# **SVM (Support Vector Machines)**

## **Objectives**

After completing this lab you will be able to:

Use scikit-learn to Support Vector Machine to classify

```
In [1]: import pandas as pd
   import numpy as np
   from sklearn import preprocessing
   from sklearn.model_selection import train_test_split
   import matplotlib.pyplot as plt
```

#### Load the Cancer data

The example is based on a dataset that is publicly available from the UCI Machine Learning Repository (Asuncion and Newman, 2007)[http://mlearn.ics.uci.edu/MLRepository.html]. The dataset consists of several hundred human cell sample records, each of which contains the values of a set of cell characteristics. The fields in each record are:

Description	Field name
Clump thickness	ID
Clump thickness	Clump
Uniformity of cell size	UnifSize
Uniformity of cell shape	UnifShape
Marginal adhesion	MargAdh
Single epithelial cell size	SingEpiSize
Bare nuclei	BareNuc
Bland chromatin	BlandChrom
Normal nucleoli	NormNucl
Mitoses	Mit
Benign or malignant	Class

For the purposes of this example, we're using a dataset that has a relatively small number of predictors in each record. To download the data, we will use <code>!wget</code> to download it from IBM Object Storage.

#### **Load Data From CSV File**

In [2]: cell\_df = pd.read\_csv("cell\_samples.csv")
 cell\_df

Out[2]:

	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	BareNuc	BlandChrom	NormNu
0	1000025	5	1	1	1	2	1	3	
1	1002945	5	4	4	5	7	10	3	
2	1015425	3	1	1	1	2	2	3	
3	1016277	6	8	8	1	3	4	3	
4	1017023	4	1	1	3	2	1	3	
694	776715	3	1	1	1	3	2	1	
695	841769	2	1	1	1	2	1	1	
696	888820	5	10	10	3	7	3	8	1
697	897471	4	8	6	4	3	4	10	
698	897471	4	8	8	5	4	5	10	

699 rows × 11 columns

In [3]: cell\_df.head()

Out[3]:

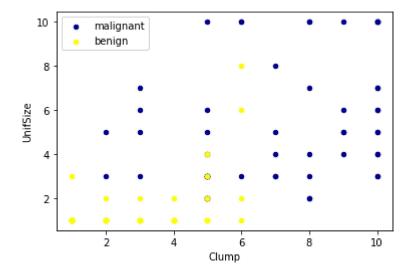
	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	BareNuc	BlandChrom	NormNucl
0	1000025	5	1	1	1	2	1	3	1
1	1002945	5	4	4	5	7	10	3	2
2	1015425	3	1	1	1	2	2	3	1
3	1016277	6	8	8	1	3	4	3	7
4	1017023	4	1	1	3	2	1	3	1
4									•

In [4]: cell\_df.tail()

Out[4]:

	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	BareNuc	BlandChrom	NormNuc
694	776715	3	1	1	1	3	2	1	1
695	841769	2	1	1	1	2	1	1	1
696	888820	5	10	10	3	7	3	8	10
697	897471	4	8	6	4	3	4	10	•
698	897471	4	8	8	5	4	5	10	۷
4									<b>&gt;</b>

```
In [5]: ax = cell_df[cell_df['Class'] == 4][0:50].plot(kind='scatter', x='Clump', y='Unif
cell_df[cell_df['Class'] == 2][0:50].plot(kind='scatter', x='Clump', y='UnifSize'
plt.show()
```



### Data pre-processing and selection

Lets first look at columns data types:

```
In [6]:
        cell_df.dtypes
Out[6]: ID
                          int64
         Clump
                          int64
         UnifSize
                          int64
         UnifShape
                          int64
         MargAdh
                          int64
         SingEpiSize
                          int64
         BareNuc
                         object
                          int64
         BlandChrom
         NormNucl
                          int64
        Mit
                          int64
         Class
                          int64
         dtype: object
```

It looks like the **BareNuc** column includes some values that are not numerical. We can drop those rows:

```
In [7]: cell df = cell df[pd.to numeric(cell df['BareNuc'], errors='coerce').notnull()]
        cell_df['BareNuc'] = cell_df['BareNuc'].astype('int')
        cell_df.dtypes
        <ipython-input-7-df8bc795062c>:2: SettingWithCopyWarning:
        A value is trying to be set on a copy of a slice from a DataFrame.
        Try using .loc[row_indexer,col_indexer] = value instead
        See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
        ble/user guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
        ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
        opy)
          cell_df['BareNuc'] = cell_df['BareNuc'].astype('int')
Out[7]: ID
                        int64
        Clump
                        int64
        UnifSize
                        int64
        UnifShape
                       int64
        MargAdh
                       int64
        SingEpiSize
                       int64
        BareNuc
                        int32
        BlandChrom
                       int64
        NormNuc1
                        int64
        Mit
                       int64
        Class
                       int64
        dtype: object
In [8]: | feature_df = cell_df[['Clump', 'UnifSize', 'UnifShape', 'MargAdh', 'SingEpiSize'
        X = np.asarray(feature df)
        X[0:5]
Out[8]: array([[ 5,
                                                  1],
                             1,
                                  2,
                          1,
                                      1,
                                              1,
               [ 5,
                         4,
                            5,
                                 7, 10,
                                          3, 2,
                                                  1],
                                      2,
               [ 3,
                     1, 1,
                             1,
                                  2,
                                          3,
                                              1,
                                                  1],
                                  3,
                                                  1],
                        8,
                            1,
                                      4,
                                          3,
                                             7,
               [6,
                                                  1]], dtype=int64)
                                          3,
                                              1,
```

We want the model to predict the value of Class (that is, benign (=2) or malignant (=4)). As this field can have one of only two possible values, we need to change its measurement level to reflect this.

#### Train/Test dataset

Okay, we split our dataset into train and test set:

```
In [10]: X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.2, random_print ('Train set:', X_train.shape, y_train.shape)
print ('Test set:', X_test.shape, y_test.shape)

Train set: (546, 9) (546,)
Test set: (137, 9) (137,)
```

### Modeling (SVM with Scikit-learn)

```
In [11]: from sklearn import svm
    clf = svm.SVC(kernel='rbf')
    clf.fit(X_train, y_train)
```

Out[11]: SVC()

After being fitted, the model can then be used to predict new values:

#### **Evaluation**

```
In [13]: from sklearn.metrics import classification_report, confusion_matrix
import itertools
```

```
In [14]: def plot confusion matrix(cm, classes,
                                    normalize=False,
                                    title='Confusion matrix',
                                    cmap=plt.cm.Blues):
             0.00
             This function prints and plots the confusion matrix.
             Normalization can be applied by setting `normalize=True`.
             0.00
             if normalize:
                 cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                 print("Normalized confusion matrix")
                 print('Confusion matrix, without normalization')
             print(cm)
             plt.imshow(cm, interpolation='nearest', cmap=cmap)
             plt.title(title)
             plt.colorbar()
             tick marks = np.arange(len(classes))
             plt.xticks(tick_marks, classes, rotation=45)
             plt.yticks(tick_marks, classes)
             fmt = '.2f' if normalize else 'd'
             thresh = cm.max() / 2.
             for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
                 plt.text(j, i, format(cm[i, j], fmt),
                           horizontalalignment="center",
                           color="white" if cm[i, j] > thresh else "black")
             plt.tight_layout()
             plt.ylabel('True label')
             plt.xlabel('Predicted label')
```

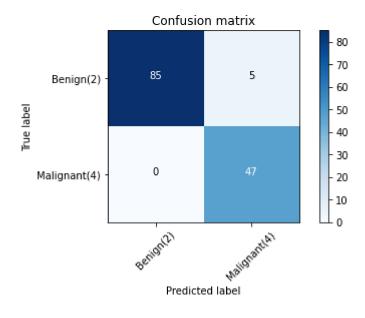
```
In [15]: # Compute confusion matrix
    cnf_matrix = confusion_matrix(y_test, yhat, labels=[2,4])
    np.set_printoptions(precision=2)

print (classification_report(y_test, yhat))

# Plot non-normalized confusion matrix
    plt.figure()
    plot_confusion_matrix(cnf_matrix, classes=['Benign(2)','Malignant(4)'],normalize=
```

	precision	recall	f1-score	support
2	1.00	0.94	0.97	90
	0.90	1.00	0.95	47
accuracy			0.96	137
macro avg	0.95	0.97	0.96	137
weighted avg	0.97	0.96	0.96	137

Confusion matrix, without normalization [[85 5] [ 0 47]]



```
In [16]: from sklearn.metrics import f1_score
f1_score(y_test, yhat, average='weighted')
```

Out[16]: 0.9639038982104676

### THE END