (361 MB/s) - ‘loan_test.csv’ saved [3642/3642]
```

Load Test set for evaluation

In [285]:

```
test_df = pd.read_csv('loan_test.csv')
test_df.head()
```

Out[285]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	education	Gender
0	1	1	PAIDOFF	1000	30	9/8/2016	10/7/2016	50	Bechalor	female
1	5	5	PAIDOFF	300	7	9/9/2016	9/15/2016	35	Master or Above	male
2	21	21	PAIDOFF	1000	30	9/10/2016	10/9/2016	43	High School or Below	female
3	24	24	PAIDOFF	1000	30	9/10/2016	10/9/2016	26	college	male
4	35	35	PAIDOFF	800	15	9/11/2016	9/25/2016	29	Bechalor	male

In [286]:

```
# We have to clean & transform test data in the same way, as we did for train data
test_df['due_date'] = pd.to_datetime(test_df['due_date'])
test_df['effective_date'] = pd.to_datetime(test_df['effective_date'])
test_df['dayofweek'] = test_df['effective_date'].dt.dayofweek

test_df['weekend'] = test_df['dayofweek'].apply(lambda x: 1 if (x>3)  else 0)
test_df['Gender'].replace(to_replace=['male','female'], value=[0,1],inplace=True)

#I will replace 'loan_status' in df on PAIDOFF -> 0 and COLLECTION -> 1
test_df['loan_status'].replace(to_replace=['PAIDOFF','COLLECTION'], value=[0,1],inplace=True)

X_t = test_df[['Principal','terms','age','Gender','weekend']]
X_t = pd.concat([X_t,pd.get_dummies(test_df['education'])], axis=1)
X_t.drop(['Master or Above'], axis = 1,inplace=True)

X_t = preprocessing.StandardScaler().fit(X_t).transform(X_t)

y_t = test_df['loan_status'].values

# Now, let's test our trained modules

# KNN
knn_prediction = knn_6.predict(X_t)

print("KNN has ", metrics.accuracy_score(y_t, knn_prediction))
print("KNN acc by Jaccard is ", jaccard_similarity_score(y_t, knn_prediction))
print("KNN acc by F1 score is ", f1_score(y_t, knn_prediction, average='weighted'))
print("KNN by log loss is ", log_loss(y_t, knn_prediction))
```

```
KNN has  0.6851851851851852
KNN acc by Jaccard is  0.6851851851851852
KNN acc by F1 score is  0.626541384672668
KNN by log loss is  10.873377724133375
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/sklearn/preprocessing/data.py:645: DataConversionWarnin
g: Data with input dtype uint8, int64 were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
/opt/conda/envs/Python36/lib/python3.6/site-packages/ipykernel/__main__.py:16: DataConversionWarning: Data wi
th input dtype uint8, int64 were all converted to float64 by StandardScaler.
```

In [287]:

```
# Desicion tree
predTree = LoanTree.predict(X_t)

print("DecisionTrees's Accuracy: ", metrics.accuracy_score(y_t, predTree))
print("DecisionTrees's Accuracy by Jaccard is ", jaccard_similarity_score(y_t, predTree))
print("DecisionTrees's Accuracy by F1 score is ", f1_score(y_t, predTree, average='weighted'))
print("DecisionTrees log loss is ", log_loss(y_t, predTree))

# SVM
y_vector = vector.predict(X_t)
print("SVC Accuracy: ", metrics.accuracy_score(y_t, y_vector))
print("SVC Accuracy by Jaccard is ", jaccard_similarity_score(y_t, y_vector))
print("SVC Accuracy by F1 score is ", f1_score(y_t, y_vector, average='weighted'))
print("SVC log loss is ", log_loss(y_t, y_vector))

# LR
LR_pred = LR.predict(X_t)
print("LR Accuracy: ", metrics.accuracy_score(y_t, LR_pred))
print("LR Accuracy by Jaccard is ", jaccard_similarity_score(y_t, LR_pred))
print("LR Accuracy by F1 score is ", f1_score(y_t, LR_pred, average='weighted'))
print("LR log loss is ", log_loss(y_t, LR_pred))
```

```
DecisionTrees's Accuracy:  0.7592592592592593
DecisionTrees's Accuracy by Jaccard is  0.7592592592592593
DecisionTrees's Accuracy by F1 score is  0.6717642373556352
DecisionTrees log loss is  8.31489061358961
SVC Accuracy:  0.7407407407407407
SVC Accuracy by Jaccard is  0.7407407407407407
SVC Accuracy by F1 score is  0.6304176516942475
SVC log loss is  8.954497583865733
LR Accuracy:  0.7407407407407407
LR Accuracy by Jaccard is  0.7407407407407407
LR Accuracy by F1 score is  0.6304176516942475
LR log loss is  8.954497583865733
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
arning: F-score is ill-defined and being set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
/opt/conda/envs/Python36/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
arning: F-score is ill-defined and being set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

```
In [288]: print("Log loss is NA for KNN, DT and SVM, but if replace PAIDOFF -> 0 and COLLECTION -> 1 in 'loan_status',
           we can find them")
```

```
Log loss is NA for KNN, DT and SVM, but if replace PAIDOFF -> 0 and COLLECTION -> 1 in 'loan_status', we can
find them
```

Report

You should be able to report the accuracy of the built model using different evaluation metrics:

Algorithm	Jaccard	F1-score	LogLoss
KNN	0.68	0.62	NA (10.9)
Decision Tree	0.76	0.67	NA (8.31)
SVM	0.74	0.63	NA (8.95)
LogisticRegression	0.74	0.63	8.9