Classification ML project ¶

In [2]:
```
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

Load Data From CSV File

In [3]:
```
df = pd.read_csv('loan_train.csv')
df.head()
```

Out[3]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	edu
0	0	0	PAIDOFF	1000	30	9/8/2016	10/7/2016	45	Scl
1	2	2	PAIDOFF	1000	30	9/8/2016	10/7/2016	33	Be
2	3	3	PAIDOFF	1000	15	9/8/2016	9/22/2016	27	c
3	4	4	PAIDOFF	1000	30	9/9/2016	10/8/2016	28	c
4	6	6	PAIDOFF	1000	30	9/9/2016	10/8/2016	29	c

In [4]:
```
df.shape
```

Out[4]: (346, 10)

Convert to date time object

In [5]:
```
df['due_date'] = pd.to_datetime(df['due_date'])
df['effective_date'] = pd.to_datetime(df['effective_date'])
df.head()
```

Out[5]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	edu
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	Scl
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Be
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	c
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	c
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	c

Data visualization and pre-processing

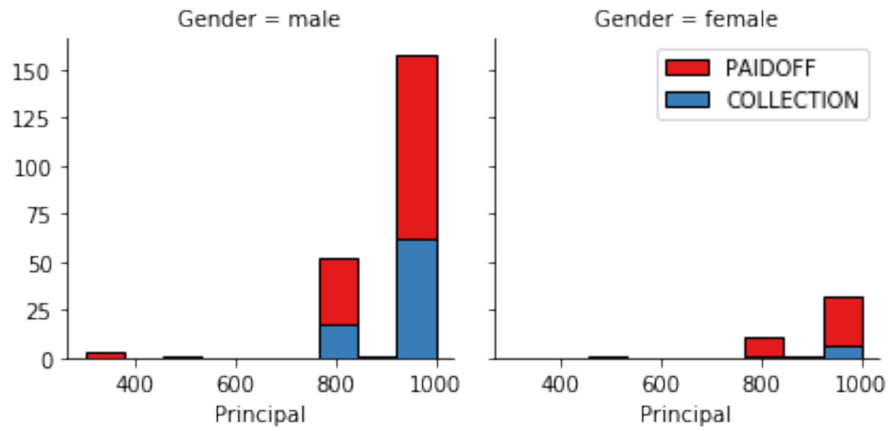
In [6]:
```
df['loan_status'].value_counts()
```

Out[6]:
```
PAIDOFF       260
COLLECTION     86
Name: loan_status, dtype: int64
```

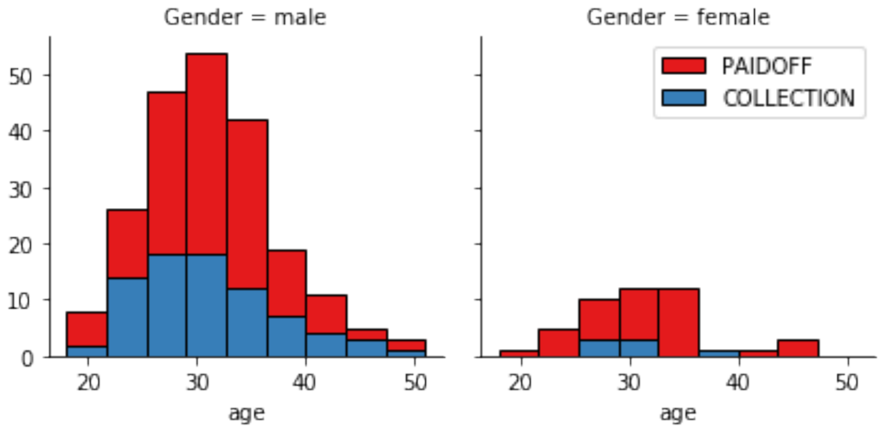
260 people have paid off the loan on time while 86 have gone into collection

Lets plot some columns to underestand data better:

In [8]:
```
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()
```



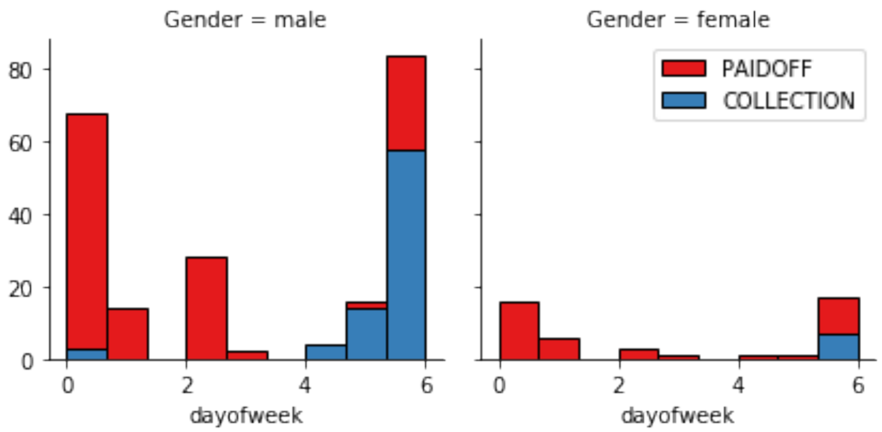
In [9]:
```
bins=np.linspace(df.age.min(), df.age.max(), 10)
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set1", col_wrap=2)
g.map(plt.hist, 'age', bins=bins, ec="k")

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



Pre-processing: Feature selection/extraction

Lets look at the day of the week people get the loan

In [10]:
```
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()
```



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

In [11]:
```
df['weekend']= df['dayofweek'].apply(lambda x: 1 if (x>3)  else 0)
df.head()
```

Out[11]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	edu
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	Sch
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Be
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	c
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	c
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	c

Convert Categorical features to numerical values

Lets look at gender:

In [12]:
```
df.groupby(['Gender'])['loan_status'].value_counts(normalize=True)
```

Out[12]:
```
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

Lets convert male to 0 and female to 1:

In [13]:
```
df['Gender'].replace(to_replace=['male','female'], value=[0,1],inpl
ace=True)
df.head()
```

Out[13]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	edu
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	Sch
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Be
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	c
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	c
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	c

One Hot Encoding

How about education?

In [14]:
```
df.groupby(['education'])['loan_status'].value_counts(normalize=Tru
e)
```

Out[14]:
```
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 befor One Hot Encoding

In [15]:
```
df[['Principal','terms','age','Gender','education']].head()
```

Out[15]:

	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

Use one hot encoding technique to conver categorical varables to binary variables and append them to the feature Data Frame

In [16]:
```
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[16]:

	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

Lets defind feature sets, X:

In [17]:
```
X = Feature
X[0:5]
```

Out[17]:

	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

What are our lables?

In [18]:
```
y = df['loan_status'].values
y[0:5]
```

Out[18]:
```
array(['PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'], dty
pe=object)
```

Normalize Data

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

In [19]:
```
X = preprocessing.StandardScaler().fit(X).transform(X)
X[0:5]
```

Out[19]:
```
array([[ 0.51578458,  0.92071769,  2.33152555, -0.42056004, -1.205
77805,
        -0.38170062,  1.13639374, -0.86968108],
       [ 0.51578458,  0.92071769,  0.34170148,  2.37778177, -1.205
77805,
         2.61985426, -0.87997669, -0.86968108],
       [ 0.51578458, -0.95911111, -0.65321055, -0.42056004, -1.205
77805,
        -0.38170062, -0.87997669,  1.14984679],
       [ 0.51578458,  0.92071769, -0.48739188,  2.37778177,  0.829
34003,
        -0.38170062, -0.87997669,  1.14984679],
       [ 0.51578458,  0.92071769, -0.3215732 , -0.42056004,  0.829
34003,
        -0.38170062, -0.87997669,  1.14984679]])
```

Classification Modeling

K Nearest Neighbor(KNN)

In [21]:
```
# We split the X into train and test to find the best k
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)
print ('Train set:', X_train.shape,  y_train.shape)
print ('Test set:', X_test.shape,  y_test.shape)
```

```
Train set: (276, 8) (276,)
Test set: (70, 8) (70,)
```

In [45]:
```
# Modeling
from sklearn.neighbors import KNeighborsClassifier
k = 3
#Train Model and Predict
kNN_model = KNeighborsClassifier(n_neighbors=k).fit(X_train,y_train
)
kNN_model
```

Out[45]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minko
wski',
           metric_params=None, n_jobs=1, n_neighbors=3, p=2,
           weights='uniform')
```

In [46]:
```
# just for sanity chaeck
yhat = kNN_model.predict(X_test)
yhat[0:5]
```

Out[46]:
```
array(['PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'], dty
pe=object)
```

In [67]:
```
# Best k
Ks=15
mean_acc=np.zeros((Ks-1))
std_acc=np.zeros((Ks-1))
ConfustionMx=[];
for n in range(1,Ks):

    #Train Model and Predict
    kNN_model = KNeighborsClassifier(n_neighbors=n).fit(X_train,y_t
rain)
    yhat = kNN_model.predict(X_test)


    mean_acc[n-1]=np.mean(yhat==y_test);

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

Out[67]:
```
array([ 0.67142857,  0.65714286,  0.71428571,  0.68571429,  0.7571
4286,
        0.71428571,  0.78571429,  0.75714286,  0.75714286,  0.6714
2857,
        0.7       ,  0.72857143,  0.7       ,  0.7       ])
```

In [68]:
```
# Building the model again, using k=7
from sklearn.neighbors import KNeighborsClassifier
k = 7
#Train Model and Predict
kNN_model = KNeighborsClassifier(n_neighbors=k).fit(X_train,y_train
)
kNN_model
```

Out[68]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minko
wski',
           metric_params=None, n_jobs=1, n_neighbors=7, p=2,
           weights='uniform')
```

Decision Tree

In [84]:
```
from sklearn.tree import DecisionTreeClassifier
DT_model = DecisionTreeClassifier(criterion="entropy", max_depth = 4)
DT_model.fit(X_train,y_train)
DT_model
```

Out[84]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=4,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

In [85]:
```
yhat = DT_model.predict(X_test)
yhat
```

Out[85]:
```
array(['COLLECTION', 'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'COLLECTION', 'PAIDOFF',
       'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'COLLECTION', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'PAIDOFF',
       'COLLECTION', 'COLLECTION', 'COLLECTION', 'PAIDOFF', 'COLLECTION',
       'COLLECTION', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'COLLECTION',
       'COLLECTION', 'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'COLLECTION', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'COLLECTION',
       'PAIDOFF', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'COLLECTION',
       'COLLECTION', 'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'COLLECTION', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'COLLECTION',
       'PAIDOFF', 'PAIDOFF'], dtype=object)
```

Support Vector Machine

In [77]:
```
from sklearn import svm
SVM_model = svm.SVC()
SVM_model.fit(X_train, y_train)
```

Out[77]:
```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='r
bf',
  max_iter=-1, probability=False, random_state=None, shrinking=Tru
e,
  tol=0.001, verbose=False)
```

In [82]:
```
yhat = SVM_model.predict(X_test)
yhat
```

Out[82]:
```
array(['COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', '
PAIDOFF',
       'COLLECTION', 'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'
,
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'COL
LECTION',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'COL
LECTION',
       'COLLECTION', 'PAIDOFF', 'COLLECTION', 'COLLECTION', 'PAIDO
FF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAI
DOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'COLLECTION', '
PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', '
PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAI
DOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAI
DOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'COL
LECTION',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAI
DOFF'], dtype=object)
```

Logistic Regression

In [80]:
```
from sklearn.linear_model import LogisticRegression
LR_model = LogisticRegression(C=0.01).fit(X_train,y_train)
LR_model
```

Out[80]:
```
LogisticRegression(C=0.01, class_weight=None, dual=False, fit_inte
rcept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_
jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol
=0.0001,
          verbose=0, warm_start=False)
```

In [81]:
```
yhat = LR_model.predict(X_test)
yhat
```

Out[81]:
```
array(['COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', '
PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAI
DOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'COLLECTION', '
PAIDOFF',
       'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'COLLECTION'
,
       'PAIDOFF', 'PAIDOFF', 'COLLECTION', 'COLLECTION', 'PAIDOFF'
,
       'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', '
PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'PAIDOFF', '
PAIDOFF',
       'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'COLLECTION', 'PAIDOFF'
,
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAI
DOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAI
DOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAI
DOFF',
       'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', '
PAIDOFF',
       'PAIDOFF'], dtype=object)
```

Model Evaluation using Test set

In [93]:
```
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:

Load Test set for evaluation

In [100]:
```
test_df = pd.read_csv('loan_test.csv')
test_df.head()
```

Out[100]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	edu
0	1	1	PAIDOFF	1000	30	9/8/2016	10/7/2016	50	Be
1	5	5	PAIDOFF	300	7	9/9/2016	9/15/2016	35	Ma
2	21	21	PAIDOFF	1000	30	9/10/2016	10/9/2016	43	Scl
3	24	24	PAIDOFF	1000	30	9/10/2016	10/9/2016	26	(
4	35	35	PAIDOFF	800	15	9/11/2016	9/25/2016	29	Be

In [101]:
```
## Preprocessing
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)
test_Feature = test_df[['Principal','terms','age','Gender','weekend
']]
test_Feature = pd.concat([test_Feature,pd.get_dummies(test_df['educ
ation'])], axis=1)
test_Feature.drop(['Master or Above'], axis = 1,inplace=True)
test_X = preprocessing.StandardScaler().fit(test_Feature).transform
(test_Feature)
test_X[0:5]
```

Out[101]:
```
array([[ 0.49362588,  0.92844966,  3.05981865,  1.97714211, -1.303
84048,
         2.39791576, -0.79772404, -0.86135677],
       [-3.56269116, -1.70427745,  0.53336288, -0.50578054,  0.766
96499,
        -0.41702883, -0.79772404, -0.86135677],
       [ 0.49362588,  0.92844966,  1.88080596,  1.97714211,  0.766
96499,
        -0.41702883,  1.25356634, -0.86135677],
       [ 0.49362588,  0.92844966, -0.98251057, -0.50578054,  0.766
96499,
        -0.41702883, -0.79772404,  1.16095912],
       [-0.66532184, -0.78854628, -0.47721942, -0.50578054,  0.766
96499,
         2.39791576, -0.79772404, -0.86135677]])
```

In [102]:
```
test_y = test_df['loan_status'].values
test_y[0:5]
```

Out[102]:
```
array(['PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'], dty
pe=object)
```

In [103]:
```
knn_yhat = kNN_model.predict(test_X)
print("KNN Jaccard index: %.2f" % jaccard_similarity_score(test_y,
knn_yhat))
print("KNN F1-score: %.2f" % f1_score(test_y, knn_yhat, average='we
ighted') )
```

```
KNN Jaccard index: 0.67
KNN F1-score: 0.63
```

In [104]:
```
DT_yhat = DT_model.predict(test_X)
print("DT Jaccard index: %.2f" % jaccard_similarity_score(test_y, DT_yhat))
print("DT F1-score: %.2f" % f1_score(test_y, DT_yhat, average='weighted') )
```

```
DT Jaccard index: 0.72
DT F1-score: 0.74
```

In [105]:
```
SVM_yhat = SVM_model.predict(test_X)
print("SVM Jaccard index: %.2f" % jaccard_similarity_score(test_y, SVM_yhat))
print("SVM F1-score: %.2f" % f1_score(test_y, SVM_yhat, average='weighted') )
```

```
SVM Jaccard index: 0.80
SVM F1-score: 0.76
```

In [106]:
```
LR_yhat = LR_model.predict(test_X)
LR_yhat_prob = LR_model.predict_proba(test_X)
print("LR Jaccard index: %.2f" % jaccard_similarity_score(test_y, LR_yhat))
print("LR F1-score: %.2f" % f1_score(test_y, LR_yhat, average='weighted') )
print("LR LogLoss: %.2f" % log_loss(test_y, LR_yhat_prob))
```

```
LR Jaccard index: 0.74
LR F1-score: 0.66
LR LogLoss: 0.57
```

Report

Algorithm	Jaccard	F1-score	LogLoss
KNN	0.67	0.63	NA
Decision Tree	0.72	0.74	NA
SVM	0.80	0.76	NA
LogisticRegression	0.74	0.66	0.57