ML0101EN-Proj-Loan-py-v1

January 7, 2019

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
        #!pip install -U scikit-learn scipy matplotlib
        from sklearn import preprocessing
        from sklearn.linear_model import LogisticRegression
        %matplotlib inline
```

0.0.1 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-courses-dat
        print('Download Successful')
```

```
--2019-01-07 05:03:25--  https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/Cogni
Resolving s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.net).
Connecting to s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.n
HTTP request sent, awaiting response... 200 OK
Length: 23101 (23K) [text/csv]
Saving to: loan_train.csv

loan_train.csv      100%[=====================>]  22.56K  --.-KB/s    in 0.02s

2019-01-07 05:03:25 (1.04 MB/s) - loan_train.csv saved [23101/23101]

Download Successful
```

0.0.2 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  \
        0           0             0     PAIDOFF       1000     30       9/8/2016
        1           2             2     PAIDOFF       1000     30       9/8/2016
        2           3             3     PAIDOFF       1000     15       9/8/2016
        3           4             4     PAIDOFF       1000     30       9/9/2016
        4           6             6     PAIDOFF       1000     30       9/9/2016

            due_date  age             education  Gender
        0  10/7/2016   45  High School or Below    male
        1  10/7/2016   33              Bechalor  female
        2  9/22/2016   27               college    male
        3  10/8/2016   28               college  female
        4  10/8/2016   29               college    male
```

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

```
Out[4]: (346, 10)
```

```
In [5]: df.groupby('loan_status').size()
```

```
Out[5]: loan_status
        COLLECTION     86
        PAIDOFF       260
        dtype: int64
```

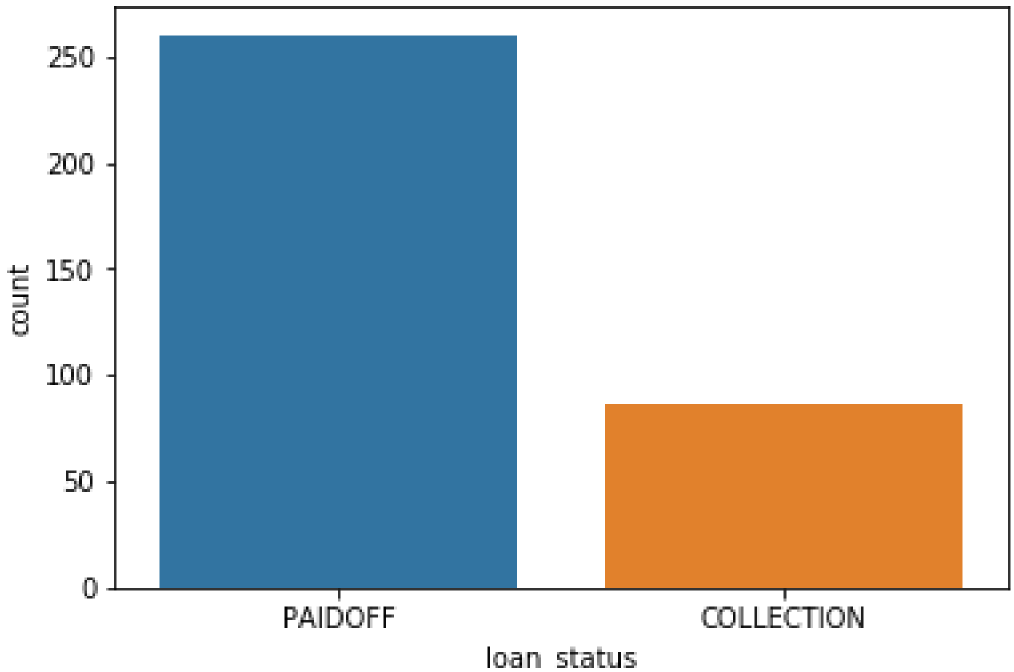
```
In [6]: !conda install -c anaconda seaborn -y
```

```
Solving environment: done

## Package Plan ##

  environment location: /home/jupyterlab/conda

  added / updated specs:
    - seaborn


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    libssh2-1.8.0              |       h1ba5d50_4         233 KB  anaconda
    ca-certificates-2018.03.07 |                0         124 KB  anaconda
    krb5-1.16.1                |       h173b8e3_7         1.4 MB  anaconda
    ------------------------------------------------------------
                                           Total:         1.7 MB

The following packages will be UPDATED:

    cryptography:    2.3.1-py36hdffb7b8_0    conda-forge --> 2.4.1-py36h1ba5d50_0    anaconda
    grpcio:          1.16.0-py36hd60e7a3_0   conda-forge --> 1.16.1-py36hf8bcb03_1   anaconda
    libarchive:      3.3.3-h823be47_0        conda-forge --> 3.3.3-h5d8350f_4        anaconda
    libcurl:         7.63.0-hbdb9355_0       conda-forge --> 7.63.0-h20c2e04_1000
    libssh2:         1.8.0-h5b517e9_3        conda-forge --> 1.8.0-h1ba5d50_4        anaconda
    openssl:         1.0.2p-h470a237_1       conda-forge --> 1.1.1-h7b6447c_0        anaconda
    pycurl:          7.43.0.2-py36hb7f436b_0             --> 7.43.0.2-py36h1ba5d50_0
    python:          3.6.6-h5001a0f_3        conda-forge --> 3.6.7-h0371630_0        anaconda

The following packages will be DOWNGRADED:

    ca-certificates: 2018.11.29-ha4d7672_0   conda-forge --> 2018.03.07-0            anaconda
    certifi:         2018.11.29-py36_1000    conda-forge --> 2018.10.15-py36_0       anaconda
    krb5:            1.16.2-hbb41f41_0       conda-forge --> 1.16.1-h173b8e3_7       anaconda


Downloading and Extracting Packages
libssh2-1.8.0        | 233 KB    | ##################################### | 100%
ca-certificates-2018 | 124 KB    | ##################################### | 100%
krb5-1.16.1          | 1.4 MB    | ##################################### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
```

```
In [7]: import seaborn as sns
```

```
sns.countplot(df['loan_status'],label="Count")
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7f352fef55f8>



0.0.3 Convert to date time object

```
In [8]: df['due_date'] = pd.to_datetime(df['due_date'])
        df['effective_date'] = pd.to_datetime(df['effective_date'])
        df.head()
```

Out[8]:

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date
0	0	0	PAIDOFF	1000	30	2016-09-08
1	2	2	PAIDOFF	1000	30	2016-09-08
2	3	3	PAIDOFF	1000	15	2016-09-08
3	4	4	PAIDOFF	1000	30	2016-09-09
4	6	6	PAIDOFF	1000	30	2016-09-09

	due_date	age	education	Gender
0	2016-10-07	45	High School or Below	male
1	2016-10-07	33	Bechalor	female
2	2016-09-22	27	college	male
3	2016-10-08	28	college	female
4	2016-10-08	29	college	male

1 Data visualization and pre-processing

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

```
In [9]: df['loan_status'].value_counts()
```

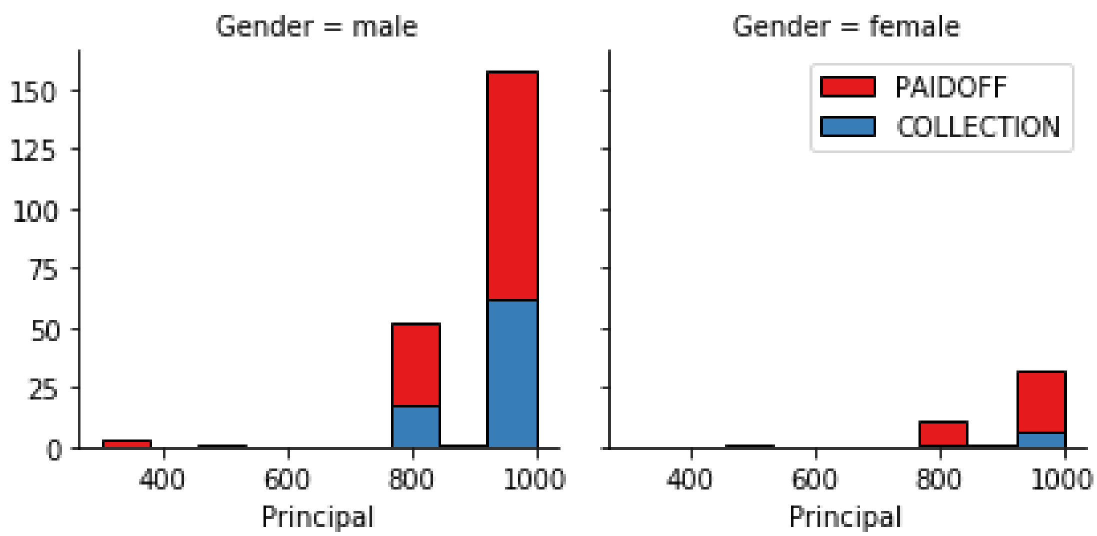
```
Out[9]: PAIDOFF       260
        COLLECTION     86
        Name: loan_status, dtype: int64
```

260 people have paid off the loan on time while 86 have gone into collection
Lets plot some columns to underestand data better:

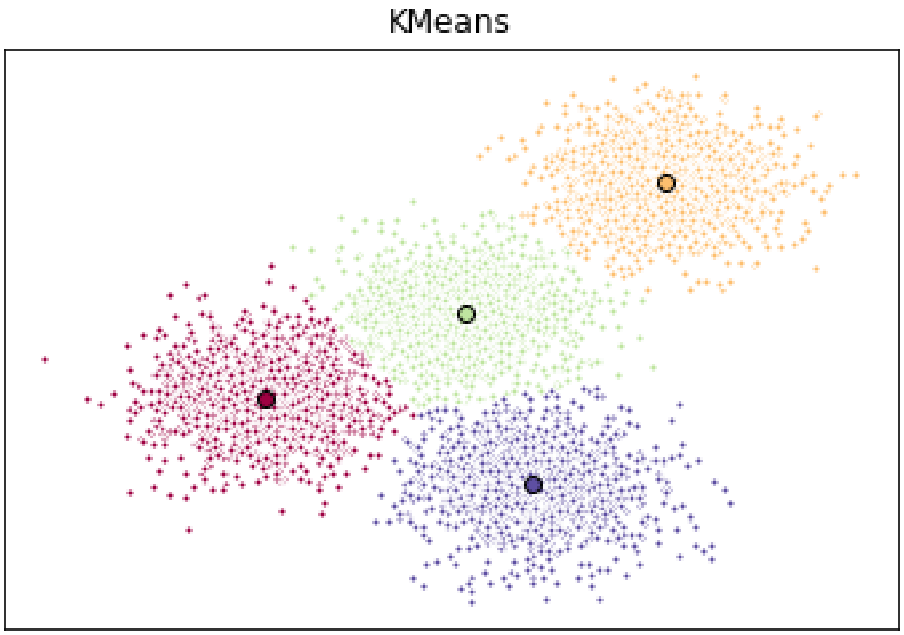
```
In [10]: # notice: installing seaborn might takes a few minutes
         #!conda install -c anaconda seaborn -y
```

```
Solving environment: done

# All requested packages already installed.
```

```
In [11]: 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()
```



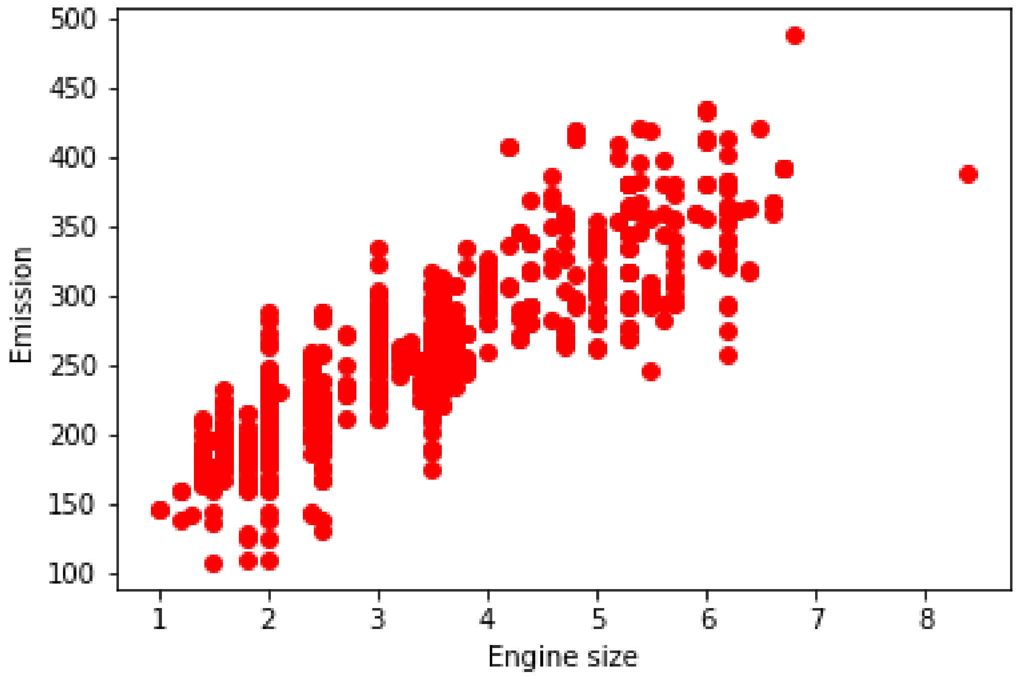
In [12]:
```
bins = np.linspace(df.age.min(), df.age.max(), 10)
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set1", col_wrap=2)
g.map(plt.hist, 'age', bins=bins, ec="k")

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



2 Pre-processing: Feature selection/extraction

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

In [13]:
```
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 [14]: df['weekend'] = df['dayofweek'].apply(lambda x: 1 if (x>3)  else 0)
         df.head()
```

```
Out[14]:    Unnamed: 0  Unnamed: 0.1 loan_status  Principal  terms effective_date  \
         0           0             0     PAIDOFF       1000     30     2016-09-08
         1           2             2     PAIDOFF       1000     30     2016-09-08
         2           3             3     PAIDOFF       1000     15     2016-09-08
         3           4             4     PAIDOFF       1000     30     2016-09-09
         4           6             6     PAIDOFF       1000     30     2016-09-09

             due_date  age             education  Gender  dayofweek  weekend
         0 2016-10-07   45  High School or Below    male          3        0
         1 2016-10-07   33              Bechalor  female          3        0
         2 2016-09-22   27               college    male          3        0
         3 2016-10-08   28               college  female          4        1
         4 2016-10-08   29               college    male          4        1
```

2.1 Convert Categorical features to numerical values

Lets look at gender:

```
In [15]: df.groupby(['Gender'])['loan_status'].value_counts(normalize=True)
```

```
Out[15]: 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 [16]: df['Gender'].replace(to_replace=['male','female'], value=[0,1],inplace=True)
         df.head()
```

```
Out[16]:    Unnamed: 0  Unnamed: 0.1 loan_status  Principal  terms effective_date  \
         0           0             0     PAIDOFF       1000     30     2016-09-08
         1           2             2     PAIDOFF       1000     30     2016-09-08
         2           3             3     PAIDOFF       1000     15     2016-09-08
         3           4             4     PAIDOFF       1000     30     2016-09-09
         4           6             6     PAIDOFF       1000     30     2016-09-09

             due_date  age             education  Gender  dayofweek  weekend
         0 2016-10-07   45  High School or Below       0          3        0
         1 2016-10-07   33              Bechalor       1          3        0
         2 2016-09-22   27               college       0          3        0
         3 2016-10-08   28               college       1          4        1
         4 2016-10-08   29               college       0          4        1
```

2.2 One Hot Encoding

How about education?

```
In [17]: df.groupby(['education'])['loan_status'].value_counts(normalize=True)
```

```
Out[17]: 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 [18]: df[['Principal','terms','age','Gender','education']].head()
```

```
Out[18]:    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 convert categorical varables to binary variables and append them to the feature Data Frame

```
In [19]: 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[19]:    Principal  terms  age  Gender  weekend  Bechalor  High School or Below  \
         0       1000     30   45       0        0         0                     1
         1       1000     30   33       1        0         1                     0
         2       1000     15   27       0        0         0                     0
         3       1000     30   28       1        1         0                     0
         4       1000     30   29       0        1         0                     0

            college
         0        0
         1        0
         2        1
         3        1
         4        1
```

2.2.1 Feature selection

Lets defind feature sets, X:

```
In [20]: X = Feature
         X[0:5]
```

```
Out[20]:    Principal  terms  age  Gender  weekend  Bechalor  High School or Below  \
         0       1000     30   45       0        0         0                     1
         1       1000     30   33       1        0         1                     0
         2       1000     15   27       0        0         0                     0
         3       1000     30   28       1        1         0                     0
         4       1000     30   29       0        1         0                     0

            college
         0        0
         1        0
         2        1
         3        1
         4        1
```

What are our lables?

```
In [21]: y = df['loan_status'].values
         y[0:5]
```

```
Out[21]: array(['PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF'],
               dtype=object)
```

2.3 Normalize Data

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

```
In [22]: #from sklearn import preprocessing
         X= preprocessing.StandardScaler().fit(X).transform(X)
         X[0:5]
```

```
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: DataConver
  return self.partial_fit(X, y)
/home/jupyterlab/conda/lib/python3.6/site-packages/ipykernel_launcher.py:2: DataConversionWarnin
```

```
Out[22]: 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]])
```

3 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

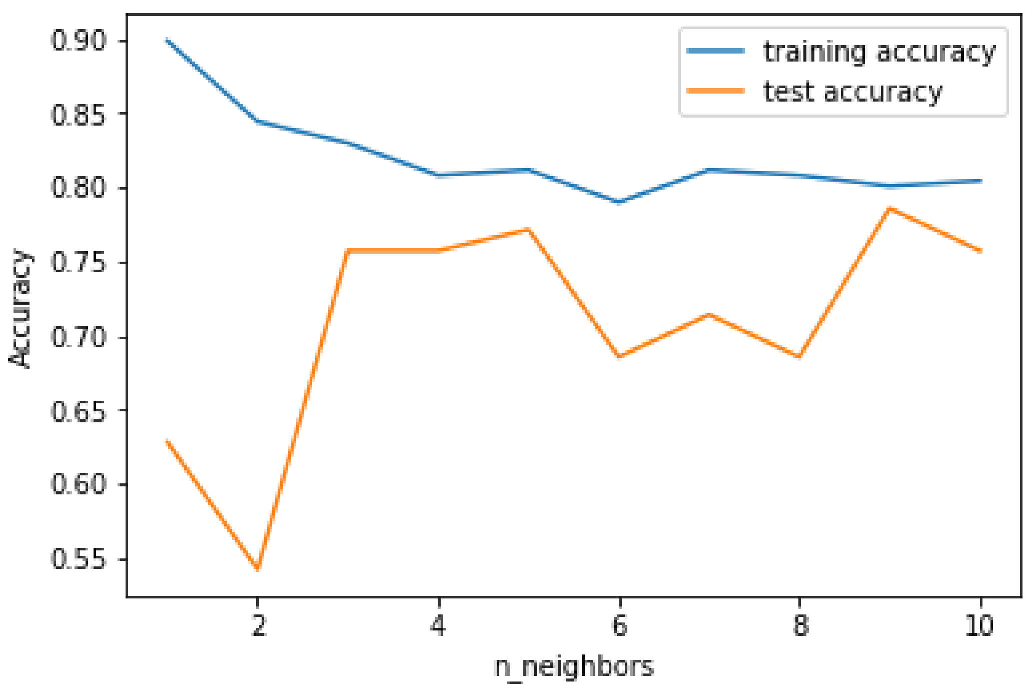
__ Notice:__ - You can go above and change the pre-processing, feature selection, feature-extraction, and so on, to make a better model. - You should use either scikit-learn, Scipy or Numpy libraries for developing the classification algorithms. - You should include the code of the algorithm in the following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

4 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 [23]:
```python
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,jaccard_similarity_score, log_loss
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=

from sklearn.neighbors import KNeighborsClassifier
training_accuracy = []
test_accuracy = []
# try n_neighbors from 1 to 10
neighbors_settings = range(1, 11)
for n_neighbors in neighbors_settings:
    # build the model
    knn = KNeighborsClassifier(n_neighbors=n_neighbors)
    knn.fit(X_train, y_train)
    # record training set accuracy
    training_accuracy.append(knn.score(X_train, y_train))
    # record test set accuracy
    test_accuracy.append(knn.score(X_test, y_test))
plt.plot(neighbors_settings, training_accuracy, label="training accuracy")
plt.plot(neighbors_settings, test_accuracy, label="test accuracy")
plt.ylabel("Accuracy")
plt.xlabel("n_neighbors")
plt.legend()
```

Out[23]: <matplotlib.legend.Legend at 0x7f352f881dd8>



```
In [24]: knn = KNeighborsClassifier(n_neighbors=8)
         knn.fit(X_train, y_train)
         print('Accuracy of K-NN classifier on training set: {:.2f}'.format(knn.score(X_train, y
         print('Accuracy of K-NN classifier on test set: {:.2f}'.format(knn.score(X_test, y_test
```

```
Accuracy of K-NN classifier on training set: 0.81
Accuracy of K-NN classifier on test set: 0.69
```

```
In [25]: knn_predict = knn.predict(X_test)
         print('Classification report:\n\n', classification_report(y_test, knn_predict))
         print('\n')
         print('jaccard_similarity_score:\n\n {:.2f}' .format(jaccard_similarity_score(y_test, k
```

```
Classification report:

               precision    recall  f1-score   support

  COLLECTION       0.29      0.58      0.39        12
     PAIDOFF       0.89      0.71      0.79        58

   micro avg       0.69      0.69      0.69        70
   macro avg       0.59      0.65      0.59        70
weighted avg       0.79      0.69      0.72        70



jaccard_similarity_score:

 68.57 %
```

5 Decision Tree

```
In [26]: from sklearn.tree import DecisionTreeClassifier

         # Prune the tree to account for overfitting
         # Max depth of 3 levels

         tree = DecisionTreeClassifier(max_depth=3, random_state=0)
         tree.fit(X_train, y_train)
         print("Accuracy on training set: {:.3f}".format(tree.score(X_train, y_train)))
         print("Accuracy on test set: {:.3f}".format(tree.score(X_test, y_test)))
```

```
Accuracy on training set: 0.732
Accuracy on test set: 0.829
```

```
In [27]: tree_predict = tree.predict(X_test)
         print('Classification report:\n\n', classification_report(y_test, tree_predict))
         print('\n')
         print('jaccard_similarity_score:\n\n', jaccard_similarity_score(y_test, tree_predict)*1
```

```
Classification report:

               precision    recall  f1-score   support

  COLLECTION       0.00      0.00      0.00        12
     PAIDOFF       0.83      1.00      0.91        58

   micro avg       0.83      0.83      0.83        70
   macro avg       0.41      0.50      0.45        70
weighted avg       0.69      0.83      0.75        70



jaccard_similarity_score:

 82.85714285714286 %


/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
```

6 Support Vector Machine

```
In [28]: from sklearn.svm import SVC
         svc = SVC(C=0.01)
         svc.fit(X_train, y_train)
         print("Accuracy on training set: {:.2f}".format(svc.score(X_train, y_train)))
         print("Accuracy on test set: {:.2f}".format(svc.score(X_test, y_test)))
```

```
Accuracy on training set: 0.73
Accuracy on test set: 0.83


/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/svm/base.py:196: FutureWarning: The d
  "avoid this warning.", FutureWarning)
```

```
In [29]: svc_predict = svc.predict(X_test)
         print('Classification report:\n\n', classification_report(y_test, svc_predict))
```

```
print('\n')
print('jaccard_similarity_score:\n\n', jaccard_similarity_score(y_test, svc_predict)*10
```

```
Classification report:

              precision    recall  f1-score   support

  COLLECTION       0.00      0.00      0.00        12
     PAIDOFF       0.83      1.00      0.91        58

   micro avg       0.83      0.83      0.83        70
   macro avg       0.41      0.50      0.45        70
weighted avg       0.69      0.83      0.75        70



jaccard_similarity_score:

 82.85714285714286 %


/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
```

7 Logistic Regression

In [30]:
```
from sklearn.metrics import classification_report,jaccard_similarity_score, log_loss

# Using C = 0.01 to improve better scoring

logreg = LogisticRegression(C=0.01).fit(X_train, y_train)
print("Training set score: {:.3f}".format(logreg.score(X_train, y_train)))
print("Test set score: {:.3f}".format(logreg.score(X_test, y_test)))
```

```
Training set score: 0.736
Test set score: 0.800


/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureW
  FutureWarning)
```

In [31]:
```
log_reg_predict = logreg.predict(X_test)
log_reg_predict_proba = logreg.predict_proba(X_test)[:, 1]
```

```
print('Classification report:\n\n', classification_report(y_test, log_reg_predict))
print('\n')
print('jaccard_similarity_score:\n\n', jaccard_similarity_score(y_test, log_reg_predict
```

```
Classification report:

              precision    recall  f1-score   support

  COLLECTION       0.38      0.25      0.30        12
     PAIDOFF       0.85      0.91      0.88        58

   micro avg       0.80      0.80      0.80        70
   macro avg       0.61      0.58      0.59        70
weighted avg       0.77      0.80      0.78        70



jaccard_similarity_score:

 80.0 %
```

8 Model Evaluation using Test set

```
In [32]: 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 [33]: !wget -O loan_test.csv https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-dat
```

```
--2019-01-07 05:09:09--  https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/Cogni
Resolving s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.net).
Connecting to s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.n
HTTP request sent, awaiting response... 200 OK
Length: 3642 (3.6K) [text/csv]
Saving to: loan_test.csv

loan_test.csv       100%[===================>]   3.56K  --.-KB/s    in 0s

2019-01-07 05:09:09 (59.9 MB/s) - loan_test.csv saved [3642/3642]
```

8.0.1 Load Test set for evaluation

```
In [34]: test_df = pd.read_csv('loan_test.csv')
         test_df.head()
```

```
Out[34]:    Unnamed: 0  Unnamed: 0.1 loan_status  Principal  terms effective_date  \
         0           1             1     PAIDOFF       1000     30       9/8/2016
         1           5             5     PAIDOFF        300      7       9/9/2016
         2          21            21     PAIDOFF       1000     30      9/10/2016
         3          24            24     PAIDOFF       1000     30      9/10/2016
         4          35            35     PAIDOFF        800     15      9/11/2016

             due_date  age             education  Gender
         0  10/7/2016   50              Bechalor  female
         1  9/15/2016   35       Master or Above    male
         2  10/9/2016   43  High School or Below  female
         3  10/9/2016   26               college    male
         4  9/25/2016   29              Bechalor    male
```

```
In [35]: df['due_date'] = pd.to_datetime(df['due_date'])
         df['effective_date'] = pd.to_datetime(df['effective_date'])
         df.head()
```

```
Out[35]:    Unnamed: 0  Unnamed: 0.1 loan_status  Principal  terms effective_date  \
         0           0             0     PAIDOFF       1000     30     2016-09-08
         1           2             2     PAIDOFF       1000     30     2016-09-08
         2           3             3     PAIDOFF       1000     15     2016-09-08
         3           4             4     PAIDOFF       1000     30     2016-09-09
         4           6             6     PAIDOFF       1000     30     2016-09-09

             due_date  age             education  Gender  dayofweek  weekend
         0 2016-10-07   45  High School or Below       0          3        0
         1 2016-10-07   33              Bechalor       1          3        0
         2 2016-09-22   27               college       0          3        0
         3 2016-10-08   28               college       1          4        1
         4 2016-10-08   29               college       0          4        1
```

```
In [36]: df['weekend'] = df['dayofweek'].apply(lambda x: 1 if (x>3)  else 0)
         df.head()
```

```
Out[36]:    Unnamed: 0  Unnamed: 0.1 loan_status  Principal  terms effective_date  \
         0           0             0     PAIDOFF       1000     30     2016-09-08
         1           2             2     PAIDOFF       1000     30     2016-09-08
         2           3             3     PAIDOFF       1000     15     2016-09-08
         3           4             4     PAIDOFF       1000     30     2016-09-09
         4           6             6     PAIDOFF       1000     30     2016-09-09

             due_date  age             education  Gender  dayofweek  weekend
         0 2016-10-07   45  High School or Below       0          3        0
         1 2016-10-07   33              Bechalor       1          3        0
         2 2016-09-22   27               college       0          3        0
         3 2016-10-08   28               college       1          4        1
         4 2016-10-08   29               college       0          4        1
```

In [37]:
```
df.groupby(['Gender'])['loan_status'].value_counts(normalize=True)
#df['Gender'].replace(to_replace=['male','female'], value=[0,1],inplace=True)
```

Out[37]:
```
Gender  loan_status
0       PAIDOFF        0.731293
        COLLECTION     0.268707
1       PAIDOFF        0.865385
        COLLECTION     0.134615
Name: loan_status, dtype: float64
```

In [38]:
```
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)
X = Feature
y = df['loan_status'].values
```

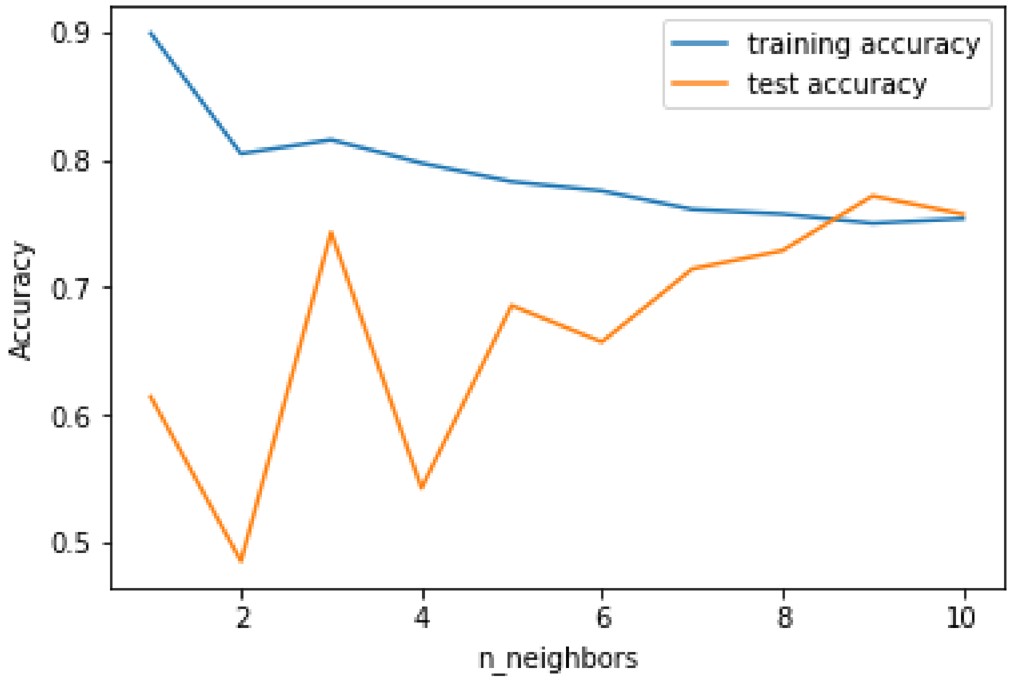
9 Train-Test-Split

In [39]:
```
#Test_Train_Split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=
```

10 K Nearest Neighbor(KNN)

In [40]:
```
from sklearn.neighbors import KNeighborsClassifier
training_accuracy = []
test_accuracy = []
# try n_neighbors from 1 to 10
neighbors_settings = range(1, 11)
for n_neighbors in neighbors_settings:
    # build the model
    knn = KNeighborsClassifier(n_neighbors=n_neighbors)
    knn.fit(X_train, y_train)
    # record training set accuracy
    training_accuracy.append(knn.score(X_train, y_train))
    # record test set accuracy
    test_accuracy.append(knn.score(X_test, y_test))
plt.plot(neighbors_settings, training_accuracy, label="training accuracy")
plt.plot(neighbors_settings, test_accuracy, label="test accuracy")
plt.ylabel("Accuracy")
plt.xlabel("n_neighbors")
plt.legend()
```

Out[40]:
```
<matplotlib.legend.Legend at 0x7f352f6eb8d0>
```



In [41]:
```
knn = KNeighborsClassifier(n_neighbors=8)
knn.fit(X_train, y_train)
print('Accuracy of K-NN classifier on training set: {:.2f}'.format(knn.score(X_train, y
print('Accuracy of K-NN classifier on test set: {:.2f}'.format(knn.score(X_test, y_test
```

```
Accuracy of K-NN classifier on training set: 0.76
Accuracy of K-NN classifier on test set: 0.73
```

In [42]:
```
knn_predict = knn.predict(X_test)
print('Classification report:\n\n', classification_report(y_test, knn_predict))
print('\n')
print('jaccard_similarity_score:\n\n', jaccard_similarity_score(y_test, knn_predict)*10
```

```
Classification report:

              precision    recall  f1-score   support

  COLLECTION       0.23      0.25      0.24        12
     PAIDOFF       0.84      0.83      0.83        58

   micro avg       0.73      0.73      0.73        70
   macro avg       0.54      0.54      0.54        70
weighted avg       0.74      0.73      0.73        70
```

```
jaccard_similarity_score:

 72.85714285714285 %
```

11 Decision Tree

```
In [43]: from sklearn.tree import DecisionTreeClassifier

         # Prune the tree to account for overfitting
         # Max depth of 3 levels

         tree = DecisionTreeClassifier(max_depth=3, random_state=0)
         tree.fit(X_train, y_train)
         print("Accuracy on training set: {:.3f}".format(tree.score(X_train, y_train)))
         print("Accuracy on test set: {:.3f}".format(tree.score(X_test, y_test)))
```

```
Accuracy on training set: 0.732
Accuracy on test set: 0.829
```

```
In [44]: tree_predict = tree.predict(X_test)
         print('Classification report:\n\n', classification_report(y_test, tree_predict))
         print('\n')
         print('jaccard_similarity_score:\n\n', jaccard_similarity_score(y_test, tree_predict)*1
```

```
Classification report:

              precision    recall  f1-score   support

  COLLECTION       0.00      0.00      0.00        12
     PAIDOFF       0.83      1.00      0.91        58

   micro avg       0.83      0.83      0.83        70
   macro avg       0.41      0.50      0.45        70
weighted avg       0.69      0.83      0.75        70



jaccard_similarity_score:

 82.85714285714286 %


/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
```

```
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
```

12 Support Vector Machine

```
In [45]: from sklearn.svm import SVC
         svc = SVC(C=0.01)
         svc.fit(X_train, y_train)
         print("Accuracy on training set: {:.2f}".format(svc.score(X_train, y_train)))
         print("Accuracy on test set: {:.2f}".format(svc.score(X_test, y_test)))
```

```
Accuracy on training set: 0.73
Accuracy on test set: 0.83
```

```
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/svm/base.py:196: FutureWarning: The d
  "avoid this warning.", FutureWarning)
```

```
In [46]: svc_predict = svc.predict(X_test)
         print('Classification report:\n\n', classification_report(y_test, svc_predict))
         print('\n')
         print('jaccard_similarity_score:\n\n', jaccard_similarity_score(y_test, svc_predict)*10
```

```
Classification report:

               precision    recall  f1-score   support

  COLLECTION       0.00      0.00      0.00        12
     PAIDOFF       0.83      1.00      0.91        58

   micro avg       0.83      0.83      0.83        70
   macro avg       0.41      0.50      0.45        70
weighted avg       0.69      0.83      0.75        70



jaccard_similarity_score:

 82.85714285714286 %
```

```
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
```

```
  'precision', 'predicted', average, warn_for)
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
```

13 Logistic Regression

```
In [47]: from sklearn.metrics import classification_report,jaccard_similarity_score, log_loss

         # Using C = 0.01 to improve better scoring

         logreg = LogisticRegression(C=0.01).fit(X_train, y_train)
         print("Training set score: {:.3f}".format(logreg.score(X_train, y_train)))
         print("Test set score: {:.3f}".format(logreg.score(X_test, y_test)))
```

```
Training set score: 0.732
Test set score: 0.829


/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureW
  FutureWarning)
```

```
In [48]: log_reg_predict = logreg.predict(X_test)
         log_reg_predict_proba = logreg.predict_proba(X_test)[:, 1]
         print('Classification report:\n\n', classification_report(y_test, log_reg_predict))
         print('\n')
         print('jaccard_similarity_score:\n\n', jaccard_similarity_score(y_test, log_reg_predict
```

```
Classification report:

               precision    recall  f1-score   support

  COLLECTION       0.00      0.00      0.00        12
     PAIDOFF       0.83      1.00      0.91        58

   micro avg       0.83      0.83      0.83        70
   macro avg       0.41      0.50      0.45        70
weighted avg       0.69      0.83      0.75        70




jaccard_similarity_score:

 82.85714285714286 %


/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
```

```
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
/home/jupyterlab/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Undef
  'precision', 'predicted', average, warn_for)
```

In [ ]:

In [ ]:

In [ ]:

14 Report

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

Algorithm	Jaccard	F1-score	LogLoss
KNN	?	?	NA
Decision Tree	?	?	NA
SVM	?	?	NA
LogisticRegression	?	?	?

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

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Thanks for completing this lesson!

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Saeed Aghabozorgi, 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.