In [1]:
```python
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
```

In [2]:
```python
from sklearn import datasets
```

In [3]:
```python
iris = datasets.load_iris()
```

In [4]:
```python
iris.keys()
```

Out[4]:
```
dict_keys(['data', 'target', 'target_names', 'DESCR', 'feature_names'])
```

In [5]:

```python
print(iris.DESCR)
```

```
Iris Plants Database
====================

Notes
-----
Data Set Characteristics:
    :Number of Instances: 150 (50 in each of three classes)
    :Number of Attributes: 4 numeric, predictive attributes and the class
    :Attribute Information:
        - sepal length in cm
        - sepal width in cm
        - petal length in cm
        - petal width in cm
        - class:
                - Iris-Setosa
                - Iris-Versicolour
                - Iris-Virginica
    :Summary Statistics:

    ============== ==== ==== ======= ===== ====================
                    Min  Max   Mean    SD   Class Correlation
    ============== ==== ==== ======= ===== ====================
    sepal length:   4.3  7.9   5.84   0.83    0.7826
    sepal width:    2.0  4.4   3.05   0.43   -0.4194
    petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)
    petal width:    0.1  2.5   1.20  0.76     0.9565  (high!)
    ============== ==== ==== ======= ===== ====================

    :Missing Attribute Values: None
    :Class Distribution: 33.3% for each of 3 classes.
    :Creator: R.A. Fisher
    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
    :Date: July, 1988

This is a copy of UCI ML iris datasets.
http://archive.ics.uci.edu/ml/datasets/Iris (http://archive.ics.uci.edu/ml/datasets/Iris)

The famous Iris database, first used by Sir R.A Fisher

This is perhaps the best known database to be found in the
pattern recognition literature.  Fisher's paper is a classic in the field and
is referenced frequently to this day.  (See Duda & Hart, for example.)  The
data set contains 3 classes of 50 instances each, where each class refers to a
type of iris plant.  One class is linearly separable from the other 2; the
latter are NOT linearly separable from each other.

References
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   - Fisher,R.A. "The use of multiple measurements in taxonomic problems"
     Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to
     Mathematical Statistics" (John Wiley, NY, 1950).
   - Duda,R.O., & Hart,P.E. (1973) Pattern Classification and Scene Analysis.
     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.
   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System
     Structure and Classification Rule for Recognition in Partially Exposed
     Environments".  IEEE Transactions on Pattern Analysis and Machine
     Intelligence, Vol. PAMI-2, No. 1, 67-71.
   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactions
     on Information Theory, May 1972, 431-433.
   - See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II
     conceptual clustering system finds 3 classes in the data.
   - Many, many more ...
```

In [6]:
```
iris.data
```

Out[6]:
```
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],
```

In [8]:
```
iris.data.shape
```

Out[8]:
```
(150, 4)
```

In [9]:
```
iris.feature_names
```

Out[9]:
```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

In [10]:
```
iris.target
```

Out[10]:
```
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, 1, 1, 1, 1, 1, 1, 1, 1, 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, 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])
```

In [11]:
```
iris.target.shape
```

Out[11]:
```
(150,)
```

In [12]:
```
iris.target_names
```

Out[12]:
```
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

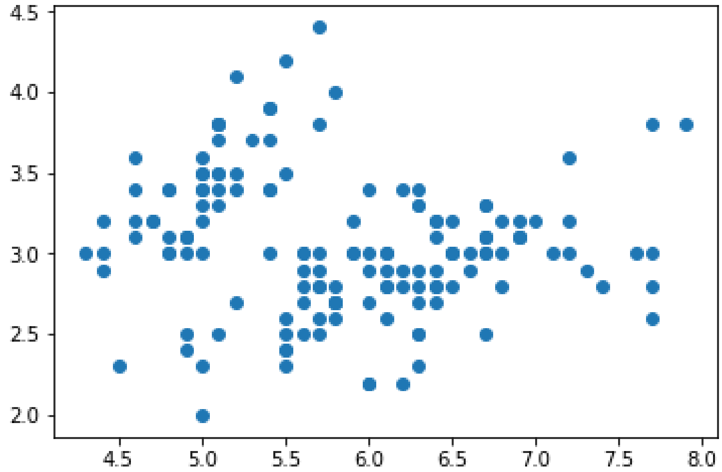
In [13]:
```
X = iris.data[:, :2]
```

In [14]:
```
X.shape
```

Out[14]:
```
(150, 2)
```

In [15]:

```
plt.scatter(X[:, 0],X [:, 1])
plt.show()
```

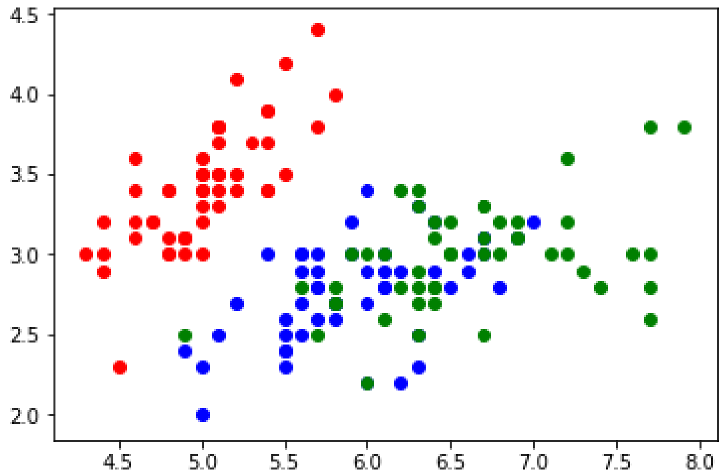


In [16]:

```
y = iris.target
```

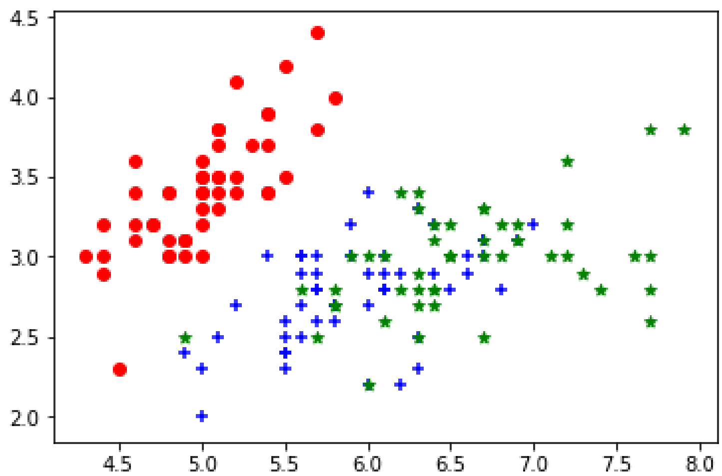
In [17]:

```
plt.scatter(X[y == 0, 0],X[y == 0, 1], color = 'red')
plt.scatter(X[y == 1, 0],X[y == 1, 1], color = 'blue')
plt.scatter(X[y == 2, 0],X[y == 2, 1], color = 'green')
plt.show()
```



In [18]:

```
plt.scatter(X[y == 0, 0],X[y == 0, 1], color = 'red', marker = 'o')
plt.scatter(X[y == 1, 0],X[y == 1, 1], color = 'blue', marker = '+')
plt.scatter(X[y == 2, 0],X[y == 2, 1], color = 'green', marker = '*')
plt.show()
```



In [19]:

```
X = iris.data[:, 2:]
```

In [20]:

```
plt.scatter(X[y == 0, 0],X[y == 0, 1], color = 'red', marker = 'o')
plt.scatter(X[y == 1, 0],X[y == 1, 1], color = 'blue', marker = '+')
plt.scatter(X[y == 2, 0],X[y == 2, 1], color = 'green', marker = '*')
plt.show()
```