Semi-Supervised Learning with Support Vector Machine (SVM)

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn import datasets
import matplotlib.pyplot as plt
# pd.set_option('display.max_rows', None)
```

Preparing the dataset

Out[15]:		alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	${\bf nonflavanoid}_{_}$
	0	13.87	1.90	2.80	19.4	107.0	2.95	2.97	
	1	13.34	0.94	2.36	17.0	110.0	2.53	1.30	
	2	14.38	3.59	2.28	16.0	102.0	3.25	3.17	
	3	13.07	1.50	2.10	15.5	98.0	2.40	2.64	
	4	12.33	1.10	2.28	16.0	101.0	2.05	1.09	
	173	12.58	1.29	2.10	20.0	103.0	1.48	0.58	
	174	12.82	3.37	2.30	19.5	88.0	1.48	0.66	
	175	12.43	1.53	2.29	21.5	86.0	2.74	3.15	
	176	12.07	2.16	2.17	21.0	85.0	2.60	2.65	
	177	12.70	3.55	2.36	21.5	106.0	1.70	1.20	

178 rows × 14 columns

Create labeled dataset

```
In [16]:
#taking half of the dataset as labled data
X = df.iloc[0:89,0:13].values
y = df.iloc[0:89,-1].values
df.iloc[0:89,0:13]
```

Out[16]:		alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_p
	0	13.87	1.90	2.80	19.4	107.0	2.95	2.97	
	1	13.34	0.94	2.36	17.0	110.0	2.53	1.30	
	2	14.38	3.59	2.28	16.0	102.0	3.25	3.17	
	3	13.07	1.50	2.10	15.5	98.0	2.40	2.64	
	4	12.33	1.10	2.28	16.0	101.0	2.05	1.09	
	84	12.33	0.99	1.95	14.8	136.0	1.90	1.85	
	85	12.42	2.55	2.27	22.0	90.0	1.68	1.84	
	86	13.16	2.36	2.67	18.6	101.0	2.80	3.24	
	87	13.29	1.97	2.68	16.8	102.0	3.00	3.23	
	88	13.20	1.78	2.14	11.2	100.0	2.65	2.76	

89 rows × 13 columns

```
In [17]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.7, random_state=1)
```

In [18]: X_train.shape

Out[18]: (26, 13)

In [19]: X_test.shape

Out[19]: (63, 13)

Create unlabeled dataset

```
# taking the other half of the data as unlabeled data
X_unl_df = df.iloc[89:,0:13].reset_index(drop=True)
```

```
X_unl = X_unl_df.values
X_unl_df
```

Out[20]:		alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_r
	0	11.64	2.06	2.46	21.6	84.0	1.95	1.69	
	1	14.22	3.99	2.51	13.2	128.0	3.00	3.04	
	2	11.82	1.72	1.88	19.5	86.0	2.50	1.64	
	3	14.19	1.59	2.48	16.5	108.0	3.30	3.93	
	4	12.37	1.13	2.16	19.0	87.0	3.50	3.10	
	84	12.58	1.29	2.10	20.0	103.0	1.48	0.58	
	85	12.82	3.37	2.30	19.5	88.0	1.48	0.66	
	86	12.43	1.53	2.29	21.5	86.0	2.74	3.15	
	87	12.07	2.16	2.17	21.0	85.0	2.60	2.65	
	88	12.70	3.55	2.36	21.5	106.0	1.70	1.20	

89 rows × 13 columns

1. Training on the labeled dataset

Out[21]: 0.7936507936507936

2. Make a prediction using the unlabeled datset (x_unl)

```
In [22]: #find the probability of each class
    clp= clf.predict_proba(X_unl)
    clf_prob = pd.DataFrame(clp, columns = ['class1', 'class2','class3'])
    # predict the the label of each class
    lab=clf.predict(X_unl)
    clf_prob["max"] = clf_prob.max(axis = 1)
    clf_prob["lab"] = lab
    clf_prob
```

Out[22]: class1 class2 class3 max lab

	class1	class2	class3	max	lab
0	0.154002	0.314076	0.531922	0.531922	1
1	0.292137	0.270598	0.437265	0.437265	2
2	0.023514	0.379967	0.596519	0.596519	1
3	0.998248	0.001364	0.000388	0.998248	0
4	0.024358	0.378537	0.597105	0.597105	1
84	0.119894	0.324574	0.555532	0.555532	2
85	0.160462	0.305302	0.534236	0.534236	2
86	0.015080	0.382361	0.602559	0.602559	1
87	0.018101	0.381986	0.599914	0.599914	1
88	0.090178	0.339134	0.570689	0.570689	2

89 rows × 5 columns

3. Choose the samples in X_unl with high confidence and add them into the labeled dataset

```
In [23]:
             th = 0.6
            clf_prob[clf_prob["max"] > th]
                  class1
                            class2
                                      class3
                                                  max
                                                        lab
Out[23]:
            3 0.998248
                                                         0
                          0.001364 0.000388
                                              0.998248
               0.014084
                          0.383017
                                   0.602899
                                              0.602899
                0.970301
                          0.019355
                                   0.010344
                                                         0
                                              0.970301
               0.994399
                         0.004148
                                   0.001453
                                              0.994399
                                                         0
                0.937449
                          0.038556
                                   0.023996
                                              0.937449
               0.994186
                          0.004298
                                   0.001517
                                                         0
            11
                                              0.994186
                0.991134
                          0.006408
                                    0.002458
                                              0.991134
           16
               0.009069
                          0.387745
                                   0.603186
                                              0.603186
                                                         1
            17
               0.819020
                          0.094391
                                   0.086589
                                              0.819020
                                                         0
            19
                0.611770
                          0.171319
                                    0.216911
                                              0.611770
               0.842308
                          0.085591 0.072101
                                              0.842308
                                                         0
           20
               0.715648
                          0.137932
                                   0.146420
                                              0.715648
           22
               0.034904
                          0.364447
                                   0.600649
                                              0.600649
                                                          2
            27
               0.968139
                          0.020916
                                   0.010945
                                              0.968139
                                                         0
                0.018317
                          0.379884
                                    0.601800
                                              0.601800
               0.913269
                          0.050632 0.036099
                                              0.913269
                                                         0
           31
```

```
class1
             class2
                     class3
                               max lab
36
   0.017267  0.382011  0.600722  0.600722
   0.012550 \quad 0.384893 \quad 0.602557 \quad 0.602557
43
   0.962569  0.024327  0.013104  0.962569
48
   0.984796  0.010579  0.004625  0.984796
55
56
   60
   0.880995 0.066579 0.052426 0.880995
                                     0
   0.009867  0.386900  0.603233  0.603233
63
                                     1
   0.976518  0.015492  0.007990  0.976518
  0.903556  0.056237  0.040207  0.903556
                                     0
66
  0.037796  0.359127  0.603077  0.603077
71
   0.937871 0.037880 0.024249 0.937871
79
  82
   1
```

```
#add the predicted labels to the training dataset
unl_size =len(X_unl[clf_prob["max"] > th])
X_train_new = np.append(X_train, X_unl[clf_prob["max"] > th], axis=0)
y_train_new = np.append(y_train, clf_prob['lab'][clf_prob["max"] >
th].values, axis=0)

X_train = X_train_new
y_train = y_train_new
```

```
In [25]: #remove the added labels from the unlabled dataset

X_unl_df = X_unl_df.drop(X_unl_df[clf_prob["max"] >
    th].index).reset_index(drop=True)

#update the unlabeled set

X_unl = X_unl_df.values

# X_unl_df
```

4. Repeat

```
score_ls = []

while len(X_unl) != 0 and unl_size != 0: # stop when there are no more

unlabeled data or when we are no confident about the data
```

```
#Step 1
    clf = svm.SVC(kernel='linear', probability=True,C=1).fit(X train,
y train)
    score ls.append(clf.score(X test, y test))
    print ('Accuracy: ',clf.score(X_test, y_test))
     print(len(X unl))
    #Step2
    #find the probability of each class
    clp= clf.predict proba(X unl)
    clf prob = pd.DataFrame(clp, columns = ['class1', 'class2','class3'])
    # predict the the label of each class
    lab=clf.predict(X unl)
    clf_prob["max"] = clf_prob.max(axis = 1)
    clf prob["lab"] = lab
    #Step3
    unl size =len(X unl[clf prob["max"] > th])
    X train new = np.append(X train, X unl[clf prob["max"] > th], axis=0)
    y train new = np.append(y train, clf prob['lab'][clf prob["max"] >
th].values, axis=0)
    X train = X train new
    y train = y train new
    X unl df = X unl df.drop(X unl df[clf prob["max"] >
th].index).reset index(drop=True)
    X unl = X unl df.values
```

Accuracy: 0.7936507936507936 Accuracy: 0.8095238095238095 Accuracy: 0.873015873015873 Accuracy: 0.873015873015873

```
In []:
```