COURSE: "ARTIFICIAL INTELLIGENCE SYSTEMS"
LABORATORY WORK #2-3-4
TOPIC: "MACHINE LEARNING WITH PYTHON"

Goal: to learn how to: Install the Python and SciPy platform; loading the dataset; summarize the dataset; visualize the dataset; evaluate some machine learning algorithms; make some predictions.

Task: to create a project for the classification of iris flowers.

(See more about the task and the given dataset here: https://en.wikipedia.org/wiki/Iris_flower_data_set)

Progress of work (the main steps):

1. Installing the Python and SciPy platform.
2. Loading the dataset.
3. Summarizing the dataset.
4. Visualizing the dataset.
5. Evaluating some algorithms.
6. Making some predictions.

1. Downloading, Installing and Starting Python SciPy

Get the Python and SciPy platform installed on your system if it is not already.

1.1 Install SciPy Libraries

This tutorial assumes Python version 2.7 or 3.6+.

There are 5 key libraries that you will need to install. Below is a list of the Python SciPy libraries required for this tutorial:

- scipy
- numpy
- matplotlib
- pandas
- sklearn

There are many ways to install these libraries. My best advice is to pick one method then be consistent in installing each library.

The scipy installation page provides excellent instructions for installing the above libraries on multiple different platforms, such as Linux, mac OS X and Windows. If you have any doubts or questions, refer to this guide, it has been followed by thousands of people.

- On Mac OS X, you can use macports to install Python 3.6 and these libraries. For more information on macports, follow: https://www.macports.org/install.php
- On Linux you can use your package manager, such as yum on Fedora to install RPMs.

If you are on Windows or you are not confident, I would recommend installing the free version of Anaconda that includes everything you need.

Note: This tutorial assumes you have scikit-learn version 0.20 or higher installed.

1.2 Start Python and Check Versions

It is a good idea to make sure your Python environment was installed successfully and is working as expected.

The script below will help you test out your environment. It imports each library required in this tutorial and prints the version.

Open a command line and start the python interpreter:

```
python
```

I recommend working directly in the interpreter or writing your scripts and running them on the command line rather than big editors and IDEs. Keep things simple and focus on the machine learning not the toolchain.

Type or copy and paste the following script:

```python
# Check the versions of libraries

# Python version
import sys
print('Python: {}'.format(sys.version))
# scipy
import scipy
print('scipy: {}'.format(scipy.__version__))
# numpy
import numpy
print('numpy: {}'.format(numpy.__version__))
# matplotlib
import matplotlib
print('matplotlib: {}'.format(matplotlib.__version__))
# pandas
import pandas
print('pandas: {}'.format(pandas.__version__))
# scikit-learn
import sklearn
print('sklearn: {}'.format(sklearn.__version__))
```

Here is the output I get on my OS X workstation:

```
Python: 3.6.11 (default, Jun 29 2020, 13:22:26)
[GCC 4.2.1 Compatible Apple LLVM 9.1.0 (clang-902.0.39.2)]
scipy: 1.5.2
numpy: 1.19.1
matplotlib: 3.3.0
pandas: 1.1.0
sklearn: 0.23.2
```

Compare the above output to your versions.

Ideally, your versions should match or be more recent. The APIs do not change quickly, so do not be too concerned if you are a few versions behind, Everything in this tutorial will very likely still work for you.

If you get an error, stop. Now is the time to fix it.

2. Load The Data

We are going to use the iris flowers dataset. This dataset is famous because it is used as the “hello world” dataset in machine learning and statistics by pretty much everyone.

The dataset contains 150 observations of iris flowers. There are four columns of measurements of the flowers in centimeters. The fifth column is the species of the flower observed. All observed flowers belong to one of three species.

You can learn more about this dataset on Wikipedia. https://en.wikipedia.org/wiki/Iris_flower_data_set

In this step we are going to load the iris data from CSV file URL.

2.1 Import libraries

First, let’s import all of the modules, functions and objects we are going to use in this tutorial

```
# Load libraries
from pandas import read_csv
from pandas.plotting import scatter_matrix
from matplotlib import pyplot
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
...
```

Everything should load without error. If you have an error, stop. You need a working SciPy environment before continuing. See the advice above about setting up your environment.

2.2 Load Dataset

We can load the data directly from the UCI Machine Learning repository.

We are using pandas to load the data. We will also use pandas next to explore the data both with descriptive statistics and data visualization.

Note that we are specifying the names of each column when loading the data. This will help later when we explore the data.

```
...
# Load dataset
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/iris.csv"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
dataset = read_csv(url, names=names)
```

The dataset should load without incident.

If you do have network problems, you can download the iris.csv file using the link: https://raw.githubusercontent.com/jbrownlee/Datasets/master/iris.csv into your working directory and load it using the same method, changing URL to the local file name.

3. Summarize the Dataset

Now it is time to take a look at the data.

In this step we are going to take a look at the data a few different ways:

1. Dimensions of the dataset.
2. Peek at the data itself.
3. Statistical summary of all attributes.
4. Breakdown of the data by the class variable.

Don’t worry, each look at the data is one command. These are useful commands that you can use again and again on future projects.

3.1 Dimensions of Dataset

We can get a quick idea of how many instances (rows) and how many attributes (columns) the data contains with the shape property.

```
...
# shape
print(dataset.shape)
```

You should see 150 instances and 5 attributes:

```
(150, 5)
```

3.2 Peek at the Data

It is also always a good idea to actually eyeball your data.

```
...
# head
print(dataset.head(20))
```

You should see the first 20 rows of the data:

```
    sepal-length  sepal-width  petal-length  petal-width        class
0            5.1          3.5           1.4          0.2  Iris-setosa
1            4.9          3.0           1.4          0.2  Iris-setosa
2            4.7          3.2           1.3          0.2  Iris-setosa
3            4.6          3.1           1.5          0.2  Iris-setosa
4            5.0          3.6           1.4          0.2  Iris-setosa
5            5.4          3.9           1.7          0.4  Iris-setosa
6            4.6          3.4           1.4          0.3  Iris-setosa
7            5.0          3.4           1.5          0.2  Iris-setosa
8            4.4          2.9           1.4          0.2  Iris-setosa
9            4.9          3.1           1.5          0.1  Iris-setosa
10           5.4          3.7           1.5          0.2  Iris-setosa
11           4.8          3.4           1.6          0.2  Iris-setosa
12           4.8          3.0           1.4          0.1  Iris-setosa
13           4.3          3.0           1.1          0.1  Iris-setosa
14           5.8          4.0           1.2          0.2  Iris-setosa
15           5.7          4.4           1.5          0.4  Iris-setosa
16           5.4          3.9           1.3          0.4  Iris-setosa
17           5.1          3.5           1.4          0.3  Iris-setosa
18           5.7          3.8           1.7          0.3  Iris-setosa
19           5.1          3.8           1.5          0.3  Iris-setosa
```

3.3 Statistical Summary

Now we can take a look at a summary of each attribute.

This includes the count, mean, the min and max values as well as some percentiles.

```
...
# descriptions
print(dataset.describe())
```

We can see that all of the numerical values have the same scale (centimeters) and similar ranges between 0 and 8 centimeters.

```
       sepal-length  sepal-width  petal-length  petal-width
count    150.000000   150.000000    150.000000   150.000000
mean       5.843333     3.054000      3.758667     1.198667
std        0.828066     0.433594      1.764420     0.763161
min        4.300000     2.000000      1.000000     0.100000
25%        5.100000     2.800000      1.600000     0.300000
50%        5.800000     3.000000      4.350000     1.300000
75%        6.400000     3.300000      5.100000     1.800000
max        7.900000     4.400000      6.900000     2.500000
```

3.4 Class Distribution

Let’s now take a look at the number of instances (rows) that belong to each class. We can view this as an absolute count

```
...
# class distribution
print(dataset.groupby('class').size())
```

We can see that each class has the same number of instances (50 or 33% of the dataset).

```
class
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
```

3.5 Complete Example

For reference, we can tie all of the previous elements together into a single script. The complete example is listed below.

```
# summarize the data
from pandas import read_csv
# Load dataset
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/iris.csv"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
dataset = read_csv(url, names=names)
# shape
print(dataset.shape)
# head
print(dataset.head(20))
# descriptions
print(dataset.describe())
# class distribution
print(dataset.groupby('class').size())
```

4. Data Visualization

We now have a basic idea about the data. We need to extend that with some visualizations.

We are going to look at two types of plots:

1. Univariate plots to better understand each attribute.
2. Multivariate plots to better understand the relationships between attributes.

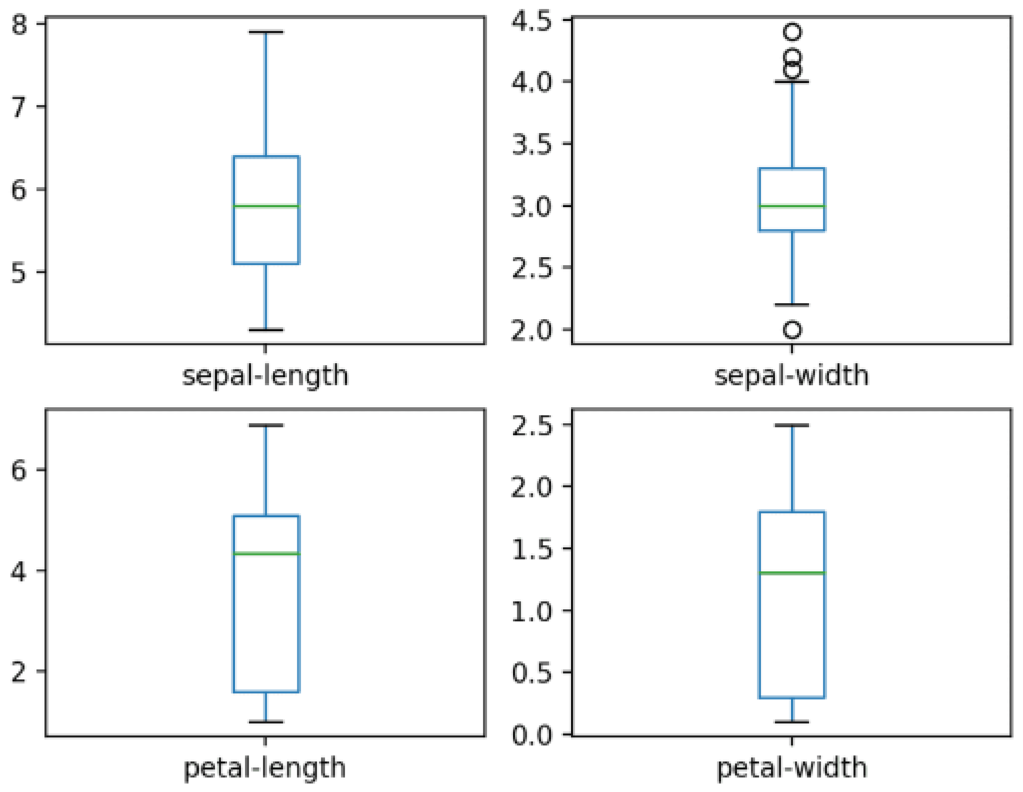
4.1 Univariate Plots

We start with some univariate plots, that is, plots of each individual variable.

Given that the input variables are numeric, we can create box and whisker plots of each.

```
...
# box and whisker plots
dataset.plot(kind='box', subplots=True, layout=(2,2), sharex=False, sharey=False)
pyplot.show()
```

This gives us a much clearer idea of the distribution of the input attributes:

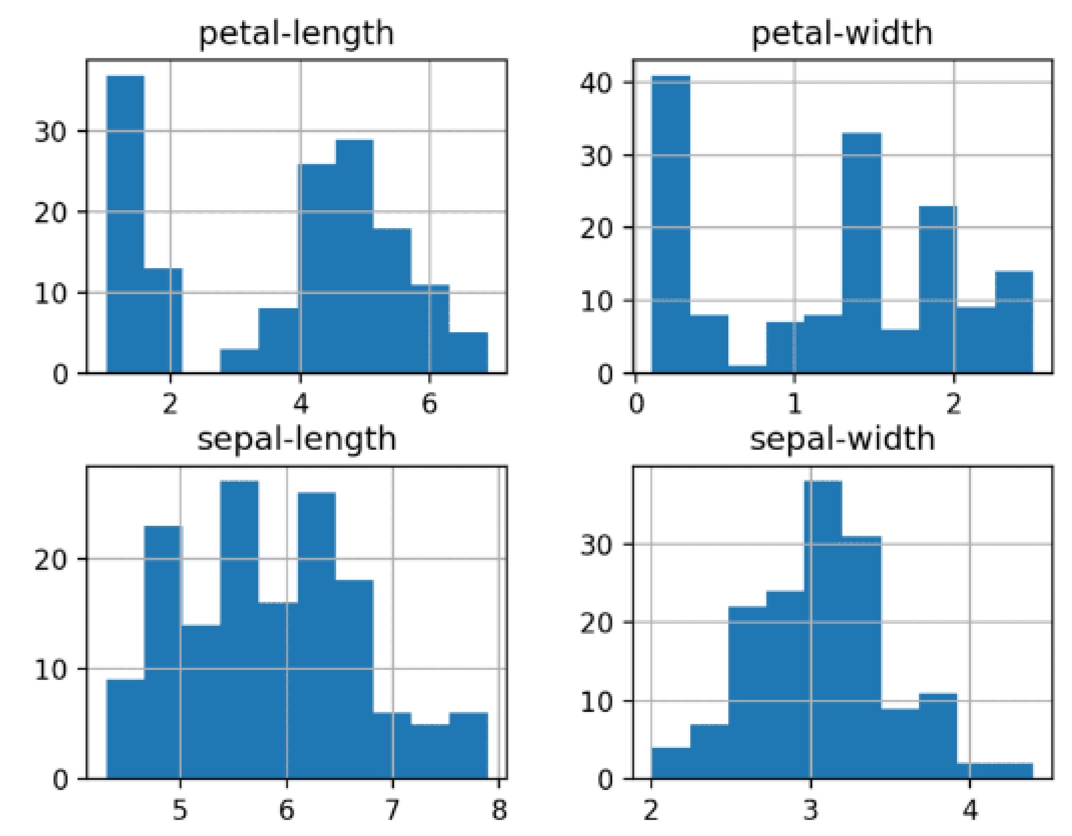


Box and Whisker Plots for Each Input Variable for the Iris Flowers Dataset

We can also create a histogram of each input variable to get an idea of the distribution.

```
...
# histograms
dataset.hist()
pyplot.show()
```

It looks like perhaps two of the input variables have a Gaussian distribution. This is useful to note as we can use algorithms that can exploit this assumption.



Histogram Plots for Each Input Variable for the Iris Flowers Dataset

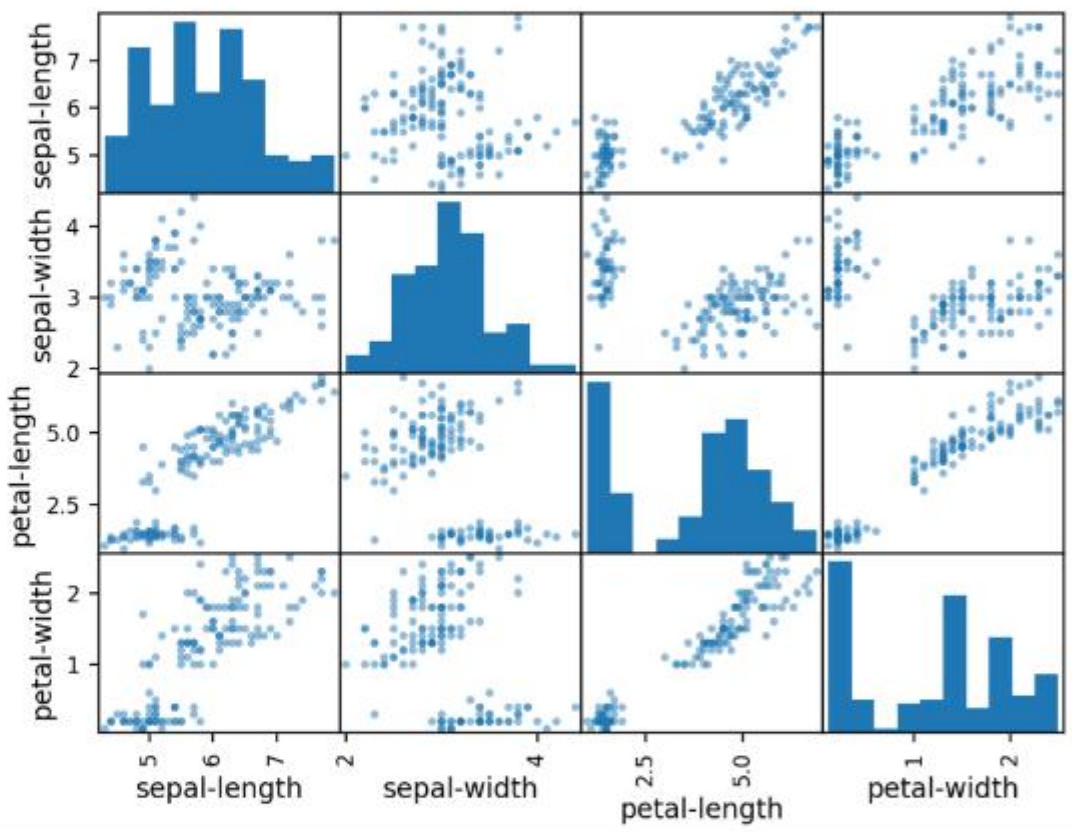
4.2 Multivariate Plots

Now we can look at the interactions between the variables.

First, let's look at scatterplots of all pairs of attributes. This can be helpful to spot structured relationships between input variables.

```
...
# scatter plot matrix
scatter_matrix(dataset)
pyplot.show()
```

Note the diagonal grouping of some pairs of attributes. This suggests a high correlation and a predictable relationship.



Scatter Matrix Plot for Each Input Variable for the Iris Flowers Dataset

4.3 Complete Example

For reference, we can tie all of the previous elements together into a single script. The complete example is listed below.

```python
# visualize the data
from pandas import read_csv
from pandas.plotting import scatter_matrix
from matplotlib import pyplot
# Load dataset
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/iris.csv"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
dataset = read_csv(url, names=names)
# box and whisker plots
dataset.plot(kind='box', subplots=True, layout=(2,2), sharex=False, sharey=False)
pyplot.show()
# histograms
dataset.hist()
pyplot.show()
# scatter plot matrix
scatter_matrix(dataset)
pyplot.show()
```

5. Evaluate Some Algorithms

Now it is time to create some models of the data and estimate their accuracy on unseen data.

Here is what we are going to cover in this step:

1. Separate out a validation dataset.
2. Set-up the test harness to use 10-fold cross validation.
3. Build multiple different models to predict species from flower measurements
4. Select the best model.

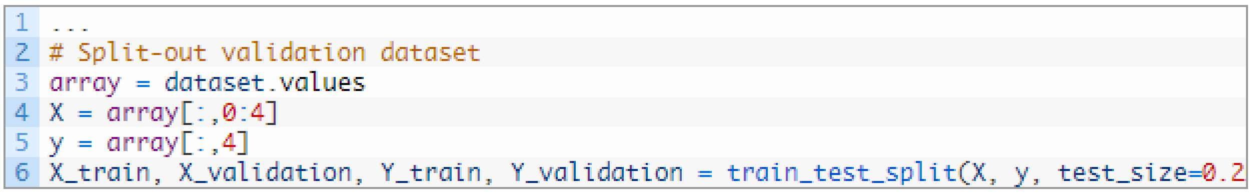
5.1 Create a Validation Dataset

We need to know that the model we created is good.

Later, we will use statistical methods to estimate the accuracy of the models that we create on unseen data. We also want a more concrete estimate of the accuracy of the best model on unseen data by evaluating it on actual unseen data.

That is, we are going to hold back some data that the algorithms will not get to see and we will use this data to get a second and independent idea of how accurate the best model might actually be.

We will split the loaded dataset into two, 80% of which we will use to train, evaluate and select among our models, and 20% that we will hold back as a validation dataset.



```
...
# Split-out validation dataset
array = dataset.values
X = array[:,0:4]
y = array[:,4]
X_train, X_validation, Y_train, Y_validation = train_test_split(X, y, test_size=0.2
```

You now have training data in the *X_train* and *Y_train* for preparing models and a *X_validation* and *Y_validation* sets that we can use later.

Notice that we used a python slice to select the columns in the NumPy array. If this is new to you, you might want to check-out this post:

https://machinelearningmastery.com/index-slice-reshape-numpy-arrays-machine-learning-python/

5.2 Test Harness

We will stratified 10-fold cross validation to estimate model accuracy.

This will split our dataset into 10 parts, train on 9 and test on 1 and repeat for all combinations of train-test splits.

Stratified means that each fold or split of the dataset will aim to have the same distribution of example by class as exist in the whole training dataset.

For more on the k-fold cross-validation technique, see the tutorial: https://machinelearningmastery.com/k-fold-cross-validation/

We set the random seed via the *random_state* argument to a fixed number to ensure that each algorithm is evaluated on the same splits of the training dataset.

The specific random seed does not matter, learn more about pseudorandom number generators here:

https://machinelearningmastery.com/introduction-to-random-number-generators-for-machine-learning/

We are using the metric of '*accuracy*' to evaluate models.

This is a ratio of the number of correctly predicted instances divided by the total number of instances in the dataset multiplied by 100 to give a percentage (e.g. 95% accurate). We will be using the *scoring* variable when we run build and evaluate each model next.

5.3 Build Models

We don't know which algorithms would be good on this problem or what configurations to use.

We get an idea from the plots that some of the classes are partially linearly separable in some dimensions, so we are expecting generally good results.

Let's test 6 different algorithms:

- Logistic Regression (LR)
- Linear Discriminant Analysis (LDA)
- K-Nearest Neighbors (KNN).
- Classification and Regression Trees (CART).
- Gaussian Naive Bayes (NB).
- Support Vector Machines (SVM).

This is a good mixture of simple linear (LR and LDA), nonlinear (KNN, CART, NB and SVM) algorithms.

TASK: add a description (program flowchart) of each algorithm into your report.

Let's build and evaluate our models:

```
...
# Spot Check Algorithms
models = []
models.append(('LR', LogisticRegression(solver='liblinear', multi_class='ovr')))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC(gamma='auto')))
# evaluate each model in turn
results = []
names = []
for name, model in models:
    kfold = StratifiedKFold(n_splits=10, random_state=1, shuffle=True)
    cv_results = cross_val_score(model, X_train, Y_train, cv=kfold, scoring='accur
    results.append(cv_results)
    names.append(name)
    print('%s: %f (%f)' % (name, cv_results.mean(), cv_results.std()))
```

5.4 Select Best Model

We now have 6 models and accuracy estimations for each. We need to compare the models to each other and select the most accurate.

Running the example above, we get the following raw results:

```
LR: 0.960897 (0.052113)
LDA: 0.973974 (0.040110)
KNN: 0.957191 (0.043263)
CART: 0.957191 (0.043263)
NB: 0.948858 (0.056322)
SVM: 0.983974 (0.032083)
```

Note: Your results may vary (see the reason: https://machinelearningmastery.com/different-results-each-time-in-machine-learning/) given the stochastic nature of the algorithm or evaluation procedure, or differences in numerical precision. Consider running the example a few times and compare the average outcome.

In this case, we can see that it looks like Support Vector Machines (SVM) has the largest estimated accuracy score at about 0.98 or 98%.

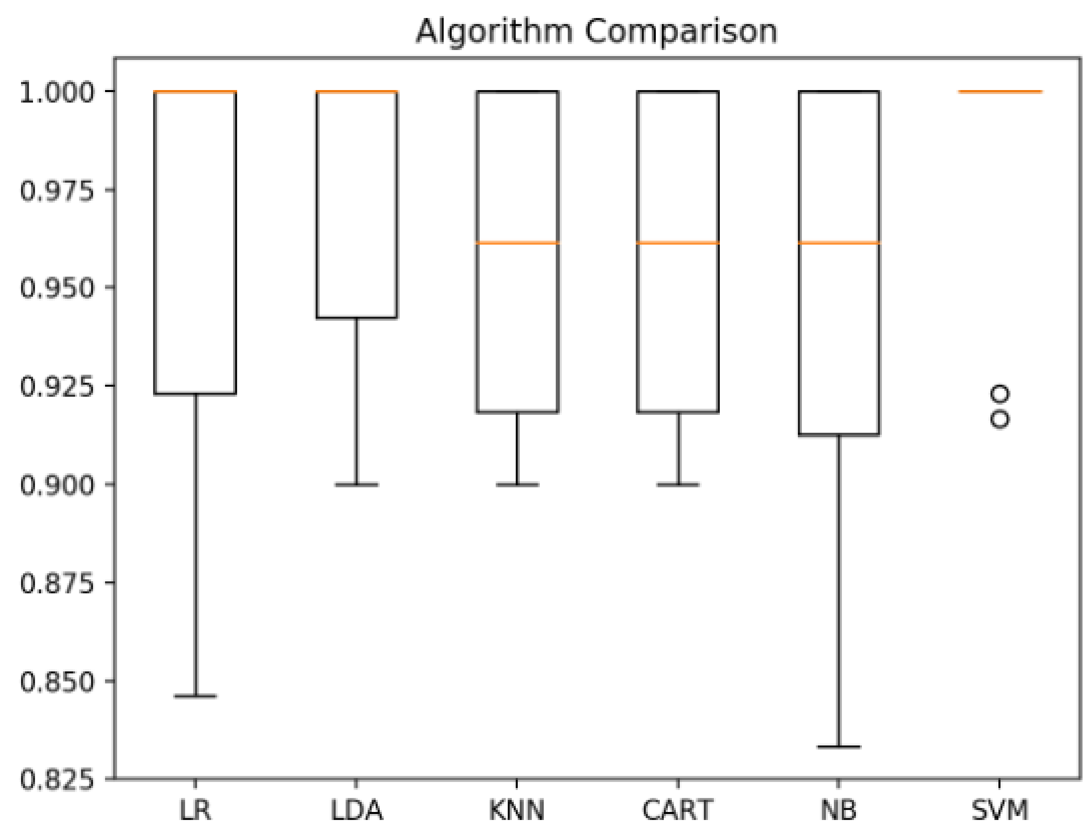
Add your own results into the report.

We can also create a plot of the model evaluation results and compare the spread and the mean accuracy of each model. There is a population of accuracy measures for each algorithm because each algorithm was evaluated 10 times (via 10 fold-cross validation).

A useful way to compare the samples of results for each algorithm is to create a box and whisker plot for each distribution and compare the distributions.

```
...
# Compare Algorithms
pyplot.boxplot(results, labels=names)
pyplot.title('Algorithm Comparison')
pyplot.show()
```

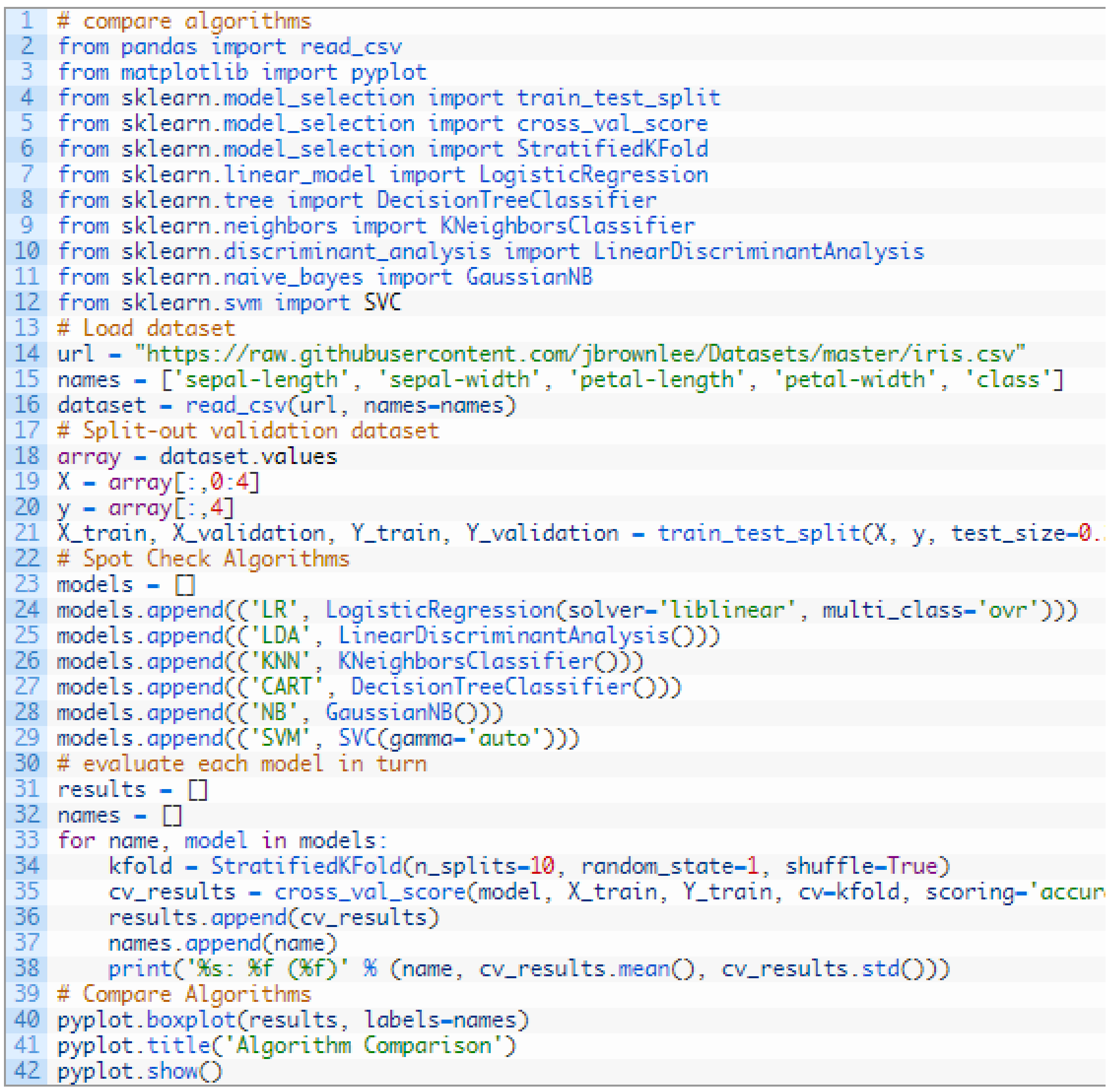
We can see that the box and whisker plots are squashed at the top of the range, with many evaluations achieving 100% accuracy, and some pushing down into the high 80% accuracies.



Box and Whisker Plot Comparing Machine Learning Algorithms on the Iris Flowers Dataset

5.5 Complete Example

For reference, we can tie all of the previous elements together into a single script. The complete example is listed below



```
# compare algorithms
from pandas import read_csv
from matplotlib import pyplot
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import StratifiedKFold
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
# Load dataset
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/iris.csv"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
dataset = read_csv(url, names=names)
# Split-out validation dataset
array = dataset.values
X = array[:,0:4]
y = array[:,4]
X_train, X_validation, Y_train, Y_validation = train_test_split(X, y, test_size=0.
# Spot Check Algorithms
models = []
models.append(('LR', LogisticRegression(solver='liblinear', multi_class='ovr')))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC(gamma='auto')))
# evaluate each model in turn
results = []
names = []
for name, model in models:
    kfold = StratifiedKFold(n_splits=10, random_state=1, shuffle=True)
    cv_results = cross_val_score(model, X_train, Y_train, cv=kfold, scoring='accur
    results.append(cv_results)
    names.append(name)
    print('%s: %f (%f)' % (name, cv_results.mean(), cv_results.std()))
# Compare Algorithms
pyplot.boxplot(results, labels=names)
pyplot.title('Algorithm Comparison')
pyplot.show()
```

6. Make Predictions

We must choose an algorithm to use to make predictions.

The results in the previous section suggest that the SVM was perhaps the most accurate model. We will use this model as our final model.

Now we want to get an idea of the accuracy of the model on our validation set.

This will give us an independent final check on the accuracy of the best model. It is valuable to keep a validation set just in case you made a slip during training, such as overfitting to the training set or a data leak. Both of these issues will result in an overly optimistic result.

6.1 Make Predictions

We can fit the model on the entire training dataset and make predictions on the validation dataset.

```
...
# Make predictions on validation dataset
model = SVC(gamma='auto')
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
```

You might also like to make predictions for single rows of data. For examples on how to do that, see the tutorial:

https://machinelearningmastery.com/make-predictions-scikit-learn/

You might also like to save the model to file and load it later to make predictions on new data. For examples on how to do this, see the tutorial:

https://machinelearningmastery.com/save-load-machine-learning-models-python-scikit-learn/

6.2 Evaluate Predictions

We can evaluate the predictions by comparing them to the expected results in the validation set, then calculate classification accuracy, as well as a confusion matrix and a classification report.

```
....
# Evaluate predictions
print(accuracy_score(Y_validation, predictions))
print(confusion_matrix(Y_validation, predictions))
print(classification_report(Y_validation, predictions))
```

We can see that the accuracy is 0.966 or about 96% on the hold out dataset.

The confusion matrix provides an indication of the errors made.

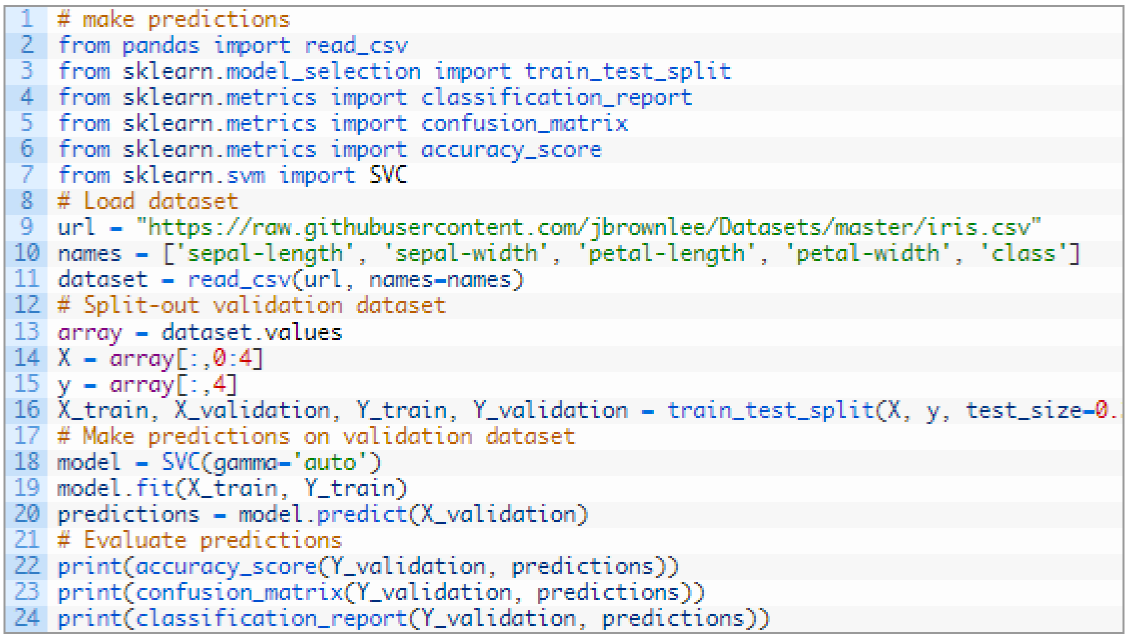
Finally, the classification report provides a breakdown of each class by precision, recall, f1-score and support showing excellent results (granted the validation dataset was small).

```
0.9666666666666667
[[11  0  0]
 [ 0 12  1]
 [ 0  0  6]]
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        11
Iris-versicolor       1.00      0.92      0.96        13
 Iris-virginica       0.86      1.00      0.92         6

       accuracy                           0.97        30
      macro avg       0.95      0.97      0.96        30
   weighted avg       0.97      0.97      0.97        30
```

6.3 Complete Example

For reference, we can tie all of the previous elements together into a single script.

The complete example is listed below.



```
# make predictions
from pandas import read_csv
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.svm import SVC
# Load dataset
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/iris.csv"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
dataset = read_csv(url, names=names)
# Split-out validation dataset
array = dataset.values
X = array[:,0:4]
y = array[:,4]
X_train, X_validation, Y_train, Y_validation = train_test_split(X, y, test_size=0.
# Make predictions on validation dataset
model = SVC(gamma='auto')
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
# Evaluate predictions
print(accuracy_score(Y_validation, predictions))
print(confusion_matrix(Y_validation, predictions))
print(classification_report(Y_validation, predictions))
```

Conclusion:

The main features of the problem:

- Attributes are numeric so you have to figure out how to load and handle data.
- It is a classification problem, allowing you to practice with perhaps an easier type of supervised learning algorithm.
- It is a multi-class classification problem (multi-nominal) that may require some specialized handling.
- It only has 4 attributes and 150 rows, meaning it is small and easily fits into memory (and a screen or A4 page).
- All of the numeric attributes are in the same units and the same scale, not requiring any special scaling or transforms to get started.