Python for Machine Learning

CMPT 498/820 Machine Learning
Tutorial 2

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1 Python for Machine Learning

In this tutorial we will be exploring a few Python packages useful for Machine Learning such as NumPy, SciPy, Matplotlib, Pandas and Scikit-learn.

1.1 NumPy

NumPy facilitates fast N-dimensional array creation, storage and manipulation. Here is the link to NumPy reference: http://docs.scipy.org/doc/numpy/user/index.html

1.1.1 Array Creation

```
In [1]: import numpy as np
        a=np.array([[1,2,3],[4,5,6],[7,8,9]])
        b=np.random.rand(5,1)
        c=np.zeros(shape = (5,2))
        a.T

Out[1]: array([[1, 4, 7],
               [2, 5, 8],
               [3, 6, 9]])

In [2]: a[0:2,1:3]

Out[2]: array([[2, 3],
               [5, 6]])
```

1.1.2 Products

```
In [3]: a=np.ones((3,3))
        b=np.random.rand(3,3)
        c=a+b
        c

Out[3]: array([[ 1.04350635,  1.83046985,  1.06401223],
               [ 1.68674648,  1.87059108,  1.47546437],
               [ 1.3589277 ,  1.91574952,  1.2485366 ]])
```

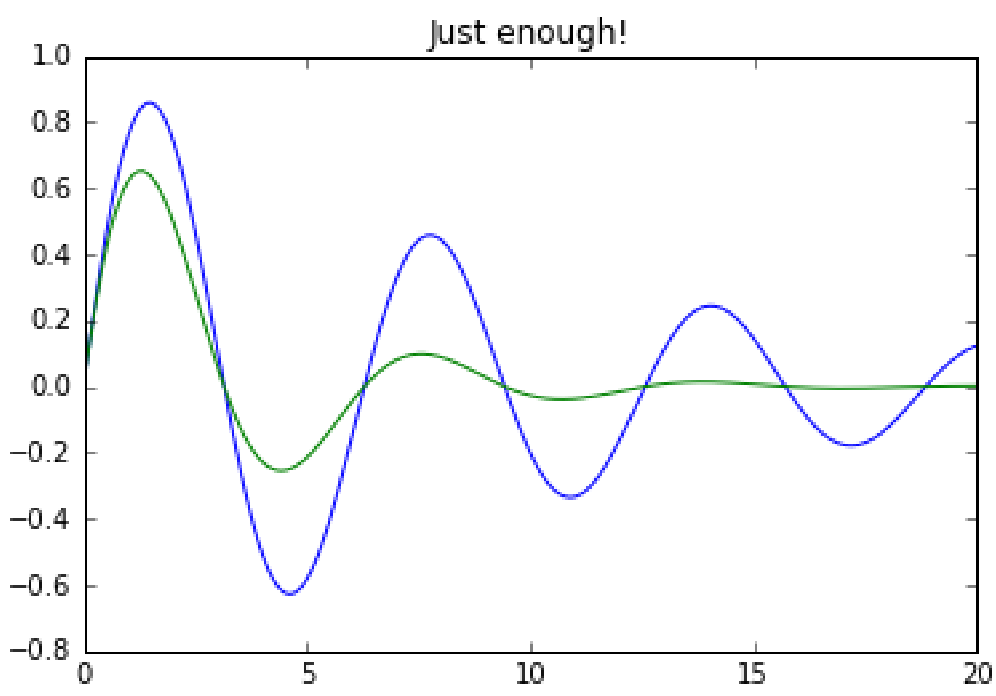
```
In [4]: a = np.ones( (3,2) )
        b = np.array([1,2])
        print('shape of a', a.shape)
        print('shape of b', b.shape)

        p = a.dot(b)
        print('shape of p', p.shape)
        print(p)
```

```
shape of a (3, 2)
shape of b (2,)
shape of p (3,)
[ 3.  3.  3.]
```

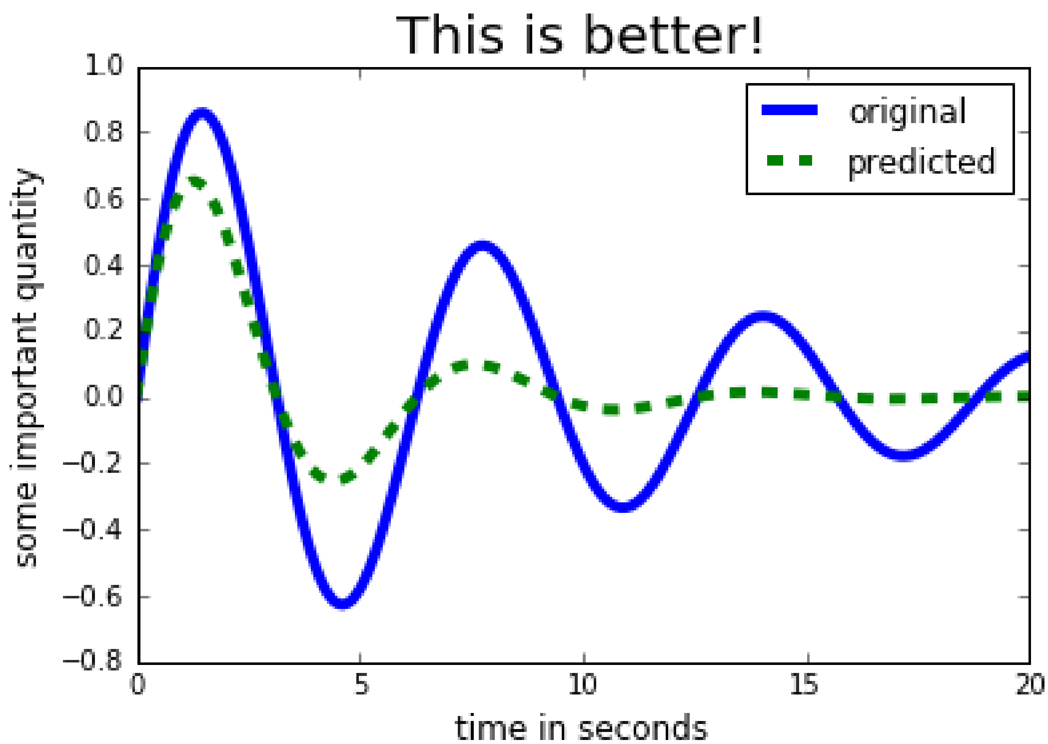
1.2 Matplotlib

Visualization of data plays a key role in Machine Learning; Python's functionality for plotting data resides in the Matplotlib package.

```
In [5]: %matplotlib inline
        from matplotlib import pyplot as plt
        x=np.linspace(0,20,200)
        y1=np.exp(-0.1*x)*np.sin(x)
        y2=np.exp(-0.3*x)*np.sin(x)
        plt.plot(x,y1)
        plt.plot(x,y2)
        plt.title('Just enough!')
        plt.show()
```



```
In [6]: plt.plot(x,y1, label='original' ,linewidth=4, linestyle='-')
        plt.plot(x,y2, label='predicted',linewidth=4, linestyle='--')
        plt.xlabel('time in seconds',fontsize=12)
        plt.ylabel(r'some important quantity',fontsize=12)
        plt.title('This is better!',fontsize=20)
        plt.legend()
        plt.show()
```



1.3 SciPy

- A collection of mathematical algorithms
- Gives Python similar capabilities as Matlab
- Many submodules are used for different domains
- We will see examples from `linalg` and `optimize` submodules
- For details: http://docs.scipy.org/doc/scipy/reference/tutorial/index.html

1.3.1 `linalg`: Linear Algebra submodule

Linear algebra submodule provides several routines for matrix computations. For example to find the inverse of matrix A

$$A = \begin{bmatrix} 5 & 3 & 5 \\ 2 & 2 & 0 \\ 1 & 3 & 1 \end{bmatrix}$$

```
In [7]: from scipy import linalg as la
        A = np.array([
                      [5,3,5], \
                      [2,2,0], \
                      [1,3,1]])
        iA = la.inv(A)
        print(iA)
```

```
[[ 0.08333333  0.5        -0.41666667]
 [-0.08333333  0.          0.41666667]
 [ 0.16666667 -0.5         0.16666667]]
```

Solving linear systems of equations

$$Ax = b$$

$$\begin{bmatrix} 5 & 3 & 5 \\ 2 & 2 & 0 \\ 1 & 3 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 2 \\ 5 \\ 1 \end{bmatrix}$$

```
In [8]: A = np.array([
                      [5,3,5], \
                      [2,2,0], \
                      [1,3,1]])
        b = np.array([ 2, 5, 1])
        x = la.solve(A,b)
        print('Solution:', x)
        # x = la.inv(A).dot(b) # same result
```

```
Solution: [ 2.25  0.25 -2.  ]
```

Matrix Decomposition

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} = \begin{bmatrix} l_{11} & 0 & 0 \\ l_{21} & l_{22} & 0 \\ l_{31} & l_{32} & l_{33} \end{bmatrix} \begin{bmatrix} u_{11} & u_{12} & u_{13} \\ 0 & u_{22} & u_{23} \\ 0 & 0 & u_{33} \end{bmatrix}$$

```
In [9]: p,l,u = la.lu(A,permute_l=False)
        print('L = \n',l)
        print('U = \n',u)
```

```
L =
 [[ 1.          0.          0.        ]
 [ 0.2         1.          0.        ]
 [ 0.4         0.33333333  1.        ]]
```

```
U =
 [[ 5.    3.    5. ]
 [ 0.    2.4   0. ]
 [ 0.    0.   -2. ]]
```

1.3.2 **`optimize`**: Optimization submodule

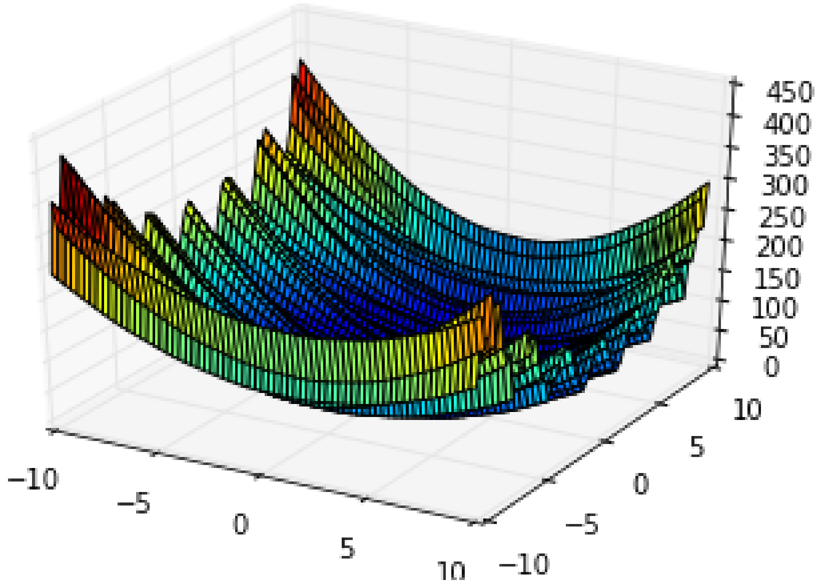
`optimize` implements several optimization algorithms. Optimization is finding the minimum or maximum value of a function. In this demonstration we will find the minimum of the `Levy` function:

$$f(x,y) = \sin^2(3\pi x) + (x-1)^2\left(1+\sin^2(3\pi y)\right) + (y-1)^2\left(1+\sin^2(2\pi y)\right) + (y-1)^2\left(1+\sin^2(2\pi y)\right)$$

```
In [10]: def obj(x):
             f = (np.sin(3*np.pi*x[0]))**2  +\
                 (x[0]-1)**2 * (1+(np.sin(3*np.pi*x[1]))**2) +\
                 (x[1]-1)**2 * (1+(np.sin(2*np.pi*x[1]))**2)
             #f=x[0]**2 + x[1]**2
             return f
```

1.3.3 Visualizing the objective function

```
In [11]: # Just for the visualization
         def obj1(x,y):
             f = (np.sin(3*np.pi*x))**2  +\
                 (x-1)**2 * (1+(np.sin(3*np.pi*y))**2) +\
                 (y-1)**2 * (1+(np.sin(2*np.pi*y))**2)
             #f=x**2 + y**2
             return f

         from mpl_toolkits.mplot3d import Axes3D
         from matplotlib import cm
         fig = plt.figure()
         ax = fig.gca(projection='3d')
         X = np.arange(-10, 10, 0.3)
         Y = np.arange(-10, 10, 0.3)
         X, Y = np.meshgrid(X, Y)
         Z = obj1(X,Y)
         surf = ax.plot_surface(X, Y, Z, cmap=cm.jet, rstride=1, cstride=1 )
         plt.show()
```



1.3.4 Minimizing the objective function

```
In [12]: # minimizing function
         from scipy import optimize as opt
         res = opt.minimize(obj, x0=[0.85,1.2], method='nelder-mead', options={'max
         print('Minimum value: ',res.fun)
         print('At x: ',res.x)
         print('Analitical global minimum is at x = [1, 1] with value 0')
```

```
Minimum value:  9.26705706273e-10
At x:  [ 1.0000027   1.00001646]
Analitical global minimum is at x = [1, 1] with value 0
```

1.4 Pandas

`pandas` provides easy-to-use data structures and data analysis tools for Python. A good reference for Pandas is the cookbook available at: http://pandas.pydata.org/pandas-docs/stable/cookbook.html

The design matrix contains features as columns and examples as rows. In `pandas` jargon the design matrix is called a data frame; the examples are called series.

$$D = \begin{pmatrix} & length & width & \cdots & type \\ S_1 & 80 & 25 & \cdots & 0 \\ S_2 & 130 & 65 & \cdots & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ S_m & 110 & 29 & \cdots & 0 \end{pmatrix}$$

1.4.1 Data Frame Creation

```
In [13]: import pandas as pd
         from matplotlib import pyplot as plt
         #url='http://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.c
         #df=pd.read_csv(url)
         #df = pd.DataFrame(data,columns=['x','y','C'])

         df=pd.read_csv('iris.data')
         df.columns=['sepal_length','sepal_width','petal_length','petal_width','flo
         df['flower_type'] = df['flower_type'].astype('category')
         df.flower_type = df.flower_type.cat.rename_categories([0,1,2])
```

1.4.2 Basic Analysis

```
In [14]: df.head()
```

```
Out[14]:    sepal_length  sepal_width  petal_length  petal_width flower_type
         0           4.9          3.0           1.4          0.2           0
         1           4.7          3.2           1.3          0.2           0
         2           4.6          3.1           1.5          0.2           0
         3           5.0          3.6           1.4          0.2           0
         4           5.4          3.9           1.7          0.4           0
```

```
In [15]: df.dtypes
```

```
Out[15]: sepal_length     float64
         sepal_width      float64
         petal_length     float64
         petal_width      float64
         flower_type     category
         dtype: object
```

```
In [16]: df.describe()
```

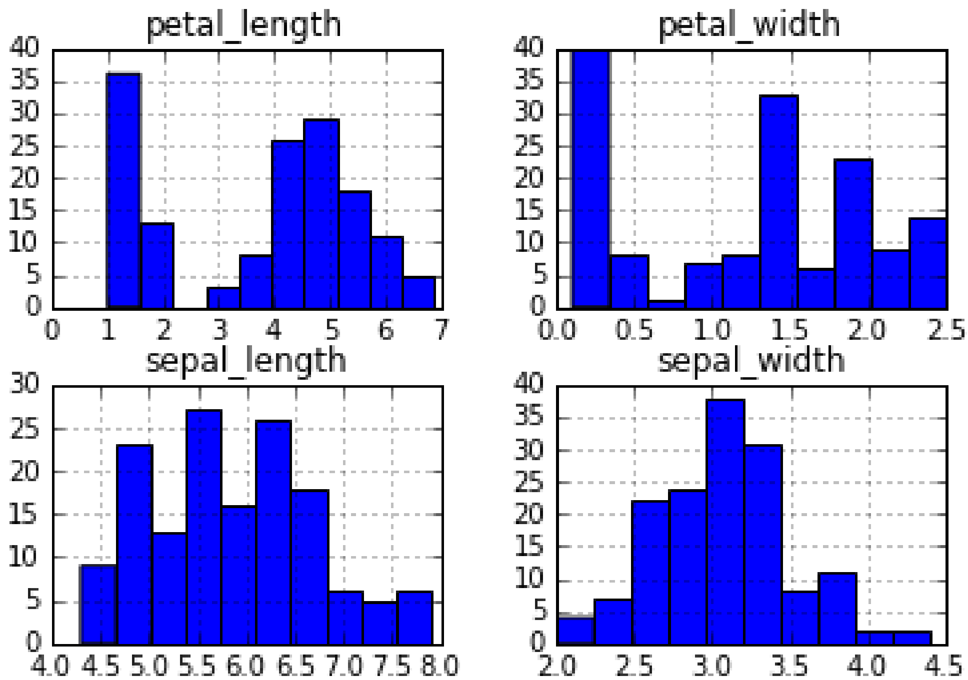
```
Out[16]:        sepal_length  sepal_width  petal_length  petal_width
         count    149.000000   149.000000    149.000000   149.000000
         mean       5.848322     3.051007      3.774497     1.205369
         std        0.828594     0.433499      1.759651     0.761292
         min        4.300000     2.000000      1.000000     0.100000
         25%        5.100000     2.800000      1.600000     0.300000
         50%        5.800000     3.000000      4.400000     1.300000
         75%        6.400000     3.300000      5.100000     1.800000
         max        7.900000     4.400000      6.900000     2.500000
```

```
In [17]: df['flower_type'].describe()
```

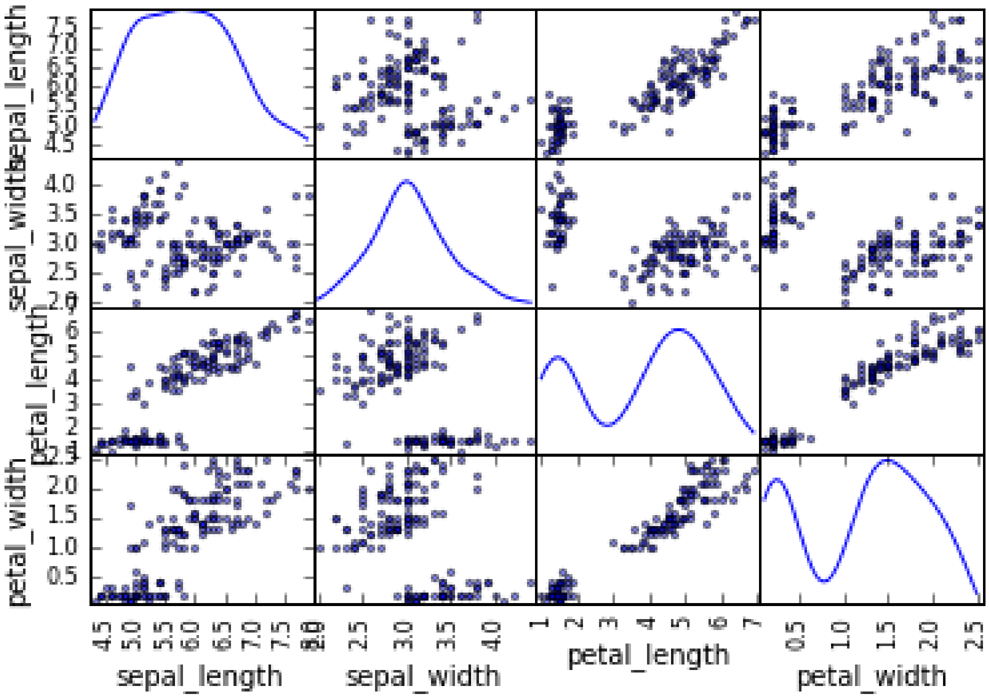
```
Out[17]: count     149
         unique      3
         top         2
         freq       50
         Name: flower_type, dtype: int64
```

1.4.3 Data Frame Visualization

In [18]:
```
df.hist()
plt.show()
```



In [19]:
```
pd.scatter_matrix(df, diagonal='kde')
plt.show()
```



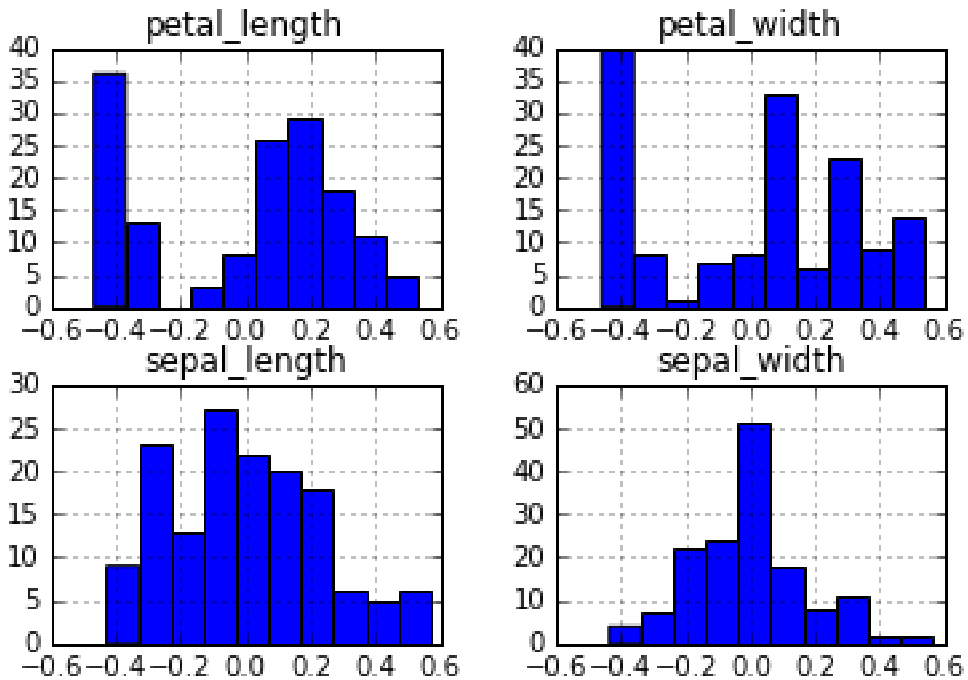
1.4.4 Operations on the Data Frame

```
In [20]: df = df.sort_values(by='sepal_width')
         df.head()
```

Out[20]:

	sepal_length	sepal_width	petal_length	petal_width	flower_type
59	5.0	2.0	3.5	1.0	1
61	6.0	2.2	4.0	1.0	1
118	6.0	2.2	5.0	1.5	2
67	6.2	2.2	4.5	1.5	1
92	5.0	2.3	3.3	1.0	1

```
In [21]: # Normalizing your data set
         df=df.ix[:,0:4].apply( lambda f: ( f - f.mean() )/( f.max() - f.min() ) )

         df.hist()
         plt.show()
```




```
In [22]: # Get a random sample from the data set
         df=df.sample(frac=1.0)
         df.head()
```

Out[22]:

	sepal_length	sepal_width	petal_length	petal_width
41	-0.402312	0.062081	-0.419406	-0.418904
127	0.153244	-0.104586	0.309407	0.372763
78	-0.041201	-0.187919	-0.046525	-0.085570
147	0.097688	0.145414	0.275509	0.456096
132	0.125466	-0.104586	0.224662	0.122763

```
In [23]: # Split the data set into test and train set
         train=df.sample(frac=0.8,random_state=123)
         test=df.drop(train.index)
```

1.4.5 Read/Write

```
In [24]: df.to_csv('iris_normalized.csv')
         new_df = pd.read_csv('iris_normalized.csv')
```

1.5 scikit-learn

A level above SciPy is Scikit-learn that implements many classification, regression and clustering algorithms. For details: http://scikit-learn.org/stable/tutorial/basic/tutorial.html

1.5.1 Import the dataset

```
In [25]: from sklearn import svm
         from sklearn import datasets
         iris = datasets.load_iris()
         X, y = iris.data, iris.target
```

1.5.2 Train the classifier

```
In [26]: clf = svm.SVC()
         clf.fit(X, y)

Out[26]: SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
           decision_function_shape=None, degree=3, gamma='auto', kernel='rbf',
           max_iter=-1, probability=False, random_state=None, shrinking=True,
           tol=0.001, verbose=False)
```

1.5.3 Make prediction

```
In [27]: clf.predict(iris.data[range(0,150,25)])

Out[27]: array([0, 0, 1, 1, 2, 2])

In [28]: iris.target[range(0,150,25)]

Out[28]: array([0, 0, 1, 1, 2, 2])
```