```
# Support Vector Machines Project


## The Data
For this project, we will be using the famous Iris flower data set
(http://en.wikipedia.org/wiki/Iris_flower_data_set).
The data set can be downloaded from
https://archive.ics.uci.edu/ml/datasets/iris

However,in this project, it is taken from taken from seaborn
library.

The data set consists of 50 samples from each of three species of
Iris -- Iris setosa, Iris virginica and Iris versicolor. So there
are 150 total samples. Four features were measured from each
sample: the length and the width of the sepals and petals, in
centimeters.
```

The iris dataset contains measurements for 150 iris flowers from three different species.

The three classes in the Iris dataset:

```
Iris-setosa (n=50)
Iris-versicolor (n=50)
Iris-virginica (n=50)
```

The four features of the Iris dataset:

```
sepal length in cm
sepal width in cm
petal length in cm
petal width in cm
```

Get the data

Use seaborn to get the iris dataset

In [1]:
```
1 import seaborn as sns
2 iris = sns.load_dataset('iris')
3 iris.head()
```

Out[1]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

Exploratory Data Analysis

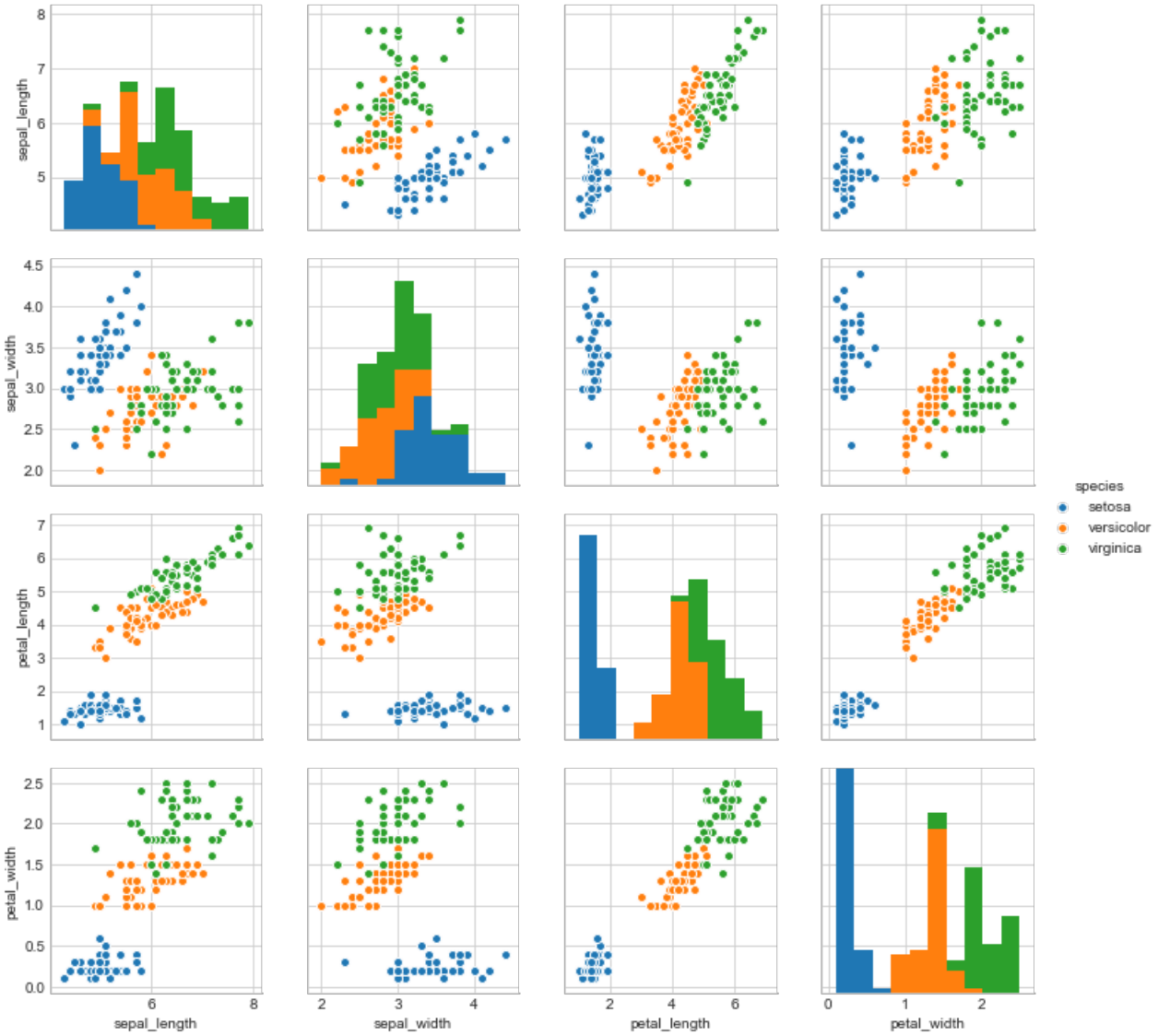
Import libraries needed for analysis and visualization

In [5]:
```
1 import pandas as pd
2 import numpy as np
3 import matplotlib.pyplot as plt
4 %matplotlib inline
```

Create a pairplot of the data set.

In [6]:
```
1 sns.pairplot(iris, hue = 'species')
```

Out[6]: <seaborn.axisgrid.PairGrid at 0x1a1b500b70>



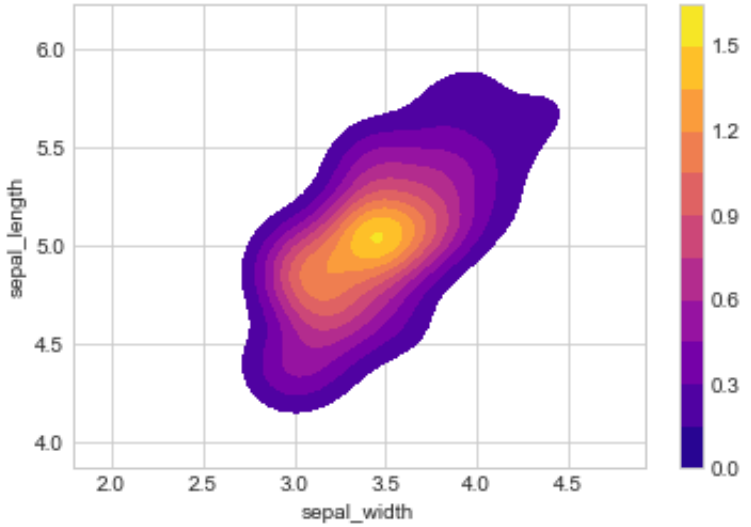
Observation: The species that seems the most separable is setosa.

Create a kde plot of sepal_length versus sepal width for setosa species of flower.

In [11]:
```
sns.set_style('whitegrid')
iris_setosa = iris[iris['species'] == 'setosa' ]
sns.kdeplot(iris_setosa['sepal_width'],
            iris_setosa['sepal_length'],
            shade = True, shade_lowest = False,
            cmap = 'plasma',
            cbar = 'plasma')
```

```
/Users/Jayashri/anaconda/lib/python3.6/site-packages/scipy/stats/stats
.py:1713: FutureWarning: Using a non-tuple sequence for multidimension
al indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`
. In the future this will be interpreted as an array index, `arr[np.ar
ray(seq)]`, which will result either in an error or a different result
.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1d141c50>



Train Test Split

Split the data into a training set and a testing set. Set test_size to 30%.

In [22]:
```
iris.columns
```

Out[22]:
```
Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width',
       'species'],
      dtype='object')
```

In [14]:
```
X = iris.drop('species', axis = 1)
y = iris['species']

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.3,
                                                    random_state=101)

```

Train a Model

Now we will train a Support Vector Machine Classifier.

Call the SVC() model from sklearn and fit the model to the training data.

In [15]:
```
from sklearn.svm import SVC
model = SVC()
```

In [16]:
```
model.fit(X_train, y_train)
```

Out[16]:
```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

Model Evaluation

Now we willget predictions from the model and create a confusion matrix and a classification report.

In [17]:
```
from sklearn.metrics import confusion_matrix, classification_report
```

In [18]:
```
predictions = model.predict(X_test)
print('Confusion Matrix')
print(confusion_matrix(y_test, predictions))
print('-------------------------------------------------')
print('Classification Report')
print(classification_report(y_test, predictions))
```

```
Confusion Matrix
[[13  0  0]
 [ 0 20  0]
 [ 0  0 12]]
-------------------------------------------------
Classification Report
             precision    recall  f1-score   support

     setosa       1.00      1.00      1.00        13
 versicolor       1.00      1.00      1.00        20
  virginica       1.00      1.00      1.00        12

avg / total       1.00      1.00      1.00        45
```

This model looks very good!

Gridsearch Practice

Import GridsearchCV from SciKit Learn.

In [19]:
```
from sklearn.grid_search import GridSearchCV

```

```
/Users/Jayashri/anaconda/lib/python3.6/site-packages/sklearn/cross_val
idation.py:41: DeprecationWarning: This module was deprecated in versi
on 0.18 in favor of the model_selection module into which all the refa
ctored classes and functions are moved. Also note that the interface o
f the new CV iterators are different from that of this module. This mo
dule will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
/Users/Jayashri/anaconda/lib/python3.6/site-packages/sklearn/grid_sear
ch.py:42: DeprecationWarning: This module was deprecated in version 0.
18 in favor of the model_selection module into which all the refactore
d classes and functions are moved. This module will be removed in 0.20
.
  DeprecationWarning)
```

Create a dictionary called param_grid and fill out some parameters for C and gamma.

In [23]:
```
param_grid = {'C': [0.1, 1, 10, 100],
              'gamma' : [0.1, 0.01, 0.001, 0.0001]}
```

Create a GridSearchCV object and fit it to the training data.

In [24]:
```
grid = GridSearchCV(SVC(), param_grid, verbose = 3, refit = True)
```

Now take that grid model and create some predictions using the test set and create classification reports and confusion matrices for them. Were you able to improve?

In [25]:
```
grid.fit(X_train, y_train)
```

```
[CV] ..................... C=1, gamma=0.0001, score=0.714286 -   0.0
s
[CV] C=1, gamma=0.0001 ................................................
.
[CV] ..................... C=1, gamma=0.0001, score=0.352941 -   0.0
s
[CV] C=10, gamma=0.1 ..................................................
.
[CV] ...................... C=10, gamma=0.1, score=1.000000 -   0.0
s
[CV] C=10, gamma=0.1 ..................................................
.
[CV] ...................... C=10, gamma=0.1, score=0.914286 -   0.0
s
[CV] C=10, gamma=0.1 ..................................................
.
[CV] ...................... C=10, gamma=0.1, score=0.911765 -   0.0
s
[CV] C=10, gamma=0.01 .................................................
.
```

In [26]:
```
grid.best_params_
```

Out[26]:
```
{'C': 1, 'gamma': 0.1}
```

In [27]:
```
grid.best_estimator_
```

Out[27]:
```
SVC(C=1, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [28]:
```
grid_predictions = grid.predict(X_test)
```

In [32]:
```
print('Confusion Matrix')
print(confusion_matrix(y_test, grid_predictions))
```

```
Confusion Matrix
[[13  0  0]
 [ 0 19  1]
 [ 0  0 12]]
```

In [34]:
```
print('Classification Report')
print(classification_report(y_test, grid_predictions))
```

```
Classification Report
             precision    recall  f1-score   support

     setosa       1.00      1.00      1.00        13
 versicolor       1.00      0.95      0.97        20
  virginica       0.92      1.00      0.96        12

avg / total       0.98      0.98      0.98        45
```

Observation: The model was already good. So using GridSearch did not seem to make it any better.