(https://www.bigdatauniversity.com)

Classification with Python

In this notebook we try to practice all the classification algorithms that we learned in this course.

We load a dataset using Pandas library, and apply the following algorithms, and find the best one for this specific dataset by accuracy evaluation methods.

Lets first load required libraries:

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
```

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 [2]:
```
!wget -O loan_train.csv https://s3-api.us-geo.objectstorage.softlayer.net/cf-course
s-data/CognitiveClass/ML0101ENv3/labs/loan_train.csv
```

```
--2020-05-10 12:27:25--  https://s3-api.us-geo.objectstorage.softlayer.net/cf-co
urses-data/CognitiveClass/ML0101ENv3/labs/loan_train.csv
Resolving s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorag
e.softlayer.net)... 67.228.254.196
Connecting to s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectsto
rage.softlayer.net)|67.228.254.196|: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 0.09s

2020-05-10 12:27:25 (263 KB/s) - 'loan_train.csv' saved [23101/23101]
```

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	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 [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	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

Let's see how many of each class is in our data set

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

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

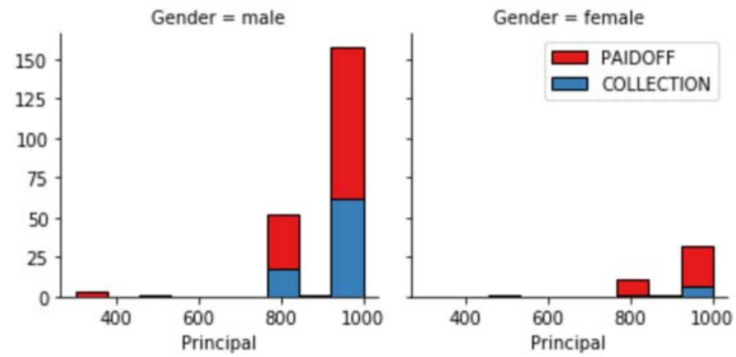
260 people have paid off the loan on time while 86 have gone into collection

Lets plot some columns to underestand data better:

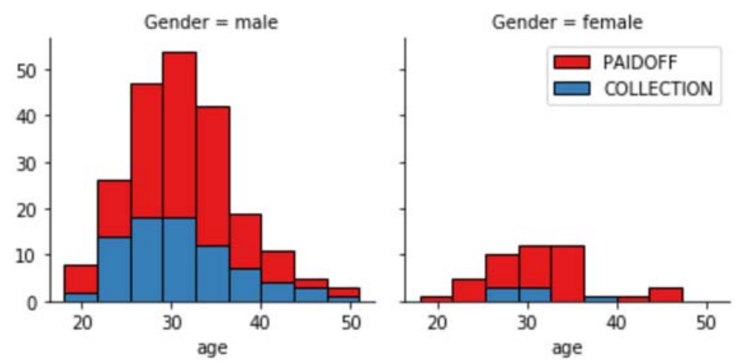
In [7]:
```
# notice: installing seaborn might takes a few minutes
!conda install -c anaconda seaborn -y
```

```
Solving environment: done

## Package Plan ##

  environment location: /opt/conda/envs/Python36

  added / updated specs:
    - seaborn


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    openssl-1.1.1g             |       h7b6447c_0         3.8 MB  anaconda
    seaborn-0.10.1             |             py_0         160 KB  anaconda
    certifi-2020.4.5.1         |           py36_0         159 KB  anaconda
    ca-certificates-2020.1.1   |                0         132 KB  anaconda
    ------------------------------------------------------------
                                           Total:         4.2 MB

The following packages will be UPDATED:

    ca-certificates: 2020.1.1-0          --> 2020.1.1-0         anaconda
    certifi:         2020.4.5.1-py36_0   --> 2020.4.5.1-py36_0 anaconda
    openssl:         1.1.1g-h7b6447c_0   --> 1.1.1g-h7b6447c_0 anaconda
    seaborn:         0.9.0-pyh91ea838_1 --> 0.10.1-py_0       anaconda


Downloading and Extracting Packages
openssl-1.1.1g       | 3.8 MB    | ##################################### | 100%
seaborn-0.10.1       | 160 KB    | ##################################### | 100%
certifi-2020.4.5.1   | 159 KB    | ##################################### | 100%
ca-certificates-2020 | 132 KB    | ##################################### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
```

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()
```



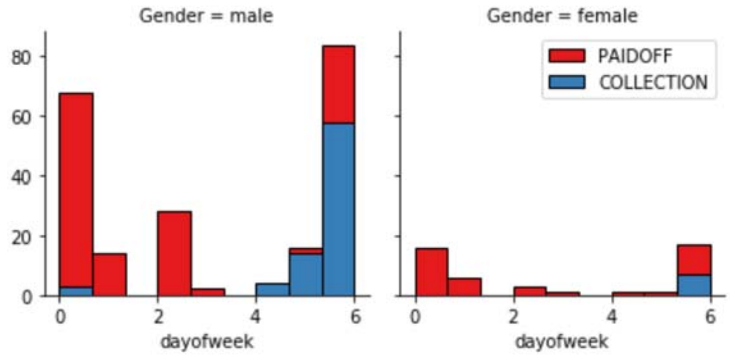
In [9]:
```
bins = np.linspace(df.age.min(), df.age.max(), 10)
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set1", col_wrap=2)
g.map(plt.hist, 'age', bins=bins, ec="k")

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	education	Gender	da
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	

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],inplace=True)
df.head()
```

Out[13]:

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

One Hot Encoding

How about education?

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

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 [88]:
```
X = Feature
X[0:5]
```

Out[88]:

	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'],
      dtype=object)
```

In [125]:
```
df['loan_status_cat']=df['loan_status'].replace(to_replace=['COLLECTION','PAIDOFF
'], value=[0,1])
df.head()
```

Out[125]:

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

In [128]:
```
y2=df['loan_status_cat']
```

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]
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/sklearn/preprocessing/data.
py:645: DataConversionWarning: Data with input dtype uint8, int64 were all conve
rted to float64 by StandardScaler.
  return self.partial_fit(X, y)
/opt/conda/envs/Python36/lib/python3.6/site-packages/ipykernel/__main__.py:1: Da
taConversionWarning: Data with input dtype uint8, int64 were all converted to fl
oat64 by StandardScaler.
  if __name__ == '__main__':
```

Out[19]:
```
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

Now, it is your turn, use the training set to build an accurate model. Then use the test set to report the accuracy of the model
You should use the following algorithm:

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

Notice:

- You can go above and change the pre-processing, feature selection, feature-extraction, and so on, to make a better model.
- You should use either scikit-learn, Scipy or Numpy libraries for developing the classification algorithms.
- You should include the code of the algorithm in the following cells.

K Nearest Neighbor(KNN)

Notice: You should find the best k to build the model with the best accuracy.
warning: You should not use the **loan_test.csv** for finding the best k, however, you can split your train_loan.csv into train and test to find the best **k**.

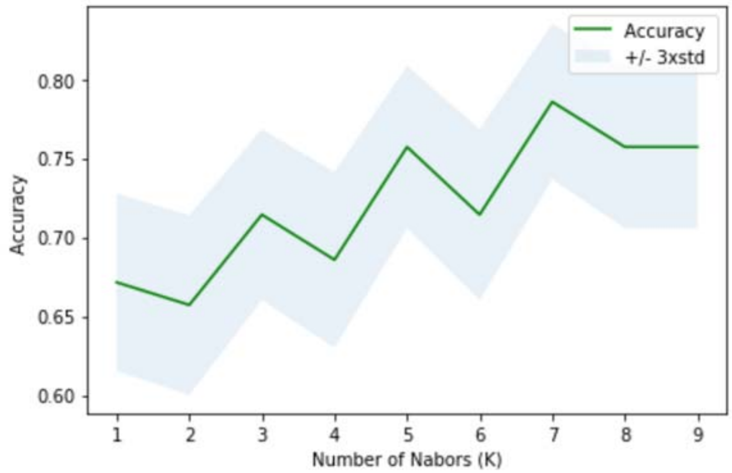
In [20]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.2, random_st
ate=4)
print ('Train set:', X_train.shape, y_train.shape)
print ('Test set:', X_test.shape, y_test.shape)
```

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

In [28]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics

Ks = 10
mean_acc = np.zeros((Ks-1))
std_acc = np.zeros((Ks-1))
ConfustionMx = [];
for n in range(1,Ks):
    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])

mean_acc
```

Out[28]:
```
array([0.67142857, 0.65714286, 0.71428571, 0.68571429, 0.75714286,
       0.71428571, 0.78571429, 0.75714286, 0.75714286])
```

In [29]:
```
plt.plot(range(1,Ks),mean_acc,'g')
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()
```



In [26]:
```
print( "The best accuracy is with", mean_acc.max(), "with k=", mean_acc.argmax()+1)
```

```
The best accuracy is with 0.7857142857142857 with k= 7
```

In [155]:
```
neigh = KNeighborsClassifier(n_neighbors = 7).fit(X_train,y_train)
neigh
```

Out[155]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=7, p=2,
                     weights='uniform')
```

Decision Tree

In [156]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [157]:
```
Tree = DecisionTreeClassifier(criterion="entropy", max_depth = 4)
Tree.fit(X_train, y_train)
```

Out[157]:
```
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 [158]:
```
yhat_tree=Tree.predict(X_test)
yhat_tree
```

Out[158]:
```
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)
```

In [71]:
```
y_test[0:5]
```

Out[71]:
```
array(['PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'],
      dtype=object)
```

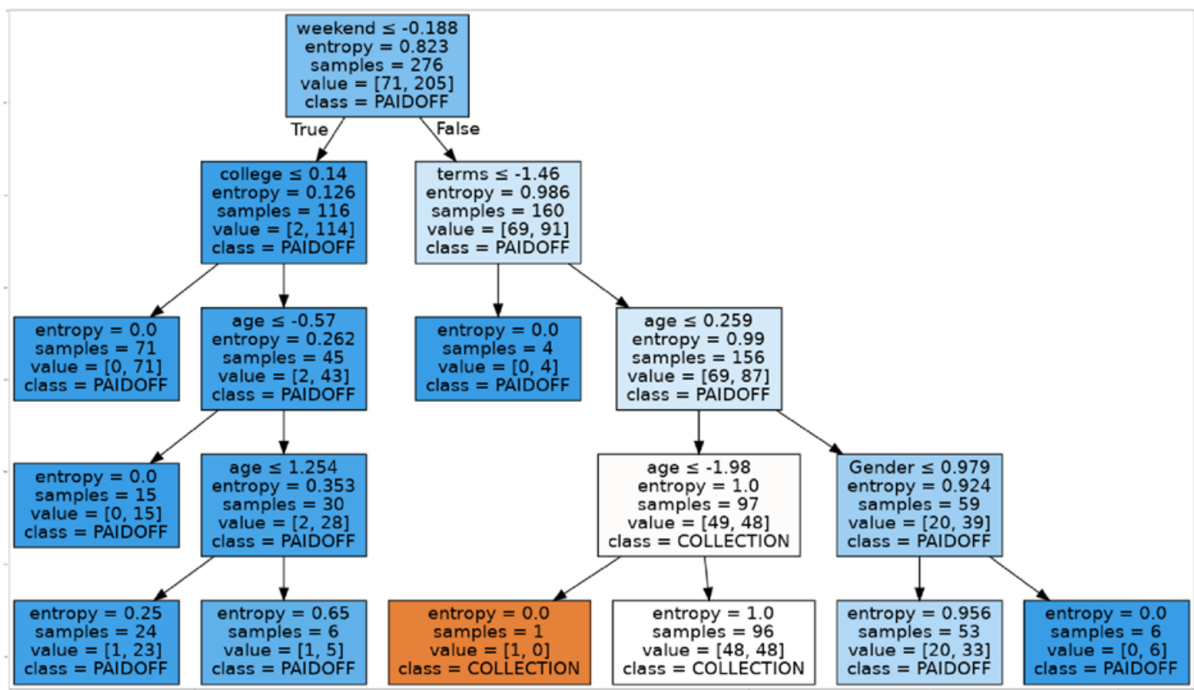
In [91]:
```
print("DecisionTrees's Accuracy: ", metrics.accuracy_score(y_testtree, predTree))
```

```
DecisionTrees's Accuracy:  0.7403846153846154
```

In [179]:
```
!pip install graphviz
!pip install pydotplus
import graphviz
import pydotplus

dot_data = StringIO()
filename = "tree.png"
featureNames = Feature.columns
out=tree.export_graphviz(Tree,feature_names=featureNames, out_file=dot_data, class
_names= np.unique(y_train), filled=True,  special_characters=True,rotate=False)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png(filename)
img = mpimg.imread(filename)
plt.figure(figsize=(100, 200))
plt.imshow(img,interpolation='nearest')
```

```
Requirement already satisfied: graphviz in /opt/conda/envs/Python36/lib/python3.
6/site-packages (0.14)
Requirement already satisfied: pydotplus in /opt/conda/envs/Python36/lib/python
3.6/site-packages (2.0.2)
Requirement already satisfied: pyparsing>=2.0.1 in /opt/conda/envs/Python36/lib/
python3.6/site-packages (from pydotplus) (2.3.1)
```

Out[179]: `<matplotlib.image.AxesImage at 0x7f7193754470>`



Support Vector Machine

In [159]:
```
from sklearn import svm
```

In [161]:
```
model_svm = svm.SVC(kernel='rbf')
model_svm.fit(X_train, y_train)
yhatsvm = model_svm.predict(X_test)
yhatsvm
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/sklearn/svm/base.py:196: Fu
tureWarning: The default value of gamma will change from 'auto' to 'scale' in ve
rsion 0.22 to account better for unscaled features. Set gamma explicitly to 'aut
o' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

Out[161]:
```
array(['COLLECTION', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'COLLECTION', 'COLLECTION', 'PAIDOFF', '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', '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', 'COLLECTION',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'],
      dtype=object)
```

Logistic Regression

In [162]:
```
from sklearn.linear_model import LogisticRegression
LR = LogisticRegression(C=0.01, solver='sag').fit(X_train,y_train)
LR
```

Out[162]:
```
LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='sag',
          tol=0.0001, verbose=0, warm_start=False)
```

In [164]:
```
yhat_lr = LR.predict(X_test)
yhat_lr
```

Out[164]:
```
array(['PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF',
       'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'], dtype=object)
```

Model Evaluation using Test set

In [165]:
```
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 [166]:
```
!wget -O loan_test.csv https://s3-api.us-geo.objectstorage.softlayer.net/cf-course
s-data/CognitiveClass/ML0101ENv3/labs/loan_test.csv
```

```
--2020-05-10 14:58:21--  https://s3-api.us-geo.objectstorage.softlayer.net/cf-co
urses-data/CognitiveClass/ML0101ENv3/labs/loan_test.csv
Resolving s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorag
e.softlayer.net)... 67.228.254.196
Connecting to s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectsto
rage.softlayer.net)|67.228.254.196|: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

2020-05-10 14:58:21 (275 MB/s) - ‘loan_test.csv’ saved [3642/3642]
```

Load Test set for evaluation

In [167]:
```
test_df = pd.read_csv('loan_test.csv')
test_df.head()
```

Out[167]:

	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 [168]:
```
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]
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/sklearn/preprocessing/data.
py:645: DataConversionWarning: Data with input dtype uint8, int64 were all conve
rted to float64 by StandardScaler.
  return self.partial_fit(X, y)
/opt/conda/envs/Python36/lib/python3.6/site-packages/ipykernel/__main__.py:9: Da
taConversionWarning: Data with input dtype uint8, int64 were all converted to fl
oat64 by StandardScaler.
```

Out[168]:
```
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 [169]:
```
test_y = test_df['loan_status'].values
test_y[0:5]
```

Out[169]:
```
array(['PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'],
      dtype=object)
```

In [170]:
```
knn_yhat=neigh.predict(test_X)
print("Avg F1-score of KNN: %.4f" % f1_score(test_y, knn_yhat, average='weighted
'))
print("Jaccard score of KNN: %.4f" % jaccard_similarity_score(test_y, knn_yhat))
```

```
Avg F1-score of KNN: 0.6328
Jaccard score of KNN: 0.6667
```

In [172]:
```
tree_yhat=Tree.predict(test_X)
print("Avg F1-score of Decision Tree: %.4f" % f1_score(test_y, tree_yhat, average=
'weighted'))
print("Jaccard score of Decision Tree: %.4f" % jaccard_similarity_score(test_y, tr
ee_yhat))
```

```
Avg F1-score of Decision Tree: 0.7367
Jaccard score of Decision Tree: 0.7222
```

In [174]:
```
svm_yhat=model_svm.predict(test_X)
print("Avg F1-score of SVM: %.4f" % f1_score(test_y, svm_yhat, average='weighted
'))
print("Jaccard score of SVM: %.4f" % jaccard_similarity_score(test_y, svm_yhat))
```

```
Avg F1-score of SVM: 0.7584
Jaccard score of SVM: 0.7963
```

In [177]:
```
LR_yhat=model_svm.predict(test_X)
LR_yhat_prob = LR.predict_proba(test_X)
print("Avg F1-score of LR: %.4f" % f1_score(test_y, LR_yhat, average='weighted'))
print("Jaccard score of LR: %.4f" % jaccard_similarity_score(test_y, LR_yhat))
print("LogLoss score of LR: %.2f" % log_loss(test_y, LR_yhat_prob))
```

```
Avg F1-score of LR: 0.7584
Jaccard score of LR: 0.7963
LogLoss score of LR: 0.52
```

In [180]:
```
jc1=jaccard_similarity_score(test_y, knn_yhat)
fs1=f1_score(test_y, knn_yhat, average='weighted')

jc2=jaccard_similarity_score(test_y, tree_yhat)
fs2=f1_score(test_y, tree_yhat, average='weighted')

jc3=jaccard_similarity_score(test_y, svm_yhat)
fs3=f1_score(test_y, svm_yhat, average='weighted')

jc4=jaccard_similarity_score(test_y, LR_yhat)
fs4=f1_score(test_y, LR_yhat, average='weighted')
ll4=log_loss(test_y, LR_yhat_prob)

list_jc = [jc1, jc2, jc3, jc4]
list_fs = [fs1, fs2, fs3, fs4]
list_ll = ['NA', 'NA', 'NA', ll4]


import pandas as pd

# fomulate the report format
df = pd.DataFrame(list_jc, index=['KNN','Decision Tree','SVM','Logistic Regression
'])
df.columns = ['Jaccard']
df.insert(loc=1, column='F1-score', value=list_fs)
df.insert(loc=2, column='LogLoss', value=list_ll)
df.columns.name = 'Algorithm'
df
```

Out[180]:

Algorithm	Jaccard	F1-score	LogLoss
KNN	0.666667	0.632840	NA
Decision Tree	0.722222	0.736682	NA
SVM	0.796296	0.758350	NA
Logistic Regression	0.796296	0.758350	0.516366

Report

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

Algorithm	Jaccard	F1-score	LogLoss
KNN	0.6667	0.6328	NA
Decision Tree	0.7222	0.7367	NA
SVM	0.7963	0.7584	NA
LogisticRegression	0.7963	0.7584	0.52

Want to learn more?

IBM SPSS Modeler is a comprehensive analytics platform that has many machine learning algorithms. It has been designed to bring predictive intelligence to decisions made by individuals, by groups, by systems – by your enterprise as a whole. A free trial is available through this course, available here: SPSS Modeler (http://cocl.us/ML0101EN-SPSSModeler)

Also, you can use Watson Studio to run these notebooks faster with bigger datasets. Watson Studio is IBM's leading cloud solution for data scientists, built by data scientists. With Jupyter notebooks, RStudio, Apache Spark and popular libraries pre-packaged in the cloud, Watson Studio enables data scientists to collaborate on their projects without having to install anything. Join the fast-growing community of Watson Studio users today with a free account at Watson Studio (https://cocl.us/ML0101EN_DSX)

Thanks for completing this lesson!

Author: Saeed Aghabozorgi (https://ca.linkedin.com/in/saeedaghabozorgi)

Saeed Aghabozorgi (https://ca.linkedin.com/in/saeedaghabozorgi), PhD is a Data Scientist in IBM with a track record of developing enterprise level applications that substantially increases clients' ability to turn data into actionable knowledge. He is a researcher in data mining field and expert in developing advanced analytic methods like machine learning and statistical modelling on large datasets.
