In [1]:

```
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
```

In [2]:

```
df = pd.read_csv('loan_train.csv')
df.head()
```

Out[2]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educa
0	0	0	PAIDOFF	1000	30	9/8/2016	10/7/2016	45	ŀ Scho≀ B€
1	2	2	PAIDOFF	1000	30	9/8/2016	10/7/2016	33	Bech
2	3	3	PAIDOFF	1000	15	9/8/2016	9/22/2016	27	coll
3	4	4	PAIDOFF	1000	30	9/9/2016	10/8/2016	28	coll
4	6	6	PAIDOFF	1000	30	9/9/2016	10/8/2016	29	coll
4									•

In [3]:

df.shape

Out[3]:

(346, 10)

In [4]:

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

Out[4]:

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

→

In [5]:

```
df['loan_status'].value_counts()
```

Out[5]:

PAIDOFF 260 COLLECTION 86

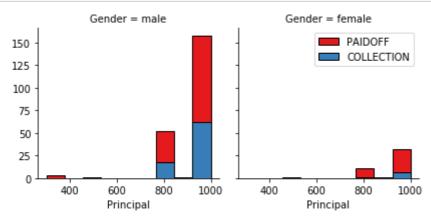
Name: loan_status, dtype: int64

In [6]:

```
import seaborn as sns

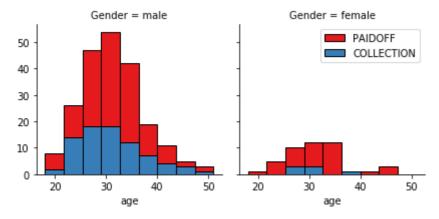
bins = np.linspace(df.Principal.min(), df.Principal.max(), 10)
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set1", col_wrap=2)
g.map(plt.hist, 'Principal', bins=bins, ec="k")

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



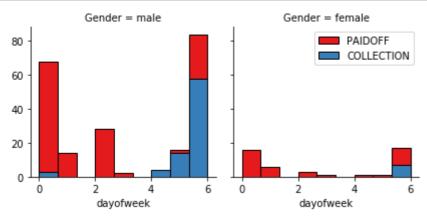
In [7]:

```
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()
```



In [8]:

```
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()
```



In [9]:

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

Out[9]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educat
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10- 07	45	F Schoo Be
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10- 07	33	Bech
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09- 22	27	coll
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10- 08	28	coll
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10- 08	29	coll
4									•

In [10]:

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

Out[10]:

Gender loan_status

female PAIDOFF 0.865385 COLLECTION 0.134615

male PAIDOFF 0.731293

COLLECTION 0.268707

Name: loan_status, dtype: float64

In [11]:

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

Out[11]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educat
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10- 07	45	F Schoo Be
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10- 07	33	Bech
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09- 22	27	coll
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10- 08	28	coll
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10- 08	29	coll
4									•

In [12]:

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

Out[12]:

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

In [13]:

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

Out[13]:

	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 [14]:

```
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[14]:

	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 [15]:

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

Out[15]:

	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 [16]:
y = df['loan status'].values
y[0:5]
Out[16]:
array(['PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'],
     dtype=object)
In [17]:
import warnings
warnings.filterwarnings('ignore')
In [18]:
X= preprocessing.StandardScaler().fit(X).transform(X)
X[0:5]
Out[18]:
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
```

```
In [19]:
```

```
# 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:', (276L, 8L), (276L,))
('Test set:', (70L, 8L), (70L,))
```

K Nearest Neighbor(KNN)

```
In [20]:
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[20]:
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=None, n_neighbors=3, p=2,
           weights='uniform')
In [21]:
yhat = kNN_model.predict(X_test)
yhat[0:5]
Out[21]:
array(['PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'],
      dtype=object)
In [22]:
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_train)
    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[22]:

```
array([0.67142857, 0.65714286, 0.71428571, 0.68571429, 0.75714286,
       0.71428571, 0.78571429, 0.75714286, 0.75714286, 0.67142857,
                                         , 0.7
       0.7
                 , 0.72857143, 0.7
                                                      1)
```

```
In [23]:
```

```
# 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[23]:
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=None, n_neighbors=7, p=2,
           weights='uniform')
Decision Tree
In [24]:
from sklearn.tree import DecisionTreeClassifier
DT_model = DecisionTreeClassifier(criterion="entropy", max_depth = 4)
DT_model.fit(X_train,y_train)
DT_model
Out[24]:
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=Non
е,
            splitter='best')
In [25]:
yhat = DT model.predict(X test)
yhat
Out[25]:
array(['COLLECTION', 'COLLECTION', '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', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'COLLECTION', 'PAIDOFF',
       'COLLECTION', 'COLLECTION', '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 [26]:
from sklearn import svm
SVM model = svm.SVC()
SVM_model.fit(X_train, y_train)
Out[26]:
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
         decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
         kernel='rbf', max_iter=-1, probability=False, random_state=None,
         shrinking=True, tol=0.001, verbose=False)
In [27]:
yhat = SVM_model.predict(X_test)
yhat
Out[27]:
array(['COLLECTION', 'PAIDOFF', 'PAIDOF
                                 'PAIDOFF', 'COLLECTION', 'COLLECTION', 'PAIDOFF', 'PAIDOFF',
                                'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
                                'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
                                 'PAIDOFF', 'COLLECTION', 'COLLECTION', 'PAIDOFF', 'COLLECTION',
                                'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
                                 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
                               'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
                                 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
                               'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 
                               'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'COLLECTION',
                                'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'],
                           dtype=object)
In [ ]:
In [ ]:
```

Logistic Regression

```
In [28]:
from sklearn.linear model import LogisticRegression
LR_model = LogisticRegression(C=0.01).fit(X_train,y_train)
LR model
Out[28]:
LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=Tr
ue,
                                             intercept_scaling=1, max_iter=100, multi_class='warn',
                                             n_jobs=None, penalty='12', random_state=None, solver='warn',
                                             tol=0.0001, verbose=0, warm_start=False)
In [29]:
yhat = LR_model.predict(X_test)
yhat
Out[29]:
array(['COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
                                'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 
                                 'COLLECTION', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'PAIDOFF',
                                 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'COLLECTION',
                                'COLLECTION', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'PAIDOFF',
                                 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
                                'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'COLLECTION',
                                 'PAIDOFF', 'PAIDOFF', 'COLLECTION', 'PAIDOFF', 'PAIDOFF',
                                'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 
                                 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
                                 'COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
                                 'PAIDOFF', 'PAIDOFF'], dtype=object)
In [ ]:
In [ ]:
```

Model Evaluation using Test set

```
In [30]:
```

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

In [31]:

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

Out[31]:

ı	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educa
	1	1	PAIDOFF	1000	30	9/8/2016	10/7/2016	50	Bech
	5	5	PAIDOFF	300	7	9/9/2016	9/15/2016	35	Maste Ab
	21	21	PAIDOFF	1000	30	9/10/2016	10/9/2016	43	l Scho≀ B€
	24	24	PAIDOFF	1000	30	9/10/2016	10/9/2016	26	coll
	35	35	PAIDOFF	800	15	9/11/2016	9/25/2016	29	Bech
									>

In [32]:

```
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['education'])], 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[32]:

```
array([[ 0.49362588,  0.92844966,  3.05981865,  1.97714211, -1.30384048,  2.39791576, -0.79772404, -0.86135677],  [-3.56269116, -1.70427745,  0.53336288, -0.50578054,  0.76696499, -0.41702883, -0.79772404, -0.86135677],  [ 0.49362588,  0.92844966,  1.88080596,  1.97714211,  0.76696499, -0.41702883,  1.25356634, -0.86135677],  [ 0.49362588,  0.92844966, -0.98251057, -0.50578054,  0.76696499, -0.41702883, -0.79772404,  1.16095912],  [ -0.66532184, -0.78854628, -0.47721942, -0.50578054,  0.76696499, 2.39791576, -0.79772404, -0.86135677]])
```

In [33]:

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

Out[33]:

```
In [34]:
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='weighted') )
KNN Jaccard index: 0.67
KNN F1-score: 0.63
In [35]:
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 [36]:
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 [37]:
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

In []:

Report

oss	Algorithm	Jaccard	F1-score	LogL
033	ZAIN	0.67	0.63	N.
Α	KNN	0.67	0.63	N
	Decision Tree	0.72	0.74	N
А	SVM	0.80	0.76	N
Α	l aniati Danasain	0.74	0.66	0
57	LogisticRegression	0.74	0.66	0.