iris dataset classification using KMeans

importing libraries

In [1]:
```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
iris = load_iris()
```

In [2]:
```
dir(iris)
```

Out[2]:
```
['DESCR',
 'data',
 'data_module',
 'feature_names',
 'filename',
 'frame',
 'target',
 'target_names']
```

In [3]:
```
iris.data
```

Out[3]:
```
array([[5.1, 3.5, 1.4, 0.2],
       [4.9, 3. , 1.4, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5. , 3.6, 1.4, 0.2],
       [5.4, 3.9, 1.7, 0.4],
       [4.6, 3.4, 1.4, 0.3],
       [5. , 3.4, 1.5, 0.2],
       [4.4, 2.9, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5.4, 3.7, 1.5, 0.2],
       [4.8, 3.4, 1.6, 0.2],
       [4.8, 3. , 1.4, 0.1],
       [4.3, 3. , 1.1, 0.1],
       [5.8, 4. , 1.2, 0.2],
       [5.7, 4.4, 1.5, 0.4],
       [5.4, 3.9, 1.3, 0.4],
       [5.1, 3.5, 1.4, 0.3],
       [5.7, 3.8, 1.7, 0.3],
       [5.1, 3.8, 1.5, 0.3],
       [5.4, 3.4, 1.7, 0.2],
       [5.1, 3.7, 1.5, 0.4],
       [4.6, 3.6, 1. , 0.2],
       [5.1, 3.3, 1.7, 0.5],
       [4.8, 3.4, 1.9, 0.2],
       [5. , 3. , 1.6, 0.2],
       [5. , 3.4, 1.6, 0.4],
       [5.2, 3.5, 1.5, 0.2],
       [5.2, 3.4, 1.4, 0.2],
       [4.7, 3.2, 1.6, 0.2],
       [4.8, 3.1, 1.6, 0.2],
       [5.4, 3.4, 1.5, 0.4],
       [5.2, 4.1, 1.5, 0.1],
       [5.5, 4.2, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.2],
       [5. , 3.2, 1.2, 0.2],
       [5.5, 3.5, 1.3, 0.2],
       [4.9, 3.6, 1.4, 0.1],
       [4.4, 3. , 1.3, 0.2],
       [5.1, 3.4, 1.5, 0.2],
       [5. , 3.5, 1.3, 0.3],
       [4.5, 2.3, 1.3, 0.3],
       [4.4, 3.2, 1.3, 0.2],
       [5. , 3.5, 1.6, 0.6],
       [5.1, 3.8, 1.9, 0.4],
       [4.8, 3. , 1.4, 0.3],
       [5.1, 3.8, 1.6, 0.2],
       [4.6, 3.2, 1.4, 0.2],
       [5.3, 3.7, 1.5, 0.2],
       [5. , 3.3, 1.4, 0.2],
       [7. , 3.2, 4.7, 1.4],
       [6.4, 3.2, 4.5, 1.5],
       [6.9, 3.1, 4.9, 1.5],
       [5.5, 2.3, 4. , 1.3],
       [6.5, 2.8, 4.6, 1.5],
       [5.7, 2.8, 4.5, 1.3],
       [6.3, 3.3, 4.7, 1.6],
       [4.9, 2.4, 3.3, 1. ],
       [6.6, 2.9, 4.6, 1.3],
       [5.2, 2.7, 3.9, 1.4],
       [5. , 2. , 3.5, 1. ],
       [5.9, 3. , 4.2, 1.5],
       [6. , 2.2, 4. , 1. ],
       [6.1, 2.9, 4.7, 1.4],
       [5.6, 2.9, 3.6, 1.3],
       [6.7, 3.1, 4.4, 1.4],
       [5.6, 3. , 4.5, 1.5],
       [5.8, 2.7, 4.1, 1. ],
       [6.2, 2.2, 4.5, 1.5],
       [5.6, 2.5, 3.9, 1.1],
       [5.9, 3.2, 4.8, 1.8],
       [6.1, 2.8, 4. , 1.3],
       [6.3, 2.5, 4.9, 1.5],
       [6.1, 2.8, 4.7, 1.2],
       [6.4, 2.9, 4.3, 1.3],
       [6.6, 3. , 4.4, 1.4],
       [6.8, 2.8, 4.8, 1.4],
       [6.7, 3. , 5. , 1.7],
       [6. , 2.9, 4.5, 1.5],
       [5.7, 2.6, 3.5, 1. ],
       [5.5, 2.4, 3.8, 1.1],
       [5.5, 2.4, 3.7, 1. ],
       [5.8, 2.7, 3.9, 1.2],
       [6. , 2.7, 5.1, 1.6],
       [5.4, 3. , 4.5, 1.5],
       [6. , 3.4, 4.5, 1.6],
       [6.7, 3.1, 4.7, 1.5],
       [6.3, 2.3, 4.4, 1.3],
       [5.6, 3. , 4.1, 1.3],
       [5.5, 2.5, 4. , 1.3],
       [5.5, 2.6, 4.4, 1.2],
       [6.1, 3. , 4.6, 1.4],
       [5.8, 2.6, 4. , 1.2],
       [5. , 2.3, 3.3, 1. ],
       [5.6, 2.7, 4.2, 1.3],
       [5.7, 3. , 4.2, 1.2],
       [5.7, 2.9, 4.2, 1.3],
       [6.2, 2.9, 4.3, 1.3],
       [5.1, 2.5, 3. , 1.1],
       [5.7, 2.8, 4.1, 1.3],
       [6.3, 3.3, 6. , 2.5],
       [5.8, 2.7, 5.1, 1.9],
       [7.1, 3. , 5.9, 2.1],
       [6.3, 2.9, 5.6, 1.8],
       [6.5, 3. , 5.8, 2.2],
       [7.6, 3. , 6.6, 2.1],
       [4.9, 2.5, 4.5, 1.7],
       [7.3, 2.9, 6.3, 1.8],
       [6.7, 2.5, 5.8, 1.8],
       [7.2, 3.6, 6.1, 2.5],
       [6.5, 3.2, 5.1, 2. ],
       [6.4, 2.7, 5.3, 1.9],
       [6.8, 3. , 5.5, 2.1],
       [5.7, 2.5, 5. , 2. ],
       [5.8, 2.8, 5.1, 2.4],
       [6.4, 3.2, 5.3, 2.3],
       [6.5, 3. , 5.5, 1.8],
       [7.7, 3.8, 6.7, 2.2],
       [7.7, 2.6, 6.9, 2.3],
       [6. , 2.2, 5. , 1.5],
       [6.9, 3.2, 5.7, 2.3],
       [5.6, 2.8, 4.9, 2. ],
       [7.7, 2.8, 6.7, 2. ],
       [6.3, 2.7, 4.9, 1.8],
       [6.7, 3.3, 5.7, 2.1],
       [7.2, 3.2, 6. , 1.8],
       [6.2, 2.8, 4.8, 1.8],
       [6.1, 3. , 4.9, 1.8],
       [6.4, 2.8, 5.6, 2.1],
       [7.2, 3. , 5.8, 1.6],
       [7.4, 2.8, 6.1, 1.9],
       [7.9, 3.8, 6.4, 2. ],
       [6.4, 2.8, 5.6, 2.2],
       [6.3, 2.8, 5.1, 1.5],
       [6.1, 2.6, 5.6, 1.4],
       [7.7, 3. , 6.1, 2.3],
       [6.3, 3.4, 5.6, 2.4],
       [6.4, 3.1, 5.5, 1.8],
       [6. , 3. , 4.8, 1.8],
       [6.9, 3.1, 5.4, 2.1],
       [6.7, 3.1, 5.6, 2.4],
       [6.9, 3.1, 5.1, 2.3],
       [5.8, 2.7, 5.1, 1.9],
       [6.8, 3.2, 5.9, 2.3],
       [6.7, 3.3, 5.7, 2.5],
       [6.7, 3. , 5.2, 2.3],
       [6.3, 2.5, 5. , 1.9],
       [6.5, 3. , 5.2, 2. ],
       [6.2, 3.4, 5.4, 2.3],
       [5.9, 3. , 5.1, 1.8]])
```

In [4]:
```
df = pd.DataFrame(iris.data,columns=iris.feature_names)
df['class'] = iris.target
```

In [5]:
```
df = df.drop(['sepal length (cm)','sepal width (cm)'],axis=1)
df
```

Out[5]:

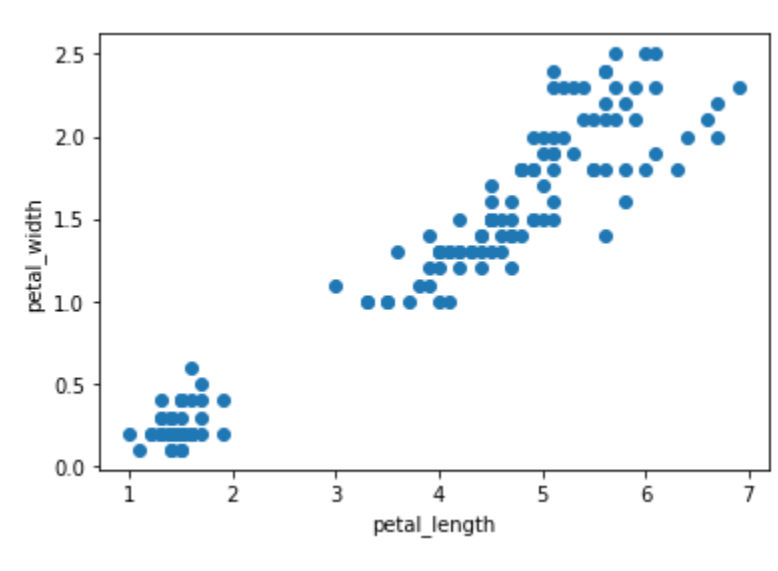
	petal length (cm)	petal width (cm)	class
0	1.4	0.2	0
1	1.4	0.2	0
2	1.3	0.2	0
3	1.5	0.2	0
4	1.4	0.2	0
...	...	...	...
145	5.2	2.3	2
146	5.0	1.9	2
147	5.2	2.0	2
148	5.4	2.3	2
149	5.1	1.8	2

150 rows × 3 columns

Data visualization

In [7]:
```
%matplotlib inline
plt.scatter(df['petal length (cm)'],df['petal width (cm)'])
plt.xlabel('petal_length')
plt.ylabel('petal_width')
```

Out[7]:
```
Text(0, 0.5, 'petal_width')
```



before preprocessing

In [8]:
```
km = KMeans(n_clusters=3)
km.fit(df[['petal length (cm)','petal width (cm)']])
ans = km.predict(df[['petal length (cm)','petal width (cm)']])
ans
```

Out[8]:
```
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, 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, 1, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

In [9]:
```
df['cluster'] = ans
df
```

Out[9]:

	petal length (cm)	petal width (cm)	class	cluster
0	1.4	0.2	0	0
1	1.4	0.2	0	0
2	1.3	0.2	0	0
3	1.5	0.2	0	0
4	1.4	0.2	0	0
...	...	...	...	...
145	5.2	2.3	2	1
146	5.0	1.9	2	1
147	5.2	2.0	2	1
148	5.4	2.3	2	1
149	5.1	1.8	2	1

150 rows × 4 columns

In [10]:
```
km.cluster_centers_
```

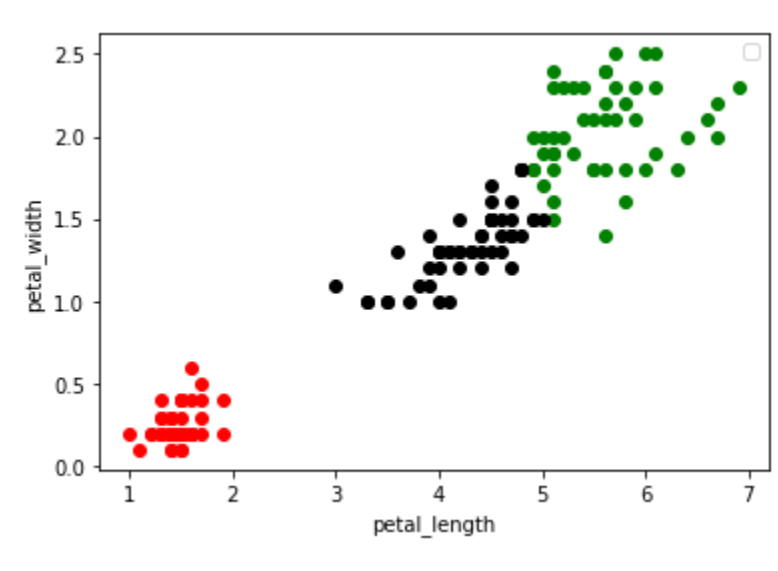
Out[10]:
```
array([[1.462     , 0.246     ],
       [5.59583333, 2.0375    ],
       [4.26923077, 1.34230769]])
```

In [11]:
```
df0 = df[df.cluster==0]
df1 = df[df.cluster==1]
df2 = df[df.cluster==2]

plt.scatter(df0['petal length (cm)'],df0['petal width (cm)'],color='red')
plt.scatter(df1['petal length (cm)'],df1['petal width (cm)'],color='green')
plt.scatter(df2['petal length (cm)'],df2['petal width (cm)'],color='black')
plt.xlabel('petal_length')
plt.ylabel('petal_width')
plt.legend()
```

```
No artists with labels found to put in legend.  Note that artists whose label start with an underscore are ignored when legend() is called with no argument.
```

Out[11]:
```
<matplotlib.legend.Legend at 0x18a756a6f40>
```



after scale down the values

In [12]:
```
from sklearn.preprocessing import MinMaxScaler
mms = MinMaxScaler()
```

In [13]:
```
df['petal length (cm)'] = mms.fit_transform(df[['petal length (cm)']])
```

In [14]:
```
df['petal width (cm)'] = mms.fit_transform(df[['petal width (cm)']])
```

In [15]:
```
df
```

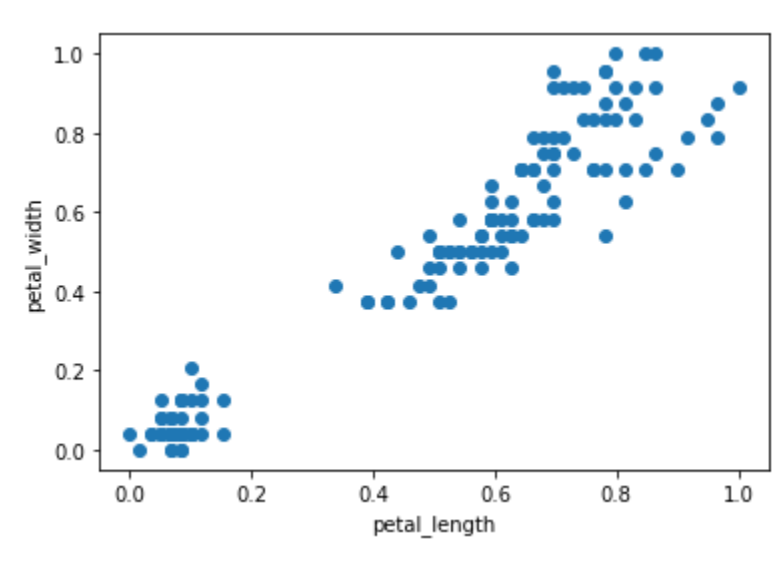
Out[15]:

	petal length (cm)	petal width (cm)	class	cluster
0	0.067797	0.041667	0	0
1	0.067797	0.041667	0	0
2	0.050847	0.041667	0	0
3	0.084746	0.041667	0	0
4	0.067797	0.041667	0	0
...	...	...	...	...
145	0.711864	0.916667	2	1
146	0.677966	0.750000	2	1
147	0.711864	0.791667	2	1
148	0.745763	0.916667	2	1
149	0.694915	0.708333	2	1

150 rows × 4 columns

In [16]:
```
%matplotlib inline
plt.scatter(df['petal length (cm)'],df['petal width (cm)'])
plt.xlabel('petal_length')
plt.ylabel('petal_width')
```

Out[16]:
```
Text(0, 0.5, 'petal_width')
```



In [17]:
```
km = KMeans(n_clusters=3)
km.fit(df[['petal length (cm)','petal width (cm)']])
ans = km.predict(df[['petal length (cm)','petal width (cm)']])
ans
```

Out[17]:
```
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, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 2, 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, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

In [18]:
```
df['new_cluster'] = ans
df
```

Out[18]:

	petal length (cm)	petal width (cm)	class	cluster	new_cluster
0	0.067797	0.041667	0	0	0
1	0.067797	0.041667	0	0	0
2	0.050847	0.041667	0	0	0
3	0.084746	0.041667	0	0	0
4	0.067797	0.041667	0	0	0
...	...	...	...	...	...
145	0.711864	0.916667	2	1	1
146	0.677966	0.750000	2	1	1
147	0.711864	0.791667	2	1	1
148	0.745763	0.916667	2	1	1
149	0.694915	0.708333	2	1	1

150 rows × 5 columns

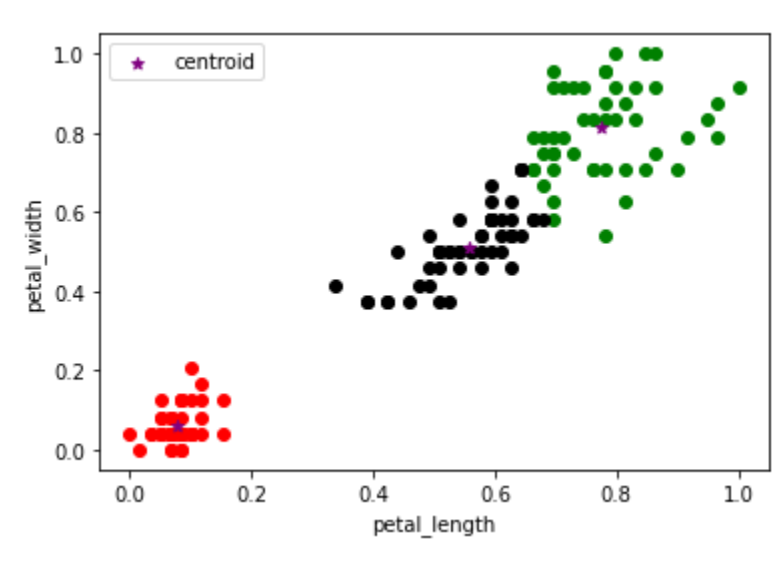
In [19]:
```
km.cluster_centers_
```

Out[19]:
```
array([[0.07830508, 0.06083333],
       [0.7740113 , 0.81510417],
       [0.55867014, 0.51041667]])
```

In [20]:
```
df0 = df[df.cluster==0]
df1 = df[df.cluster==1]
df2 = df[df.cluster==2]

plt.scatter(df0['petal length (cm)'],df0['petal width (cm)'],color='red')
plt.scatter(df1['petal length (cm)'],df1['petal width (cm)'],color='green')
plt.scatter(df2['petal length (cm)'],df2['petal width (cm)'],color='black')
plt.scatter(km.cluster_centers_[:,0],km.cluster_centers_[:,1],color='purple',marker='*',label='centroid')
plt.xlabel('petal_length')
plt.ylabel('petal_width')
plt.legend()
```

Out[20]:
```
<matplotlib.legend.Legend at 0x18a75790430>
```



find real k value using elbow method

In [21]:
```
k_range = range(1,10)
sse = []
for i in k_range:
    km = KMeans(n_clusters=i)
    km.fit(df[['petal length (cm)','petal width (cm)']])
    sse.append(km.inertia_)
```

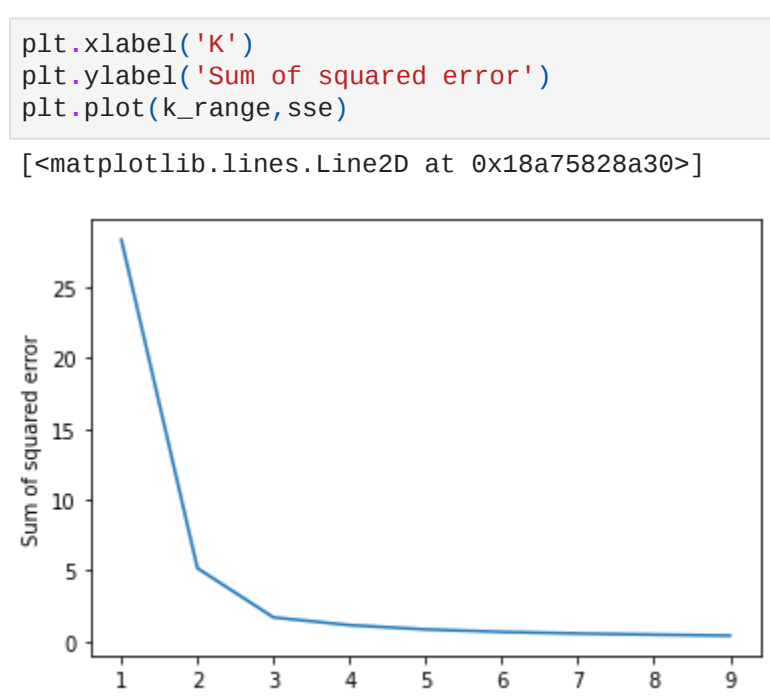
```
C:\Users\91910\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1036: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

In [22]:
```
sse
```

Out[22]:
```
[28.368353219727194,
 5.176463590044369,
 1.7018746881920963,
 1.1588792731667128,
 0.853861735391224,
 0.6795297632254397,
 0.5663174952054538,
 0.48634024603929904,
 0.41602409225888737]
```

In [23]:
```
plt.xlabel('K')
plt.ylabel('Sum of squared error')
plt.plot(k_range,sse)
```

Out[23]:
```
[<matplotlib.lines.Line2D at 0x18a75828a30>]
```



In [ ]: