In [1]:
```
# Import the necessary libraries.

import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import seaborn as sns
```

The Iris Dataset: https://en.wikipedia.org/wiki/Iris_flower_data_set

This dataset consists of data collected on 150 Iris flowers, 50 from each of three types: Setosa, Versicolour, and Virginica. For each flower in the dataset we have its Iris type, its petal and sepal length and width. The goal of this assignment is to create a model that learns the type of Iris based on its petal and sepal length and width.

In [2]:
```
# Import the Iris dataset from the sklearn library.
# The organisation of the data in the sklearn library is described at https://scikit-learn.org/stable/auto_exam

from sklearn.datasets import load_iris
iris_dataset = load_iris()

#Check the "keys" (column names) of the dataset
print("Components of the Iris dataset:\n", iris_dataset.keys())
```

```
Components of the Iris dataset:
 dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names', 'filename', 'data_module'])
```

In [3]:
```
# Check the component "data"
print('The type of the feature "data" is',type(iris_dataset['data']))
print('The shape of the "data" is',iris_dataset['data'].shape)
print("Check the first five rows of data:\n", iris_dataset['data'][:5])
```

```
The type of the feature "data" is <class 'numpy.ndarray'>
The shape of the "data" is (150, 4)
Check the first five rows of data:
 [[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]]
```

In [4]:
```
# Check the component "target"
print('The type of feature "target" is',type(iris_dataset['target']))
print('The shape of the "target" is',iris_dataset['target'].shape)
print('Check the first five targets:', iris_dataset['target'][:5])
print('Check the distinct values of "target":', np.unique(iris_dataset['target']))
```

```
The type of feature "target" is <class 'numpy.ndarray'>
The shape of the "target" is (150,)
Check the first five targets: [0 0 0 0 0]
Check the distinct values of "target": [0 1 2]
```

We conclude that "target" is a vector with 150 entries, one for each of the corresponding rows in "data". There is a numerical (categorical) encoding for the type of Iris of the flower described in that data point.

In [5]:
```
# Check the component "target_names"
print('The type of feature "target_names" is',type(iris_dataset['target_names']))
print('The shape of the "target_names" is',iris_dataset['target_names'].shape)
print('Check the values of "target_names":', iris_dataset['target_names'])
```

```
The type of feature "target_names" is <class 'numpy.ndarray'>
The shape of the "target_names" is (3,)
Check the values of "target_names": ['setosa' 'versicolor' 'virginica']
```

In [6]:
```
# Check the component "feature_names"
print('The type of feature "feature_names" is',type(iris_dataset['feature_names']))
print('Check the values of "feature_names":', iris_dataset['feature_names'])
```

```
The type of feature "feature_names" is <class 'list'>
Check the values of "feature_names": ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal widt
h (cm)']
```

Data exploration

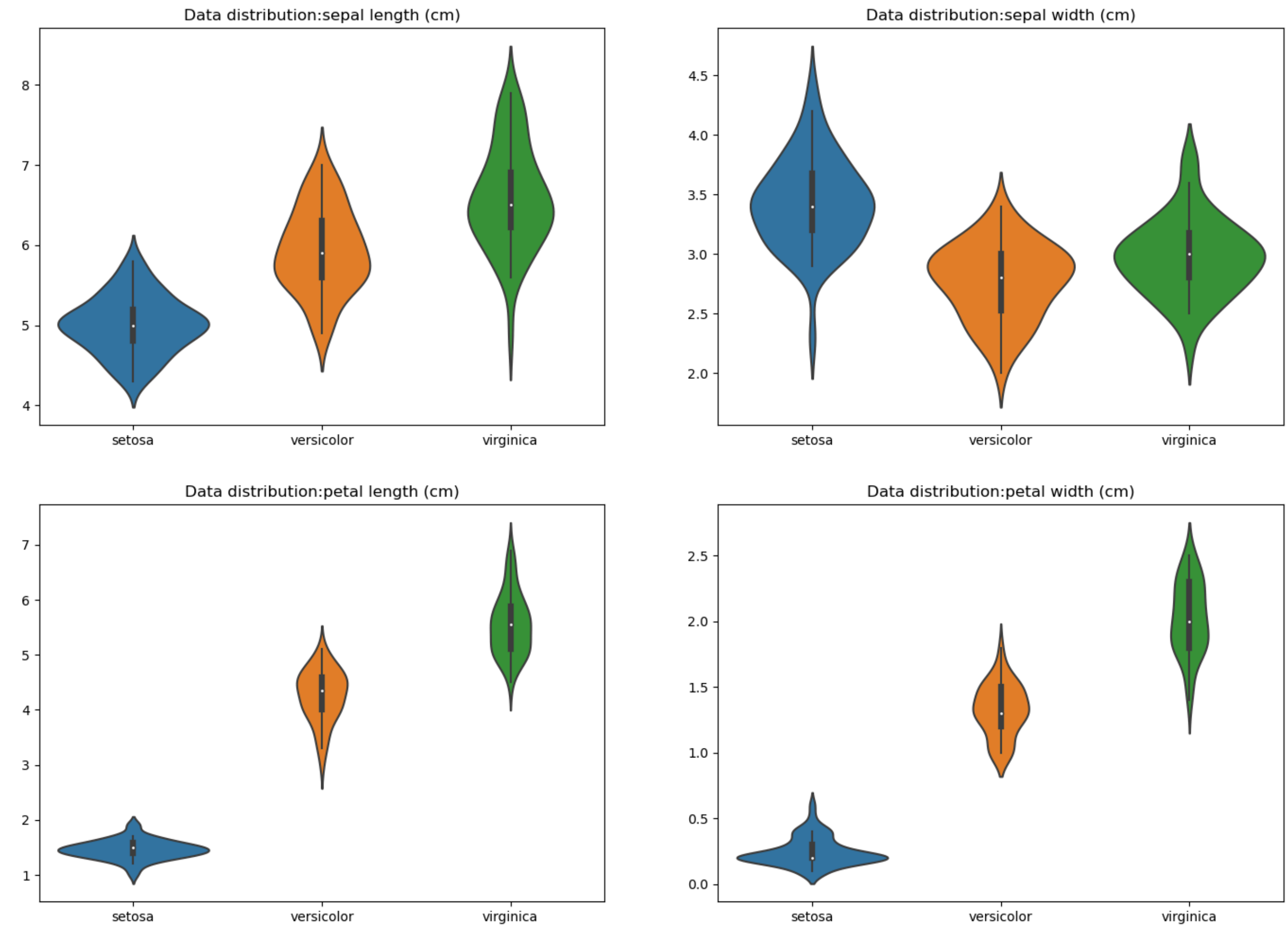
Visualization code adapted from: https://www.kaggle.com/code/kostasmar/exploring-the-iris-data-set-scikit-learn

In [7]:
```
# Just for visualisation purposes we will use the Iris type names, rather than their numerical encoding
iris_dataset_target_n = iris_dataset['target'].astype(str)
for i in range(3):
    iris_dataset_target_n[iris_dataset_target_n == str(i)] = iris_dataset['target_names'][i]

# The plotting function: a violin plot of the data, one feature at a time, grouped by the Iris type
```

```python
def plot_violin(feature, plot_location):
    ax = plt.subplot(2,2,plot_location)
    ax.set(title='Data distribution:'+iris_dataset['feature_names'][feature])
    sns.violinplot(
        #x=iris_dataset['target'],
        x=iris_dataset_target_n,
        y=iris_dataset['data'][:,feature],
        palette = sns.color_palette('tab10', n_colors=3),
        hue = iris_dataset_target_n,
    )

# Plot the violin plots, for each of the 4 features
plt.figure(figsize=(17,12))
plot_location = 1
for feature in range(4):
    plot_violin(feature, plot_location)
    plot_location += 1
```



We conclude, especially based on the lower 2 plots, that the 3 classes can be differentiated from each other. So machine learning has a good chance of succeeding on this dataset.

Prepare for the machine learning phase: split the data into train/validation/test 60/20/20

In [8]:
```python
# Reset the seed of the random number generator, for reproducibility purposes
np.random.seed(2023)
```

In [9]:
```python
# First split the data into 20% for the testing data and 80% for the training and validation.
# The data is split in a stratified fashion:
#       the three classes contribute proportionally to the train and the test datasets

from sklearn.model_selection import train_test_split

X_train_valid, X_test, y_train_valid, y_test = train_test_split(
    iris_dataset['data'],
    iris_dataset['target'],
    test_size=0.20,
    shuffle=True,
    random_state=100,
    stratify=iris_dataset['target']
)
```

In [10]:
```python
# Check the split
```

```
print("X_train_valid shape:", X_train_valid.shape)
print("y_train_valid shape:", y_train_valid.shape)
print("X_test shape:", X_test.shape)
print("y_test shape:", y_test.shape)
```

```
X_train_valid shape: (120, 4)
y_train_valid shape: (120,)
X_test shape: (30, 4)
y_test shape: (30,)
```

Data very often should be normalised and/or scaled to help the learning of the model. This is the right place to normalise/scale the train data, after the split is done, to avoid any data leakage. The exact same normalisation/scaling must be applied separately to the validation and to the test data.

In our case, we scale each of the features to the [0, 1] range. Other choices may also work fine.

In [11]:

```
from sklearn.preprocessing import MinMaxScaler

min_max_scaler = MinMaxScaler()
min_max_scaler = min_max_scaler.fit(X_train)
X_train = min_max_scaler.transform(X_train)
```

Train your first model: decision tree

A decision tree is a simple machine learning model that aims to classify datapoints through a series of "decisions". The yes/no outcome of each decision can be seen as a binary tree, and more decisions can be taken further down on the tree. We only use on this dataset a decision tree of depth at most 2, in other words we aim to classify the Irises through two consequetive questions/decision on their feature.

Decision trees will be discussed in details later in the course.

In [12]:

```
from sklearn import tree

clf2 = tree.DecisionTreeClassifier(
    criterion="gini",
    max_depth=2,
    random_state=2023
)

clf2.fit(X_train, y_train)
```

Out[15]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=2, random_state=2023)
```

Evaluating the Model

In [13]:

```
#Test the performance on the train data
print("Model score on the training data: {:.2f}".format(clf2.score(X_train, y_train)))

y_pred_train = clf2.predict(X_train)
print("Predictions on the training set:\n", y_pred_train)
print("Real labels:\n", y_train)
```

```
Model score on the training data: 0.98
Predictions on the training set:
 [1 0 0 0 0 0 0 2 0 2 0 1 2 0 1 2 2 2 2 0 0 1 2 2 0 1 1 2 2 2 2 2 0 1 2 1 1
 2 1 2 1 1 1 1 0 1 1 2 0 1 2 1 2 2 0 1 1 0 1 1 1 0 2 2 2 0 1 1 0 0 1 2 2 0
 2 0 2 2 0 2 0 0 1 2 0 0 0 2 1 0]
Real labels:
 [1 0 0 0 0 0 0 2 0 2 0 1 2 0 1 2 2 2 2 0 0 1 2 2 0 1 1 1 2 2 2 1 0 1 2 1 1
 2 1 2 1 1 1 1 0 1 1 2 0 1 2 1 2 2 0 1 1 0 1 1 1 0 2 2 2 0 1 1 0 0 1 2 2 0
 2 0 2 2 0 2 0 0 1 2 0 0 0 2 1 0]
```

We conclude that the model has an excellent performance on the training dataset with 98% accuracy. Let's check its performance on the validation dataset.

In [14]:

```
#Test the performance on the validation data
print("Model score on the validation data: {:.2f}".format(clf2.score(X_valid, y_valid)))

y_pred_valid = clf2.predict(X_valid)
print("Predictions on the validation set:\n", y_pred_valid)
print("Real labels:\n", y_valid)
```

```
Model score on the validation data: 0.33
Predictions on the validation set:
 [2 2 1 2 1 1 2 2 2 1 2 1 2 1 2 2 2 2 2 1 2 1 1 2 2 2 2 1 2 2]
Real labels:
 [1 1 0 2 0 0 2 1 1 0 2 0 1 0 1 2 2 2 1 0 2 0 0 1 2 2 1 0 1 2]
```