8.Problem : Apply EM algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using k-Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering. You can add Python ML library classes/API in the program.

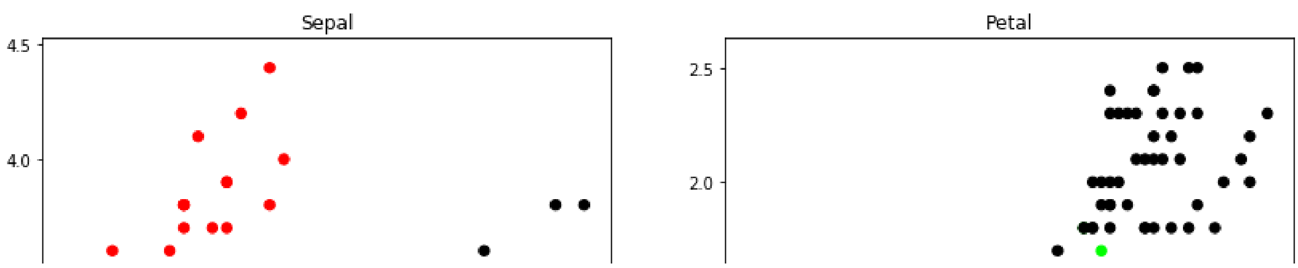
K Means

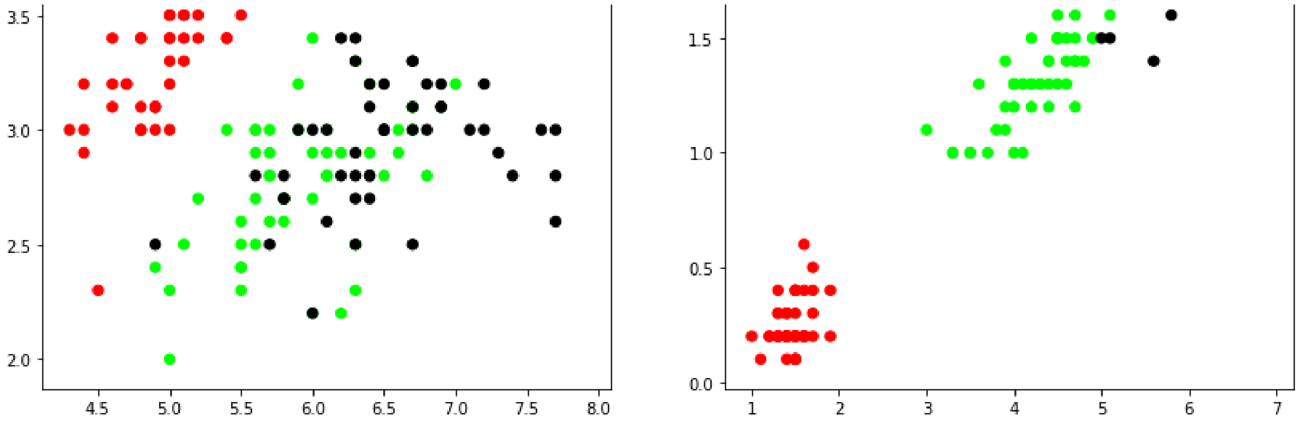
In [2]:

```
# Author : Dr.Thyagaraju G S , Context Innovations Lab , DEpt of CSE , SDMIT - Ujire
# Date : July 11 2018
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import sklearn.metrics as sm
import pandas as pd
import numpy as np
%matplotlib inline

# import some data to play with
iris = datasets.load_iris()

#print("\n IRIS DATA :",iris.data);
#print("\n IRIS FEATURES :\n",iris.feature_names)
#print("\n IRIS TARGET :\n",iris.target)
#print("\n IRIS TARGET NAMES:\n",iris.target_names)

# Store the inputs as a Pandas Dataframe and set the column names
X = pd.DataFrame(iris.data)

#print(X)
X.columns = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width']
#print(X.columns)
#print("X:",x)
#print("Y:",y)
y = pd.DataFrame(iris.target)
y.columns = ['Targets']

# Set the size of the plot
plt.figure(figsize=(14,7))

# Create a colormap
colormap = np.array(['red', 'lime', 'black'])

# Plot Sepal
plt.subplot(1, 2, 1)
plt.scatter(X.Sepal_Length,X.Sepal_Width, c=colormap[y.Targets], s=40)
plt.title('Sepal')

plt.subplot(1, 2, 2)
plt.scatter(X.Petal_Length,X.Petal_Width, c=colormap[y.Targets], s=40)
plt.title('Petal')
```

Out[2]:

```
Text(0.5,1,'Petal')
```





Build the K Means Model

In [3]:

```
# K Means Cluster
model = KMeans(n_clusters=3)
model.fit(X)
# This is what KMeans thought
model.labels_
```

Out[3]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 1, 1,
       2, 2, 2, 2, 1, 2, 1, 2, 1, 2, 2, 1, 1, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2,
       1, 2, 2, 2, 1, 2, 2, 2, 1, 2, 2, 1])
```

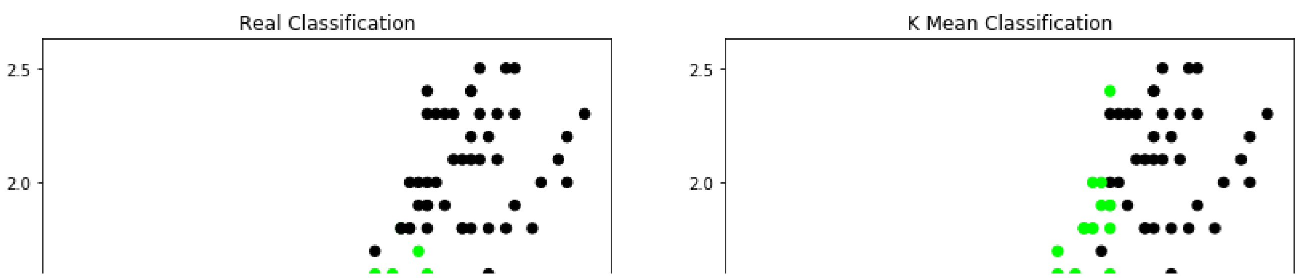
Visualise the classifier results

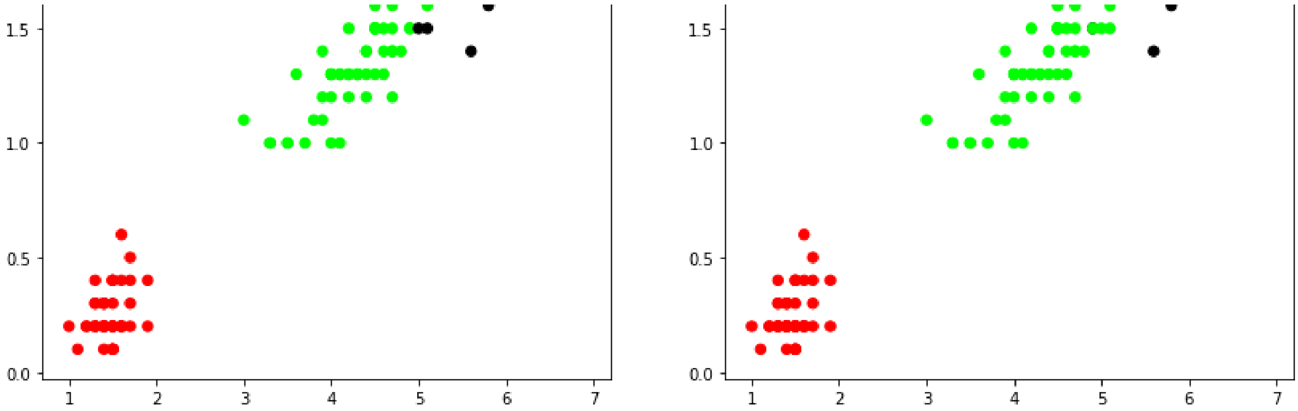
In [4]:

```
# View the results
# Set the size of the plot
plt.figure(figsize=(14,7))

# Create a colormap
colormap = np.array(['red', 'lime', 'black'])

# Plot the Original Classifications
plt.subplot(1, 2, 1)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y.Targets], s=40)
plt.title('Real Classification')

# Plot the Models Classifications
plt.subplot(1, 2, 2)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[model.labels_], s=40)
plt.title('K Mean Classification')
```

Out[4]:

```
Text(0.5,1,'K Mean Classification')
```





The Fix

In [5]:

```
# The fix, we convert all the 1s to 0s and 0s to 1s.
predY = np.choose(model.labels_, [0, 1, 2]).astype(np.int64)
print (predY)
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 2 2 2 2 1 2 2 2 2
 2 2 1 1 2 2 2 2 1 2 1 2 1 2 2 1 1 2 2 2 2 2 1 2 2 2 2 1 2 2 2 1 2 2 2 1 2
 2 1]
```

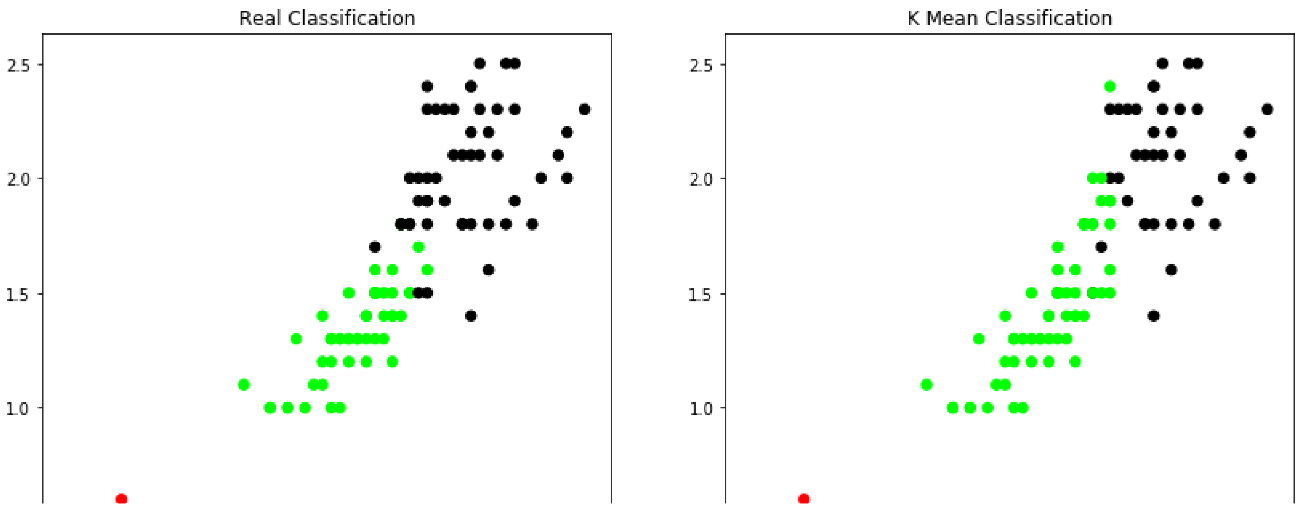
Re-plot

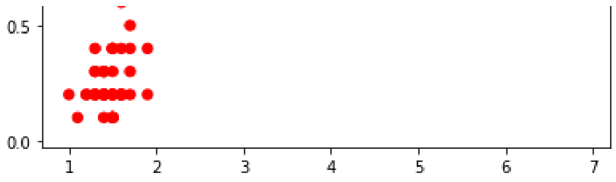
In [6]:

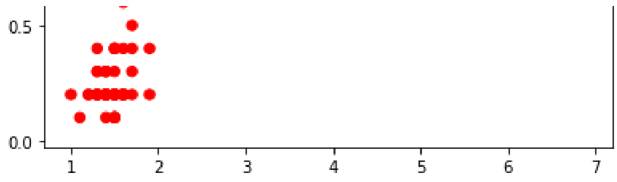
```
# View the results
# Set the size of the plot
plt.figure(figsize=(14,7))

# Create a colormap
colormap = np.array(['red', 'lime', 'black'])

# Plot Orginal
plt.subplot(1, 2, 1)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y.Targets], s=40)
plt.title('Real Classification')

# Plot Predicted with corrected values
plt.subplot(1, 2, 2)
plt.scatter(X.Petal_Length,X.Petal_Width, c=colormap[predY], s=40)
plt.title('K Mean Classification')
```

Out[6]:

```
Text(0.5,1,'K Mean Classification')
```







Performance Measures

Accuracy

Performance Metrics sm.accuracy_score(y, predY)

In [7]:

```
sm.accuracy_score(y, model.labels_)
```

Out[7]:

```
0.89333333333333331
```

Confusion Matrix

In [8]:

```
# Confusion Matrix
sm.confusion_matrix(y, model.labels_)
```

Out[8]:

```
array([[50,  0,  0],
       [ 0, 48,  2],
       [ 0, 14, 36]], dtype=int64)
```

Gaussian Mixtures

In [9]:

```
from sklearn import preprocessing

scaler = preprocessing.StandardScaler()
X = pd.DataFrame(iris.data)
X.columns = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width']
scaler.fit(X)
xsa = scaler.transform(X)
xs = pd.DataFrame(xsa, columns = X.columns)
xs.sample(5)
```

Out[9]:

	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width
68	0.432165	-1.976181	0.421564	0.396172
51	0.674501	0.337848	0.421564	0.396172
52	1.280340	0.106445	0.649027	0.396172
32	-0.779513	2.420475	-1.284407	-1.444450
42	-1.748856	0.337848	-1.398138	-1.312977

In [12]:

```
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=3)
gmm.fit(xs)
```

```
gmm.fit(xs)
```

Out[12]:

```
GaussianMixture(covariance_type='full', init_params='kmeans', max_iter=100,
        means_init=None, n_components=3, n_init=1, precisions_init=None,
        random_state=None, reg_covar=1e-06, tol=0.001, verbose=0,
        verbose_interval=10, warm_start=False, weights_init=None)
```

In [13]:

```
y_cluster_gmm = gmm.predict(xs)
y_cluster_gmm
```

Out[13]:

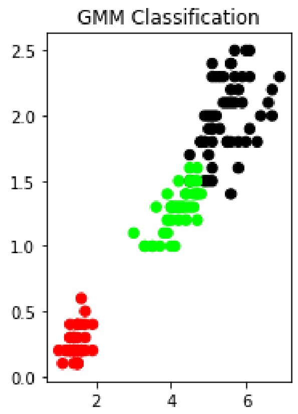
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2,
       1, 2, 1, 2, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2], dtype=int32)
```

In [14]:

```
plt.subplot(1, 2, 1)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y_cluster_gmm], s=40)
plt.title('GMM Classification')
```

Out[14]:

```
Text(0.5,1,'GMM Classification')
```



In [15]:

```
sm.accuracy_score(y, y_cluster_gmm)
```

Out[15]:

```
0.9666666666666667
```

In [16]:

```
# Confusion Matrix
sm.confusion_matrix(y, y_cluster_gmm)
```

Out[16]:

```
array([[50,  0,  0],
       [ 0, 45,  5],
       [ 0,  0, 50]], dtype=int64)
```

So the GMM clustering matched the true labels more closely than the Kmeans, as expected from the plots.

the plots.