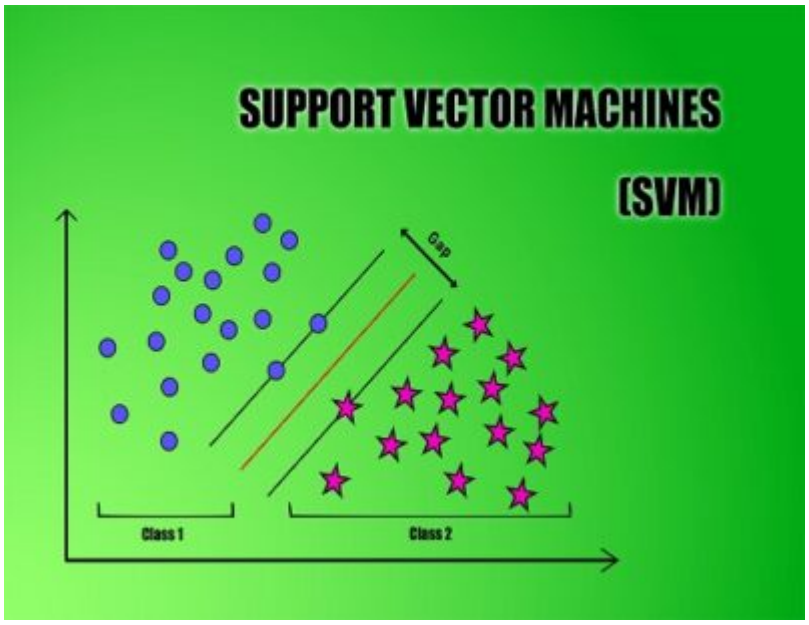
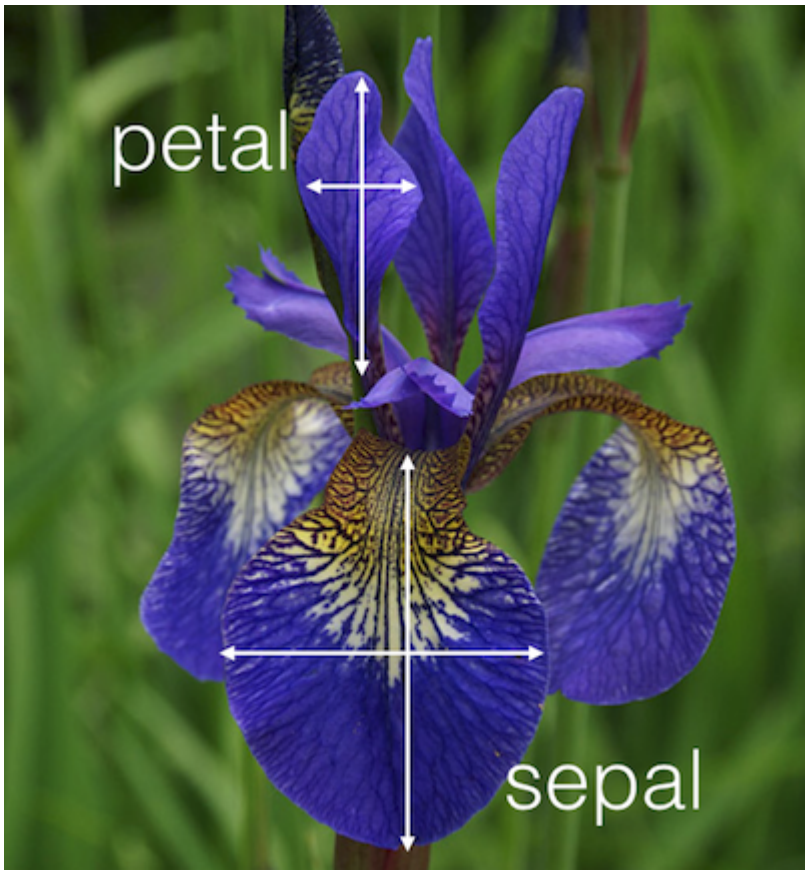
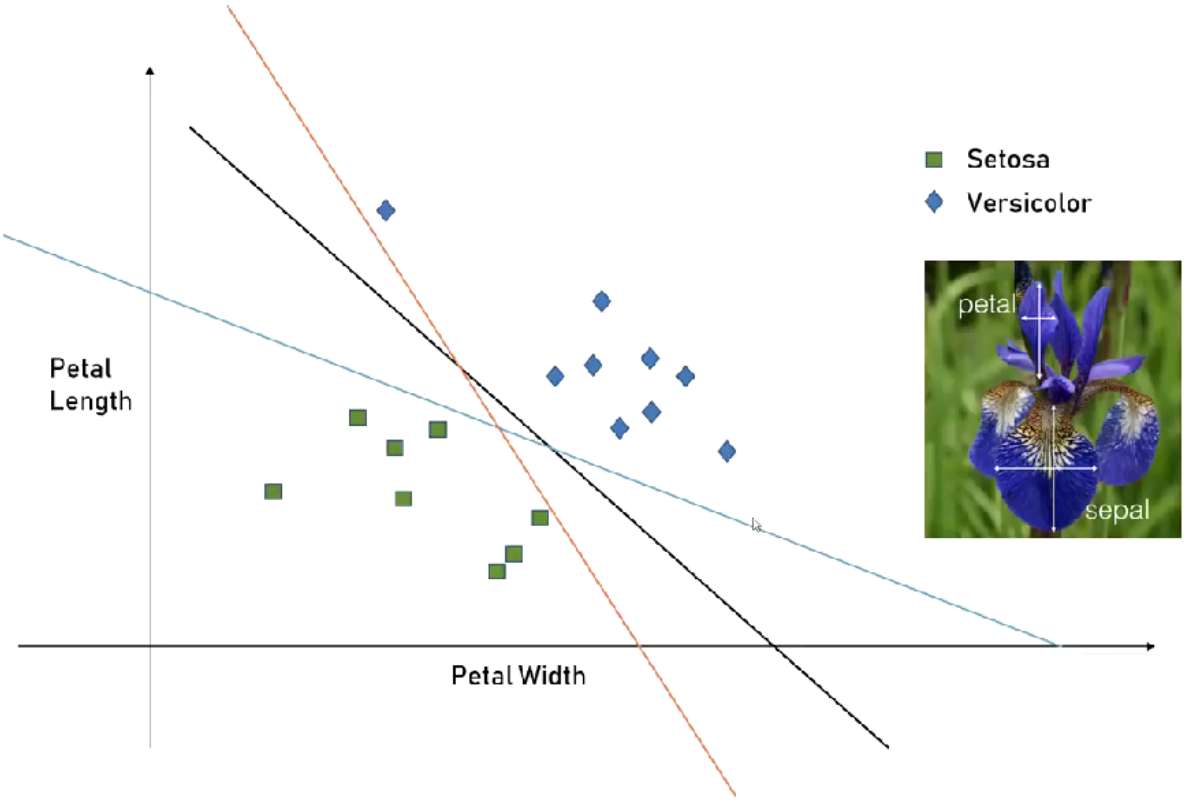
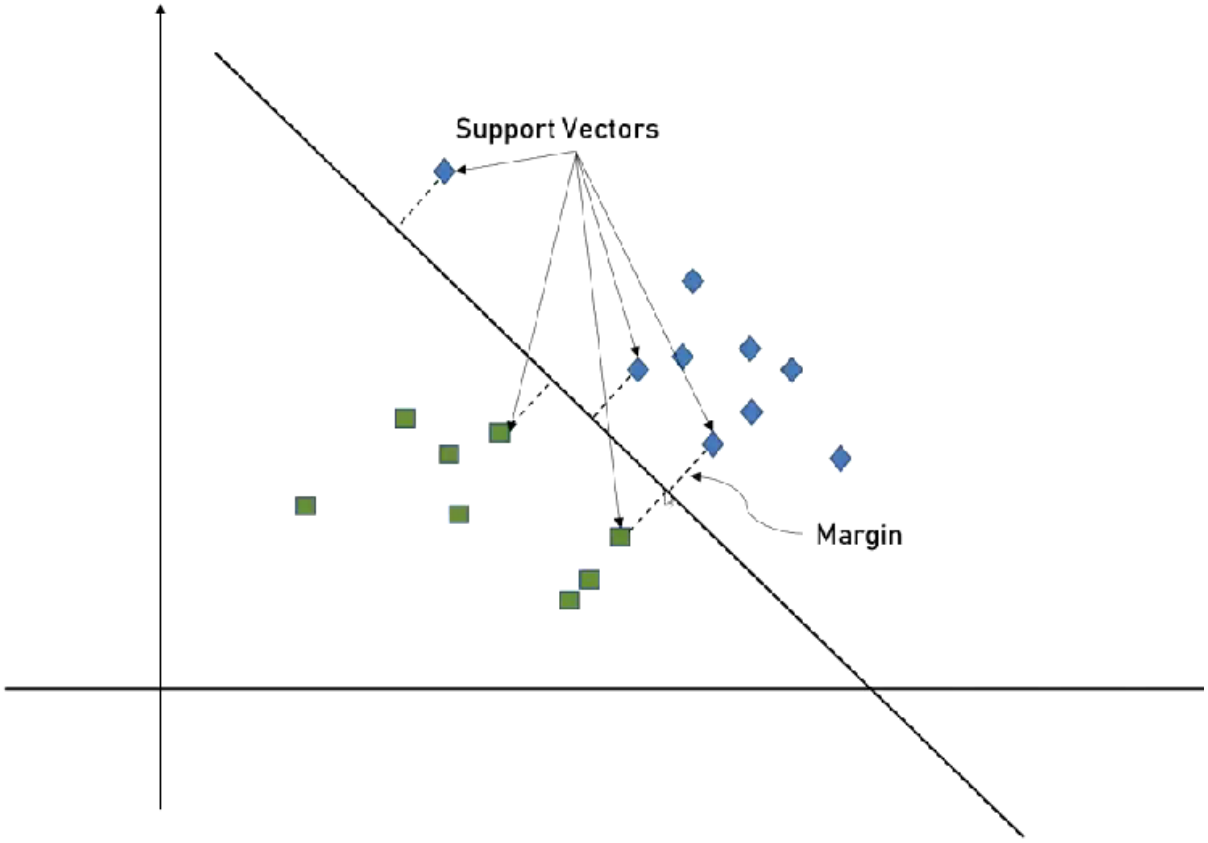
# Support Vector Machine

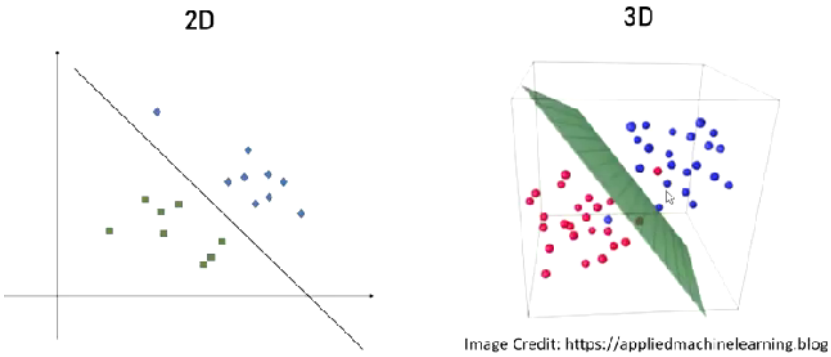




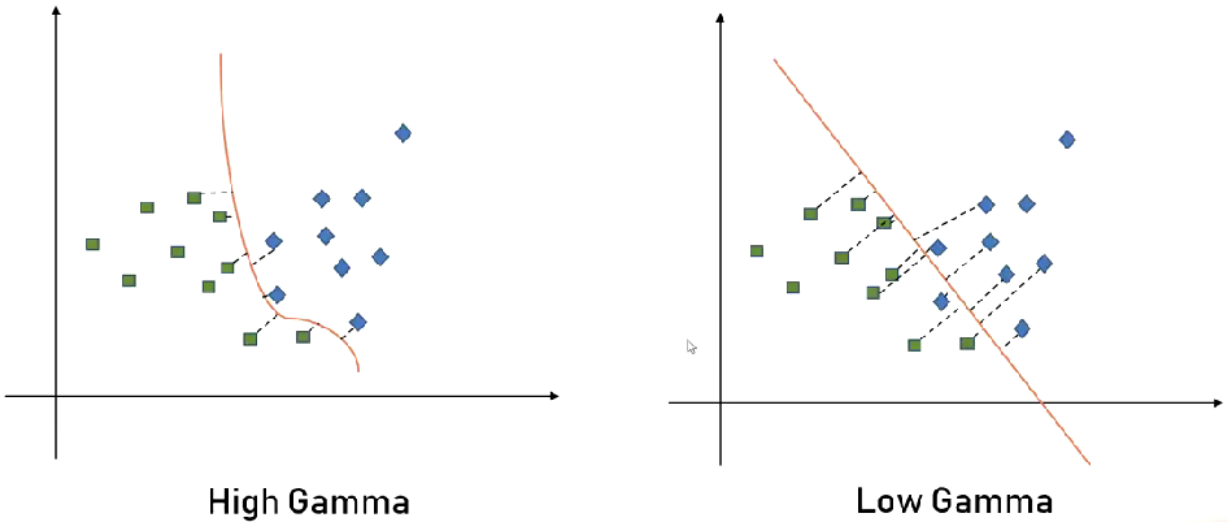

**The line with higher margin is better because it classifies these 2 groups in a better way.**



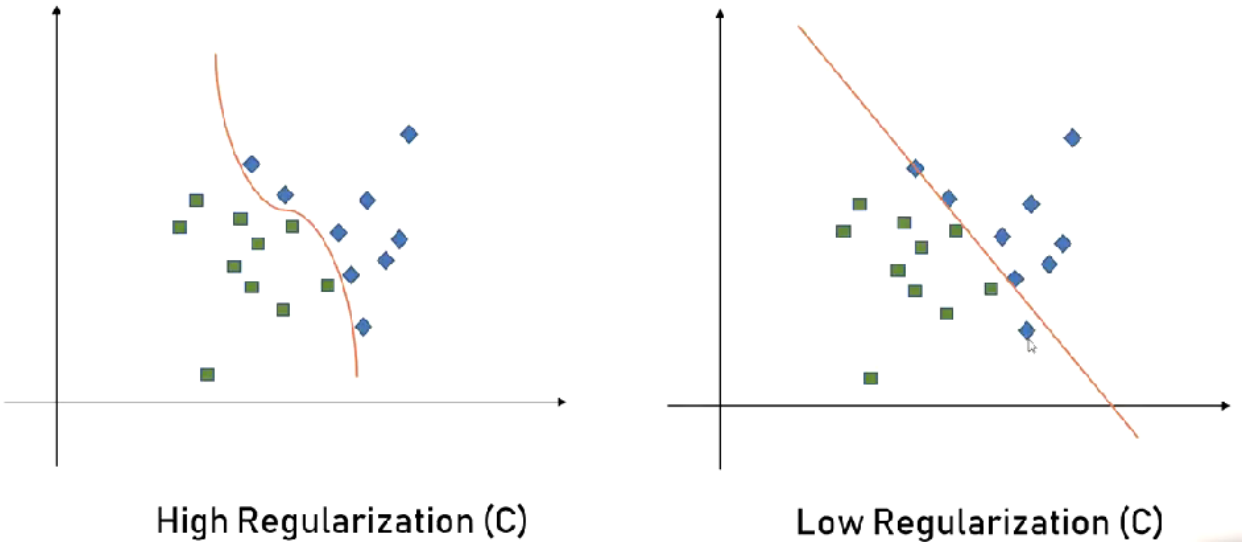

## What is Support vector machine?

Support vector machine draws a hyper plane in n dimentional space such that it maximizes margin between classification groups.

## Gamma & Regularization

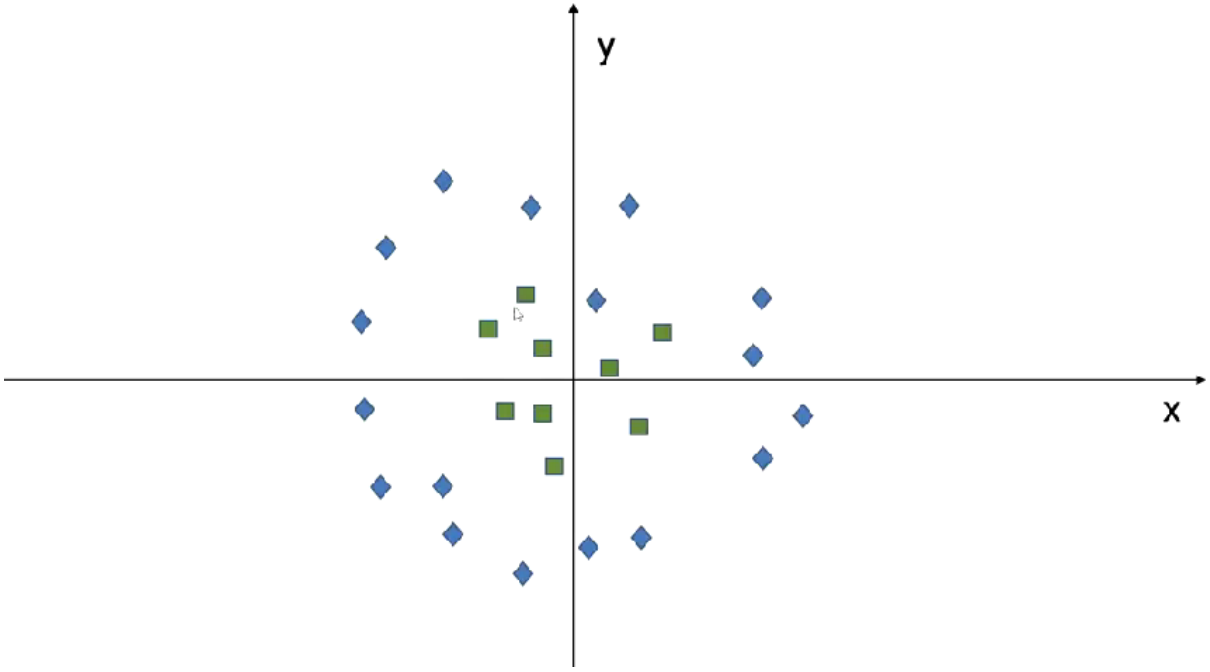



High Gamma: The decision boundary considered the data point which are very near to it.
Low Gamma: The decision boundary considered the data point which are very far to it. (more accuracy, more efficient)

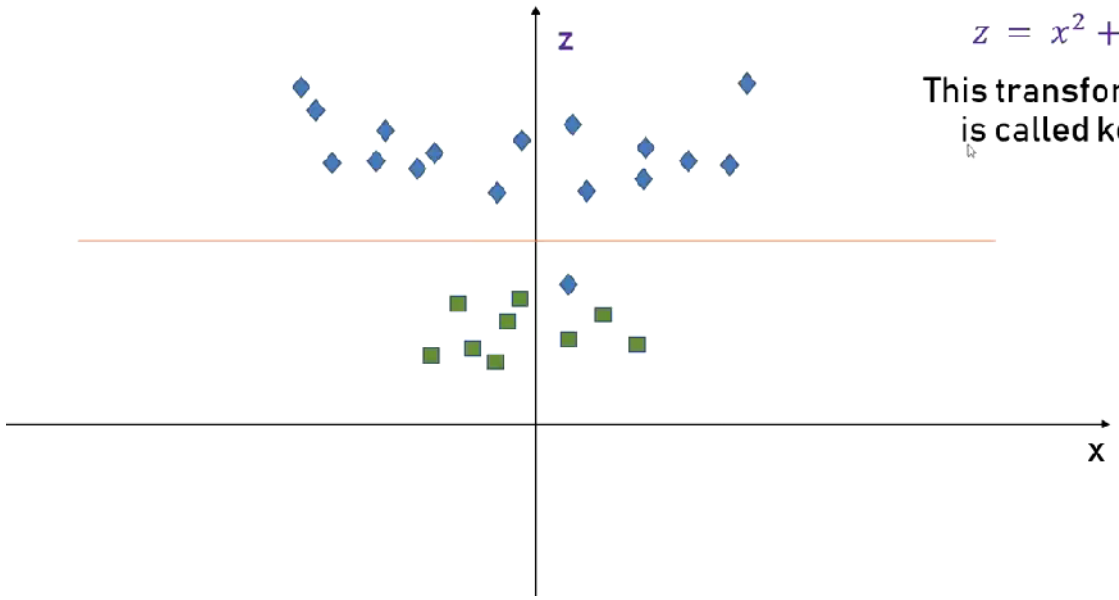



High Regularization: use for very complex data set, line is very zigzag.
Low Regularization: accept some errors, line is more smmother.

## You might have a very complex dataset like this!!!




One approcal to deal with this dataset is to create a third dimention(z).




## Implement SVM By Python

In [3]:
```
import pandas as pd
from sklearn.datasets import load_iris
iris=load_iris()
```

In [4]:
```
dir(iris)
```

Out[4]:
```
['DESCR',
 'data',
 'feature_names',
 'filename',
 'frame',
 'target',
 'target_names']
```

In [5]:
```
iris.feature_names
```

Out[5]:
```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

In [6]:
```
#create a new dataframe based on iris feature names
df=pd.DataFrame(iris.data, columns=iris.feature_names)
df.head()
```

Out[6]:

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) |
|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 |

In [8]:
```
# append a target varible into my df
df['target'] = iris.target
df.head()
```

Out[8]:

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target |
|---|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 | 0 |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 | 0 |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 | 0 |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 | 0 |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 | 0 |

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

Out[9]:
```
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

**The meaning & labling of target names: 0=setosa;1=versicolor;2=virginica**

In [10]:
```
## which rows are 1?
df[df.target==1].head()
```

Out[10]:

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target |
|---|---|---|---|---|---|
| **50** | 7.0 | 3.2 | 4.7 | 1.4 | 1 |
| **51** | 6.4 | 3.2 | 4.5 | 1.5 | 1 |
| **52** | 6.9 | 3.1 | 4.9 | 1.5 | 1 |
| **53** | 5.5 | 2.3 | 4.0 | 1.3 | 1 |
| **54** | 6.5 | 2.8 | 4.6 | 1.5 | 1 |

In [11]:
```
len(df[df.target==1])
```

Out[11]:
```
50
```

In [12]:
```
len(df[df.target==2])
```

Out[12]: 50

In [13]:
```
len(df[df.target==0])
```

Out[13]: 50

In [14]:
```
# create flower_name columns from target clomun by using apply function
# by using this code the value of target is returned
df['flower_name']= df.target.apply(lambda x:iris.target_names[x])
df.head()
```

Out[14]:

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target | flower_name |
|---|---|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 | 0 | setosa |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 | 0 | setosa |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 | 0 | setosa |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 | 0 | setosa |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 | 0 | setosa |

# Data Visualization

In [16]:
```
from matplotlib import pyplot as plt
%matplotlib inline
```

In [17]:
```
# Separate 3 dataframes
df0 = df[df.target==0]
df1 = df[df.target==1]
df2=df[df.target==2]
```

In [18]:
```
df0.head()
```

Out[18]:

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target | flower_name |
|---|---|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 | 0 | setosa |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 | 0 | setosa |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 | 0 | setosa |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 | 0 | setosa |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 | 0 | setosa |

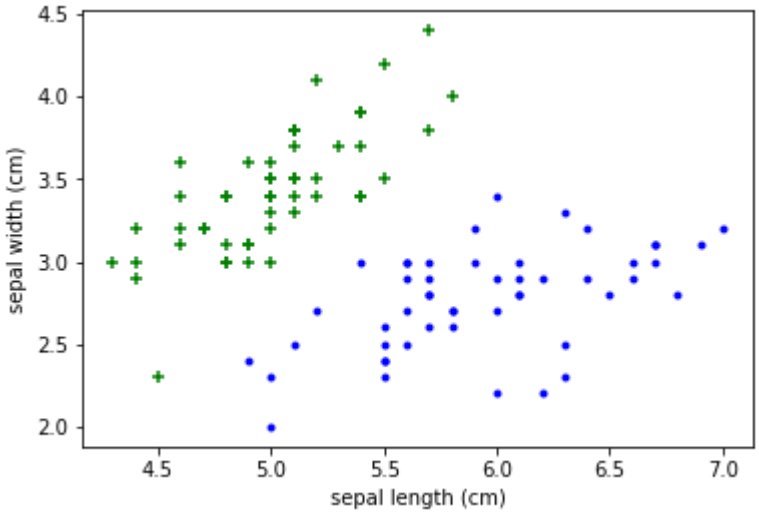
In [19]:
```
df1.head()
```

Out[19]:

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target | flower_name |
|---|---|---|---|---|---|---|
| **50** | 7.0 | 3.2 | 4.7 | 1.4 | 1 | versicolor |
| **51** | 6.4 | 3.2 | 4.5 | 1.5 | 1 | versicolor |
| **52** | 6.9 | 3.1 | 4.9 | 1.5 | 1 | versicolor |
| **53** | 5.5 | 2.3 | 4.0 | 1.3 | 1 | versicolor |
| **54** | 6.5 | 2.8 | 4.6 | 1.5 | 1 | versicolor |

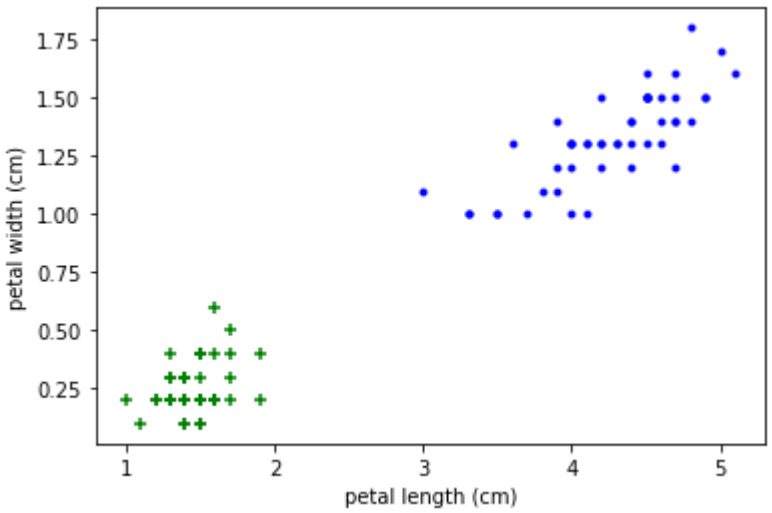
In [21]:
```
plt.xlabel('sepal length (cm)')
plt.ylabel('sepal width (cm)')
plt.scatter(df0['sepal length (cm)'],df0['sepal width (cm)'],color='green',marker=
plt.scatter(df1['sepal length (cm)'],df1['sepal width (cm)'],color='blue',marker='
```

Out[21]:
```
<matplotlib.collections.PathCollection at 0xc81c100>
```



In [22]:
```
plt.xlabel('petal length (cm)')
plt.ylabel('petal width (cm)')
plt.scatter(df0['petal length (cm)'],df0['petal width (cm)'],color='green',marker=
plt.scatter(df1['petal length (cm)'],df1['petal width (cm)'],color='blue',marker='
```

Out[22]:
```
<matplotlib.collections.PathCollection at 0xb758160>
```




In [23]:
```
from sklearn.model_selection import train_test_split
```

In [26]:
```
X = df.drop(['target','flower_name'],axis='columns')
X.head()
```

Out[26]:

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) |
|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 |

In [28]:
```
y=df.target
y.head()
```

Out[28]:
```
0    0
1    0
2    0
3    0
4    0
Name: target, dtype: int32
```

In [29]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,train_size=0.8)
```

In [30]:
```
len(X_train)
```

Out[30]:
```
120
```

In [31]:
```
len(X_test)
```

Out[31]: 30

In [34]:
```
from sklearn.svm import SVC
model = SVC()
```

In [35]:
```
model.fit(X_train,y_train)
```

Out[35]: SVC()

In [36]:
```
model.score(X_test,y_test)
```

Out[36]: 0.9666666666666667

In [62]:
```
# IF I increase gamma what happen to my score?
from sklearn.svm import SVC
model = SVC(gamma=10)
```

In [63]:
```
model.fit(X_train,y_train)
```

Out[63]: SVC(gamma=10)

In [64]:
```
model.score(X_test,y_test)
```

Out[64]: 0.9

**Increasing gamma reduce my score.**

In [77]:
```
# What happen if I increase regularization
from sklearn.svm import SVC
model = SVC(C=200)
```

In [78]:
```
model.fit(X_train,y_train)
```

Out[78]: SVC(C=200)

In [79]:
```
model.score(X_test,y_test)
```

Out[79]: 0.9666666666666667

**Normally increasing C (regularization) decrease the accuracy.**

In [80]:
```
# What happen if I change the kernel
from sklearn.svm import SVC
model = SVC(kernel='linear')
```

In [81]:
```
model.fit(X_train,y_train)
```

Out[81]: SVC(kernel='linear')

In [82]:
```
model.score(X_test,y_test)
```

Out[82]: 1.0

| Date | Author |
| --- | --- |
| 2021-09-18 | **Ehsan Zia** |