Creado por:

Isabel Maniega

IRIS DATASET: ¿Qué es?

Es un set de datos muy típico en Machine Learning para principiantes

-1- Obtención de Datos:

-1.1.- Una posible forma

In [ ]:
```
# Nos vamos a este Link:
# https://archive.ics.uci.edu/ml/datasets/iris

# Download: Data Folder, Data Set Description
# Nos iríamos a: Data Folder
# y ahí obtenemos la data.
```

In [ ]:
```
"""
INFORMACIÓN OBTENIDA DEL LINK ANTERIOR

Attribute Information:

1. sepal length in cm
2. sepal width in cm
3. petal length in cm
4. petal width in cm
5. class:
-- Iris Setosa
-- Iris Versicolour
-- Iris Virginica
"""
```

-1.2.- Otra posible forma de obtener los datos

In [ ]:
```
# 2ª forma de obtener el dataset:

# http://scikit-learn.org/stable/modules/generated/sklearn.datasets.load_iris.html#sklearn.datasets.load_iris
```

In [1]:
```
from sklearn import datasets

iris = datasets.load_iris()
iris
```

Out[1]:
```
{'data': array([[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],
        [5.4, 3.9, 1.7, 0.4],
        [4.6, 3.4, 1.4, 0.3],
        [5. , 3.4, 1.5, 0.2],
        [4.4, 2.9, 1.4, 0.2],
        [4.9, 3.1, 1.5, 0.1],
        [5.4, 3.7, 1.5, 0.2],
        [4.8, 3.4, 1.6, 0.2],
        [4.8, 3. , 1.4, 0.1],
        [4.3, 3. , 1.1, 0.1],
        [5.8, 4. , 1.2, 0.2],
        [5.7, 4.4, 1.5, 0.4],
        [5.4, 3.9, 1.3, 0.4],
        [5.1, 3.5, 1.4, 0.3],
        [5.7, 3.8, 1.7, 0.3],
        [5.1, 3.8, 1.5, 0.3],
        [5.4, 3.4, 1.7, 0.2],
        [5.1, 3.7, 1.5, 0.4],
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        [4.8, 3.4, 1.9, 0.2],
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        [4.7, 3.2, 1.6, 0.2],
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        [5.5, 4.2, 1.4, 0.2],
        [4.9, 3.1, 1.5, 0.2],
        [5. , 3.2, 1.2, 0.2],
        [5.5, 3.5, 1.3, 0.2],
        [4.9, 3.6, 1.4, 0.1],
        [4.4, 3. , 1.3, 0.2],
        [5.1, 3.4, 1.5, 0.2],
        [5. , 3.5, 1.3, 0.3],
        [4.5, 2.3, 1.3, 0.3],
        [4.4, 3.2, 1.3, 0.2],
        [5. , 3.5, 1.6, 0.6],
        [5.1, 3.8, 1.9, 0.4],
        [4.8, 3. , 1.4, 0.3],
        [5.1, 3.8, 1.6, 0.2],
        [4.6, 3.2, 1.4, 0.2],
        [5.3, 3.7, 1.5, 0.2],
        [5. , 3.3, 1.4, 0.2],
        [7. , 3.2, 4.7, 1.4],
        [6.4, 3.2, 4.5, 1.5],
        [6.9, 3.1, 4.9, 1.5],
        [5.5, 2.3, 4. , 1.3],
        [6.5, 2.8, 4.6, 1.5],
        [5.7, 2.8, 4.5, 1.3],
        [6.3, 3.3, 4.7, 1.6],
        [4.9, 2.4, 3.3, 1. ],
        [6.6, 2.9, 4.6, 1.3],
        [5.2, 2.7, 3.9, 1.4],
        [5. , 2. , 3.5, 1. ],
        [5.9, 3. , 4.2, 1.5],
        [6. , 2.2, 4. , 1. ],
        [6.1, 2.9, 4.7, 1.4],
        [5.6, 2.9, 3.6, 1.3],
        [6.7, 3.1, 4.4, 1.4],
        [5.6, 3. , 4.5, 1.5],
        [5.8, 2.7, 4.1, 1. ],
        [6.2, 2.2, 4.5, 1.5],
        [5.6, 2.5, 3.9, 1.1],
        [5.9, 3.2, 4.8, 1.8],
        [6.1, 2.8, 4. , 1.3],
        [6.3, 2.5, 4.9, 1.5],
        [6.1, 2.8, 4.7, 1.2],
        [6.4, 2.9, 4.3, 1.3],
        [6.6, 3. , 4.4, 1.4],
        [6.8, 2.8, 4.8, 1.4],
        [6.7, 3. , 5. , 1.7],
        [6. , 2.9, 4.5, 1.5],
        [5.7, 2.6, 3.5, 1. ],
        [5.5, 2.4, 3.8, 1.1],
        [5.5, 2.4, 3.7, 1. ],
        [5.8, 2.7, 3.9, 1.2],
        [6. , 2.7, 5.1, 1.6],
        [5.4, 3. , 4.5, 1.5],
        [6. , 3.4, 4.5, 1.6],
        [6.7, 3.1, 4.7, 1.5],
        [6.3, 2.3, 4.4, 1.3],
        [5.6, 3. , 4.1, 1.3],
        [5.5, 2.5, 4. , 1.3],
        [5.5, 2.6, 4.4, 1.2],
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        [5.8, 2.6, 4. , 1.2],
        [5. , 2.3, 3.3, 1. ],
        [5.6, 2.7, 4.2, 1.3],
        [5.7, 3. , 4.2, 1.2],
        [5.7, 2.9, 4.2, 1.3],
        [6.2, 2.9, 4.3, 1.3],
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        [5.7, 2.8, 4.1, 1.3],
        [6.3, 3.3, 6. , 2.5],
        [5.8, 2.7, 5.1, 1.9],
        [7.1, 3. , 5.9, 2.1],
        [6.3, 2.9, 5.6, 1.8],
        [6.5, 3. , 5.8, 2.2],
        [7.6, 3. , 6.6, 2.1],
        [4.9, 2.5, 4.5, 1.7],
        [7.3, 2.9, 6.3, 1.8],
        [6.7, 2.5, 5.8, 1.8],
        [7.2, 3.6, 6.1, 2.5],
        [6.5, 3.2, 5.1, 2. ],
        [6.4, 2.7, 5.3, 1.9],
        [6.8, 3. , 5.5, 2.1],
        [5.7, 2.5, 5. , 2. ],
        [5.8, 2.8, 5.1, 2.4],
        [6.4, 3.2, 5.3, 2.3],
        [6.5, 3. , 5.5, 1.8],
        [7.7, 3.8, 6.7, 2.2],
        [7.7, 2.6, 6.9, 2.3],
        [6. , 2.2, 5. , 1.5],
        [6.9, 3.2, 5.7, 2.3],
        [5.6, 2.8, 4.9, 2. ],
        [7.7, 2.8, 6.7, 2. ],
        [6.3, 2.7, 4.9, 1.8],
        [6.7, 3.3, 5.7, 2.1],
        [7.2, 3.2, 6. , 1.8],
        [6.2, 2.8, 4.8, 1.8],
        [6.1, 3. , 4.9, 1.8],
        [6.4, 2.8, 5.6, 2.1],
        [7.2, 3. , 5.8, 1.6],
        [7.4, 2.8, 6.1, 1.9],
        [7.9, 3.8, 6.4, 2. ],
        [6.4, 2.8, 5.6, 2.2],
        [6.3, 2.8, 5.1, 1.5],
        [6.1, 2.6, 5.6, 1.4],
        [7.7, 3. , 6.1, 2.3],
        [6.3, 3.4, 5.6, 2.4],
        [6.4, 3.1, 5.5, 1.8],
        [6. , 3. , 4.8, 1.8],
        [6.9, 3.1, 5.4, 2.1],
        [6.7, 3.1, 5.6, 2.4],
        [6.9, 3.1, 5.1, 2.3],
        [5.8, 2.7, 5.1, 1.9],
        [6.8, 3.2, 5.9, 2.3],
        [6.7, 3.3, 5.7, 2.5],
        [6.7, 3. , 5.2, 2.3],
        [6.3, 2.5, 5. , 1.9],
        [6.5, 3. , 5.2, 2. ],
        [6.2, 3.4, 5.4, 2.3],
        [5.9, 3. , 5.1, 1.8]]),
 'target': array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2]),
 'frame': None,
 'target_names': array(['setosa', 'versicolor', 'virginica'], dtype='<U10'),
 'DESCR': '.. _iris_dataset:\n\nIris plants dataset\n--------------------\n\n**Data Set Characteristics:**\n\n    :Number of Instances: 150 (50 in each of three classes)\n    :Number of Attributes: 4 numeric, predictive attributes and the class\n    :Attribute Information:\n        - sepal length in cm\n        - sepal width in cm\n        - petal length in cm\n        - petal width in cm\n        - class:\n                - Iris-Setosa\n                - Iris-Versicolour\n                - Iris-Virginica\n                \n    :Summary Statistics:\n\n    ============== ==== ==== ======= ===== ====================\n                    Min  Max   Mean    SD   Class Correlation\n    ============== ==== ==== ======= ===== ====================\n    sepal length:   4.3  7.9   5.84   0.83    0.7826\n    sepal width:    2.0  4.4   3.05   0.43   -0.4194\n    petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)\n    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)\n    ============== ==== ==== ======= ===== ====================\n\n    :Missing Attribute Values: None\n    :Class Distribution: 33.3% for each of 3 classes.\n    :Creator: R.A. Fisher\n    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)\n    :Date: July, 1988\n\nThe famous Iris database, first used by Sir R.A. Fisher. The dataset is taken\nfrom Fisher\'s paper. Note that it\'s the same as in R, but not as in the UCI\nMachine Learning Repository, which has two wrong data points.\n\nThis is perhaps the best known database to be found in the\npattern recognition literature.  Fisher\'s paper is a classic in the field and\nis referenced frequently to this day.  (See Duda & Hart, for example.)  The\ndata set contains 3 classes of 50 instances each, where each class refers to a\ntype of iris plant.  One class is linearly separable from the other 2; the\nlatter are NOT linearly separable from each other.\n\n.. topic:: References\n\n   - Fisher, R.A. "The use of multiple measurements in taxonomic problems"\n     Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to\n     Mathematical Statistics" (John Wiley, NY, 1950).\n   - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysis.\n     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.\n   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System\n     Structure and Classification Rule for Recognition in Partially Exposed\n     Environments".  IEEE Transactions on Pattern Analysis and Machine\n     Intelligence, Vol. PAMI-2, No. 1, 67-71.\n   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactions\n     on Information Theory, May 1972, 431-433.\n   - See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II\n     conceptual clustering system finds 3 classes in the data.\n   - Many, many more ...',
 'feature_names': ['sepal length (cm)',
  'sepal width (cm)',
  'petal length (cm)',
  'petal width (cm)'],
 'filename': '/home/isabelmaniega/FEI_projects/venv/lib/python3.8/site-packages/sklearn/datasets/data/iris.csv'}
```

In [2]:
```
iris.data
```

Out[2]:
```
array([[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],
       [5.4, 3.9, 1.7, 0.4],
       [4.6, 3.4, 1.4, 0.3],
       [5. , 3.4, 1.5, 0.2],
       [4.4, 2.9, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5.4, 3.7, 1.5, 0.2],
       [4.8, 3.4, 1.6, 0.2],
       [4.8, 3. , 1.4, 0.1],
       [4.3, 3. , 1.1, 0.1],
       [5.8, 4. , 1.2, 0.2],
       [5.7, 4.4, 1.5, 0.4],
       [5.4, 3.9, 1.3, 0.4],
       [5.1, 3.5, 1.4, 0.3],
       [5.7, 3.8, 1.7, 0.3],
       [5.1, 3.8, 1.5, 0.3],
       [5.4, 3.4, 1.7, 0.2],
       [5.1, 3.7, 1.5, 0.4],
       [4.6, 3.6, 1. , 0.2],
       [5.1, 3.3, 1.7, 0.5],
       [4.8, 3.4, 1.9, 0.2],
       [5. , 3. , 1.6, 0.2],
       [5. , 3.4, 1.6, 0.4],
       [5.2, 3.5, 1.5, 0.2],
       [5.2, 3.4, 1.4, 0.2],
       [4.7, 3.2, 1.6, 0.2],
       [4.8, 3.1, 1.6, 0.2],
       [5.4, 3.4, 1.5, 0.4],
       [5.2, 4.1, 1.5, 0.1],
       [5.5, 4.2, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.2],
       [5. , 3.2, 1.2, 0.2],
       [5.5, 3.5, 1.3, 0.2],
       [4.9, 3.6, 1.4, 0.1],
       [4.4, 3. , 1.3, 0.2],
       [5.1, 3.4, 1.5, 0.2],
       [5. , 3.5, 1.3, 0.3],
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       [4.4, 3.2, 1.3, 0.2],
       [5. , 3.5, 1.6, 0.6],
       [5.1, 3.8, 1.9, 0.4],
       [4.8, 3. , 1.4, 0.3],
       [5.1, 3.8, 1.6, 0.2],
       [4.6, 3.2, 1.4, 0.2],
       [5.3, 3.7, 1.5, 0.2],
       [5. , 3.3, 1.4, 0.2],
       [7. , 3.2, 4.7, 1.4],
       [6.4, 3.2, 4.5, 1.5],
       [6.9, 3.1, 4.9, 1.5],
       [5.5, 2.3, 4. , 1.3],
       [6.5, 2.8, 4.6, 1.5],
       [5.7, 2.8, 4.5, 1.3],
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       [6.6, 2.9, 4.6, 1.3],
       [5.2, 2.7, 3.9, 1.4],
       [5. , 2. , 3.5, 1. ],
       [5.9, 3. , 4.2, 1.5],
       [6. , 2.2, 4. , 1. ],
       [6.1, 2.9, 4.7, 1.4],
       [5.6, 2.9, 3.6, 1.3],
       [6.7, 3.1, 4.4, 1.4],
       [5.6, 3. , 4.5, 1.5],
       [5.8, 2.7, 4.1, 1. ],
       [6.2, 2.2, 4.5, 1.5],
       [5.6, 2.5, 3.9, 1.1],
       [5.9, 3.2, 4.8, 1.8],
       [6.1, 2.8, 4. , 1.3],
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       [6. , 2.9, 4.5, 1.5],
       [5.7, 2.6, 3.5, 1. ],
       [5.5, 2.4, 3.8, 1.1],
       [5.5, 2.4, 3.7, 1. ],
       [5.8, 2.7, 3.9, 1.2],
       [6. , 2.7, 5.1, 1.6],
       [5.4, 3. , 4.5, 1.5],
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       [7.1, 3. , 5.9, 2.1],
       [6.3, 2.9, 5.6, 1.8],
       [6.5, 3. , 5.8, 2.2],
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       [7.3, 2.9, 6.3, 1.8],
       [6.7, 2.5, 5.8, 1.8],
       [7.2, 3.6, 6.1, 2.5],
       [6.5, 3.2, 5.1, 2. ],
       [6.4, 2.7, 5.3, 1.9],
       [6.8, 3. , 5.5, 2.1],
       [5.7, 2.5, 5. , 2. ],
       [5.8, 2.8, 5.1, 2.4],
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       [6.5, 3. , 5.5, 1.8],
       [7.7, 3.8, 6.7, 2.2],
       [7.7, 2.6, 6.9, 2.3],
       [6. , 2.2, 5. , 1.5],
       [6.9, 3.2, 5.7, 2.3],
       [5.6, 2.8, 4.9, 2. ],
       [7.7, 2.8, 6.7, 2. ],
       [6.3, 2.7, 4.9, 1.8],
       [6.7, 3.3, 5.7, 2.1],
       [7.2, 3.2, 6. , 1.8],
       [6.2, 2.8, 4.8, 1.8],
       [6.1, 3. , 4.9, 1.8],
       [6.4, 2.8, 5.6, 2.1],
       [7.2, 3. , 5.8, 1.6],
       [7.4, 2.8, 6.1, 1.9],
       [7.9, 3.8, 6.4, 2. ],
       [6.4, 2.8, 5.6, 2.2],
       [6.3, 2.8, 5.1, 1.5],
       [6.1, 2.6, 5.6, 1.4],
       [7.7, 3. , 6.1, 2.3],
       [6.3, 3.4, 5.6, 2.4],
       [6.4, 3.1, 5.5, 1.8],
       [6. , 3. , 4.8, 1.8],
       [6.9, 3.1, 5.4, 2.1],
       [6.7, 3.1, 5.6, 2.4],
       [6.9, 3.1, 5.1, 2.3],
       [5.8, 2.7, 5.1, 1.9],
       [6.8, 3.2, 5.9, 2.3],
       [6.7, 3.3, 5.7, 2.5],
       [6.7, 3. , 5.2, 2.3],
       [6.3, 2.5, 5. , 1.9],
       [6.5, 3. , 5.2, 2. ],
       [6.2, 3.4, 5.4, 2.3],
       [5.9, 3. , 5.1, 1.8]])
```

In [3]:
```
iris.target
# 'target_names': array(['setosa', 'versicolor', 'virginica'], dtype='<U10'),
```

Out[3]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
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       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

Para nuestro ejemplo proporcionaremos el .csv directamente

In [4]:
```
# La forma que usaremos será la obtención de datos desde el CSV
```

-2- Importamos algunas dependencias generales

In [5]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

-3- Hacemos uso de pandas para importar la información .csv

Para ello tenemos en cuenta las siguientes aclaraciones

In [6]:
```
df = pd.read_csv("2_IrisSpecies.csv")
df.head()
```

Out[6]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

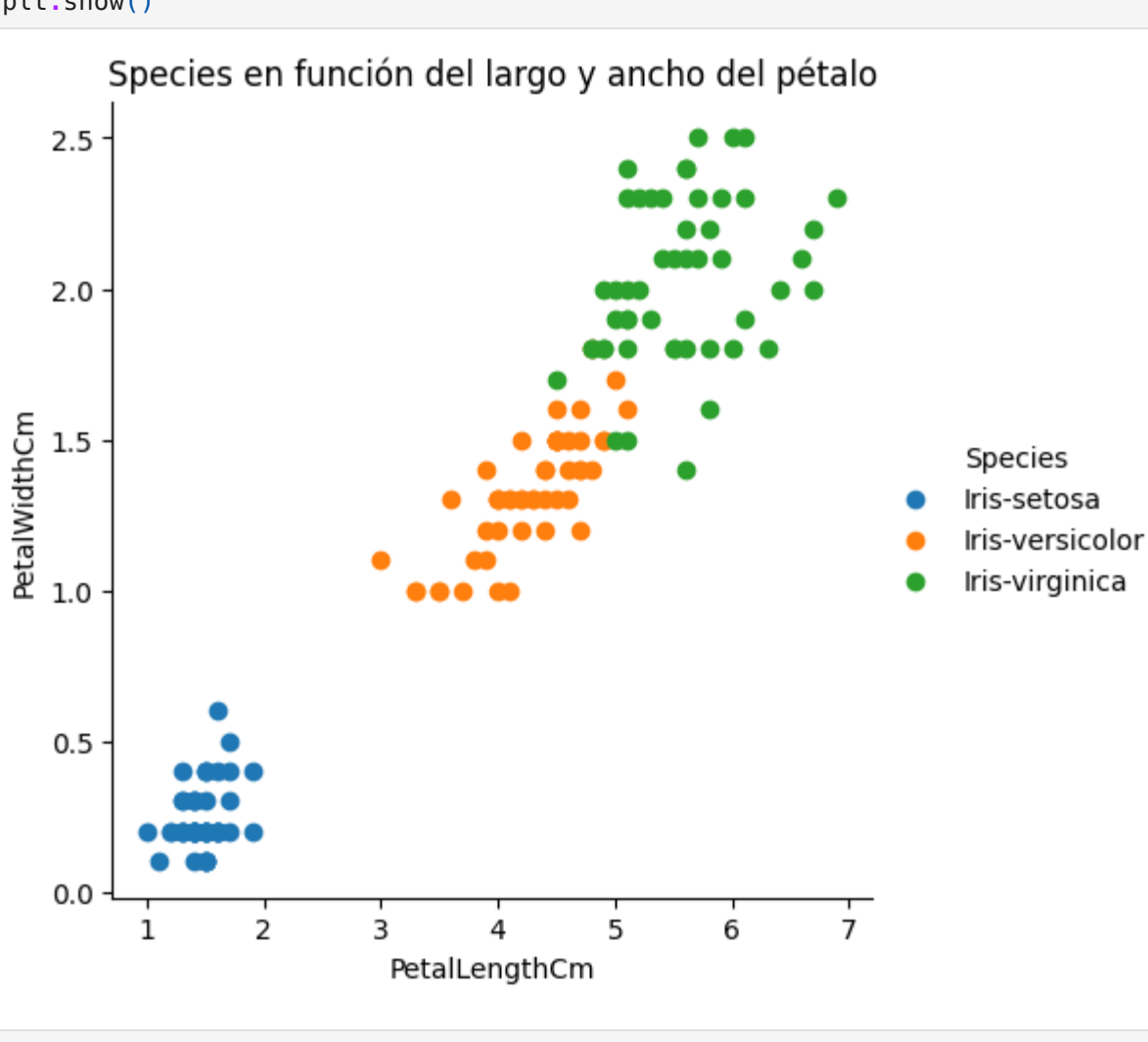
-4- Ploteo algunas gráficas

Usando Seaborn y matplotlib

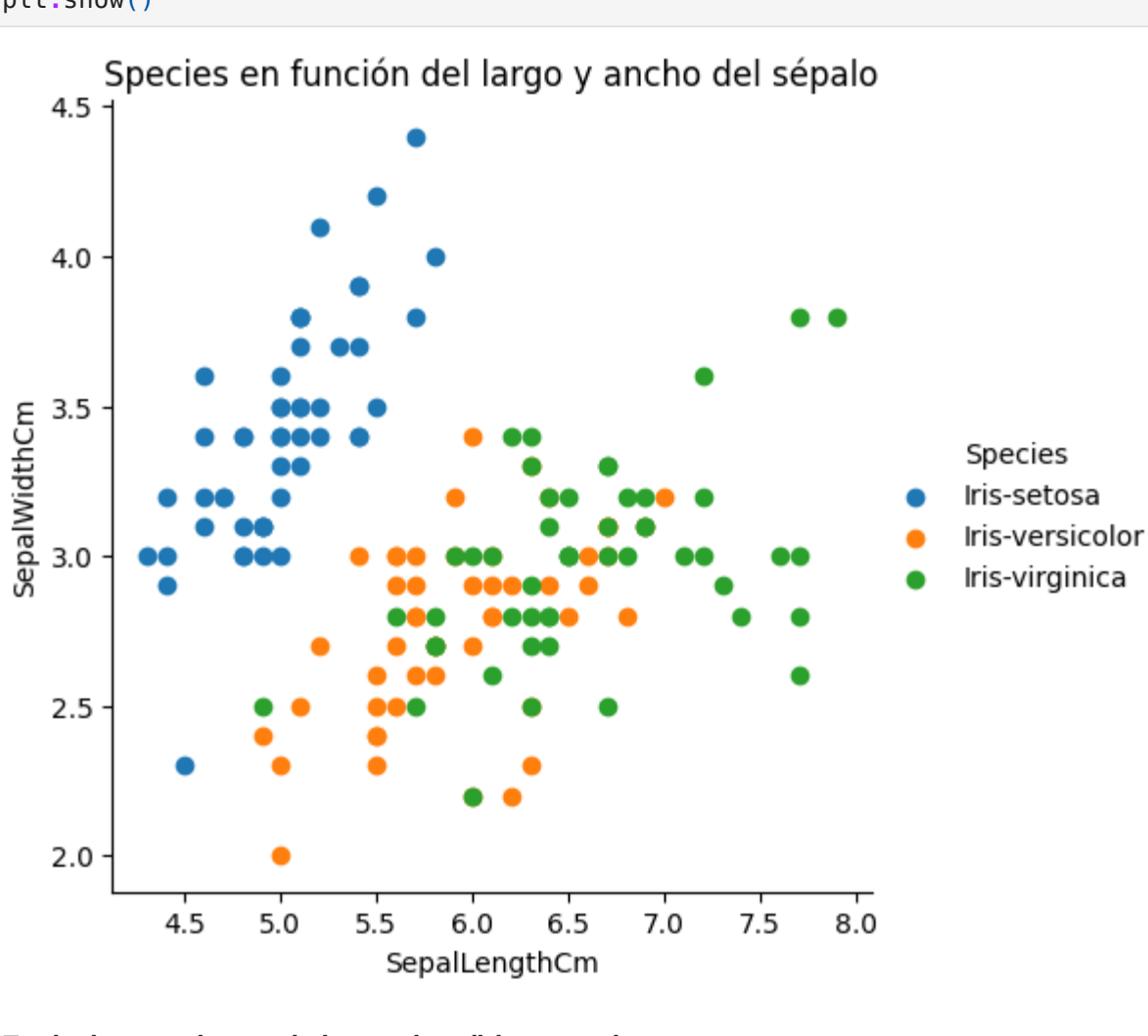
In [7]:
```
# https://seaborn.pydata.org/installing.html
# !pip install seaborn
```

In [8]:
```
import seaborn as sns
```

In [9]:
```
# Para el pétalo

sns.FacetGrid(df, hue="Species", height=4.8) \
   .map(plt.scatter, "PetalLengthCm", "PetalWidthCm") \
   .add_legend()

plt.title("Species en función del largo y ancho del pétalo")
plt.show()
```



In [10]:
```
# para el sépalo
sns.FacetGrid(df, hue="Species", height = 4.8) \
   .map(plt.scatter, "SepalLengthCm", "SepalWidthCm") \
   .add_legend() \
   .set(title="Species en función del largo y ancho del sépalo")

# plt.title("Species en función del largo y ancho del sépalo")
plt.show()
```



Es decir para el caso de las azules: (iris-setosa)

- Para un largo de 4.3-5.8 y ancho de 2.9-4.4 (aprox) es generalmente de ese tipo
- Las demas es mas complejo de decidir

In [11]:
```
# boxplot
df.boxplot(column=["SepalLengthCm", "SepalWidthCm", "PetalLengthCm", "PetalWidthCm"])
```

Out[11]: `<AxesSubplot:>`

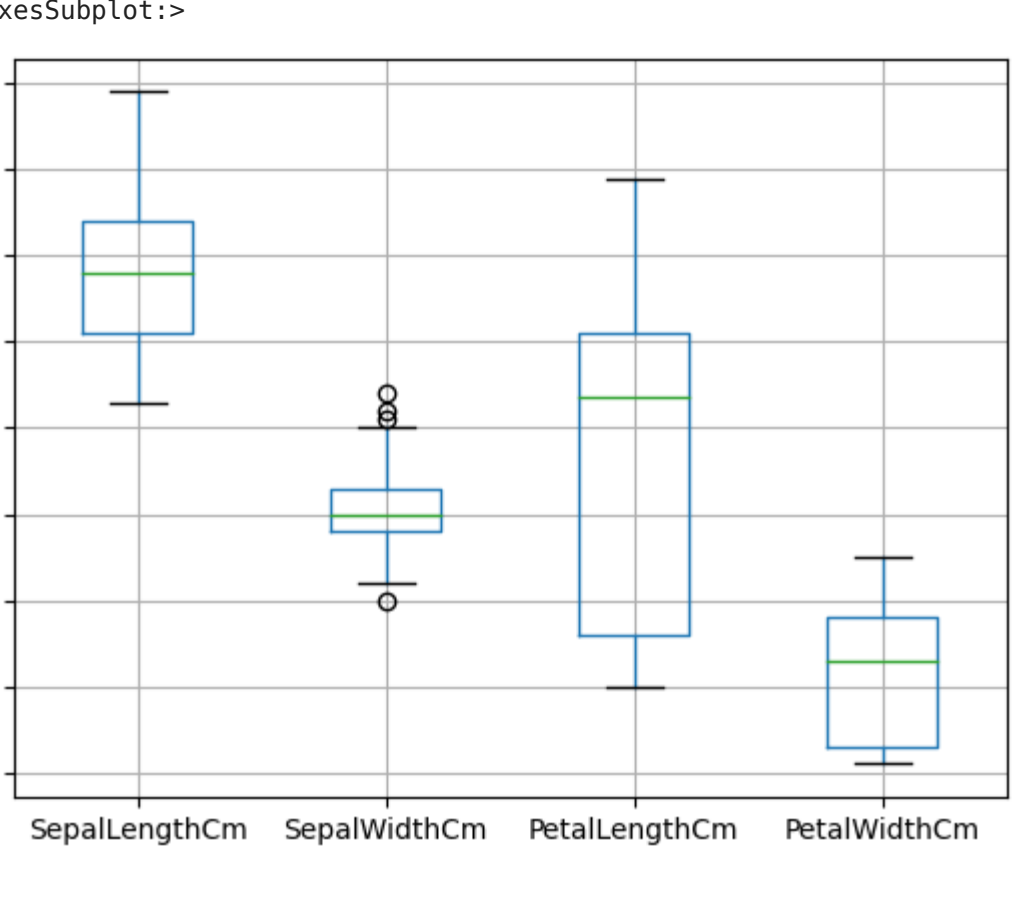


Gráfico de cajas para setosa

In [12]:
```
# Filtrar por cada uno de los tipos
setosa = df[df["Species"] == "Iris-setosa"]
setosa.head()
```

Out[12]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

In [13]:
```
# boxplot para setosa
setosa.boxplot(column=["SepalLengthCm", "SepalWidthCm", "PetalLengthCm", "PetalWidthCm"])
```

Out[13]: `<AxesSubplot:>`

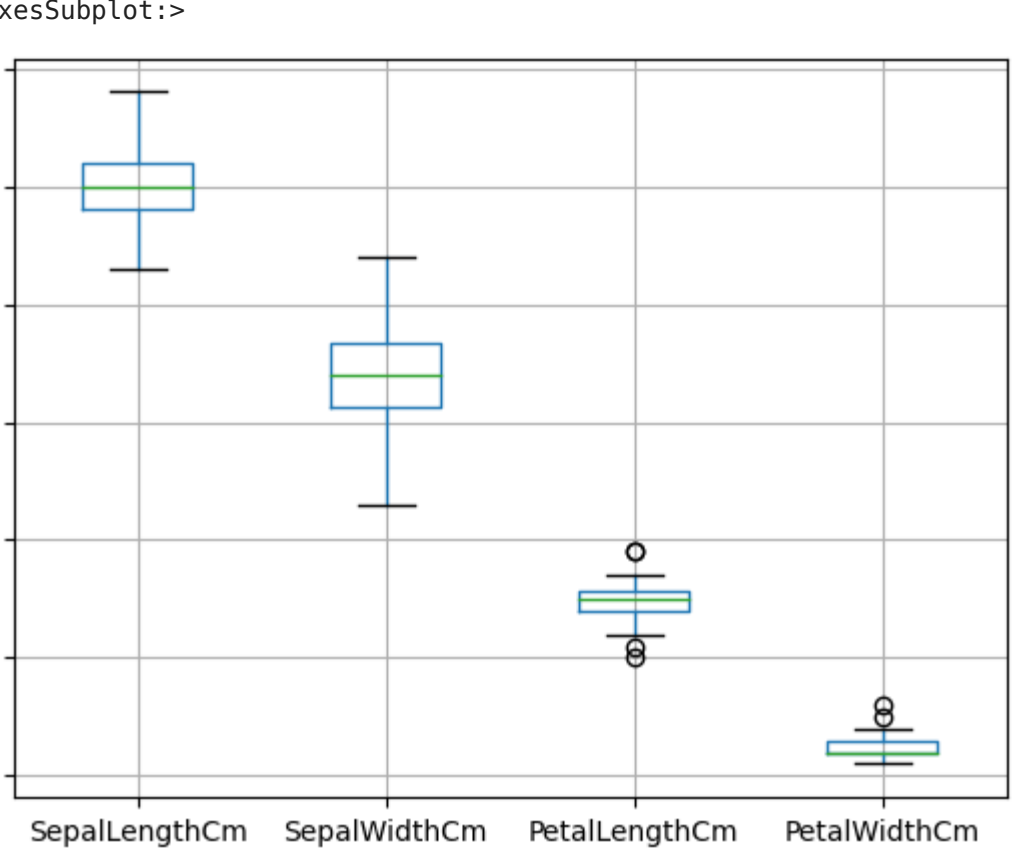


Gráfico de cajas para versicolor

In [14]:
```
# Filtrar por cada uno de los tipos
versicolor = df[df["Species"] == "Iris-versicolor"]
versicolor.head()
```

Out[14]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
50	51	7.0	3.2	4.7	1.4	Iris-versicolor
51	52	6.4	3.2	4.5	1.5	Iris-versicolor
52	53	6.9	3.1	4.9	1.5	Iris-versicolor
53	54	5.5	2.3	4.0	1.3	Iris-versicolor
54	55	6.5	2.8	4.6	1.5	Iris-versicolor

In [15]:
```
# boxplot para setosa
versicolor.boxplot(column=["SepalLengthCm", "SepalWidthCm", "PetalLengthCm", "PetalWidthCm"])
```

Out[15]: `<AxesSubplot:>`

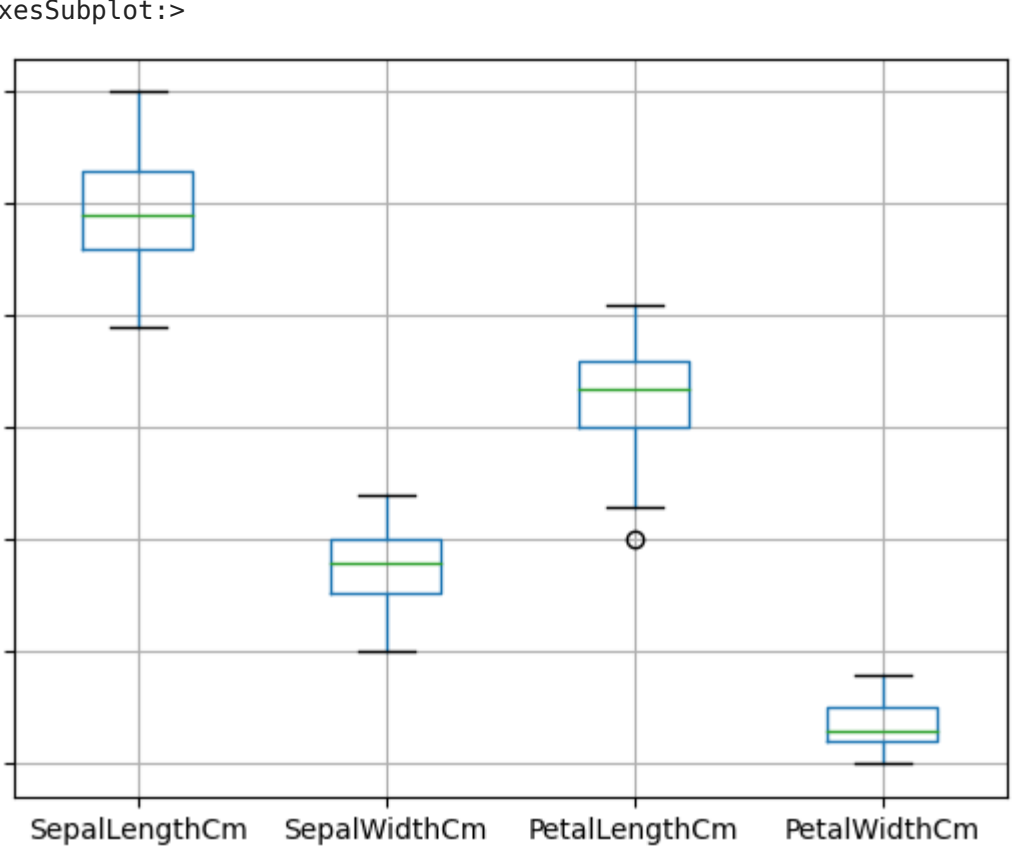


Gráfico de cajas para virgínica

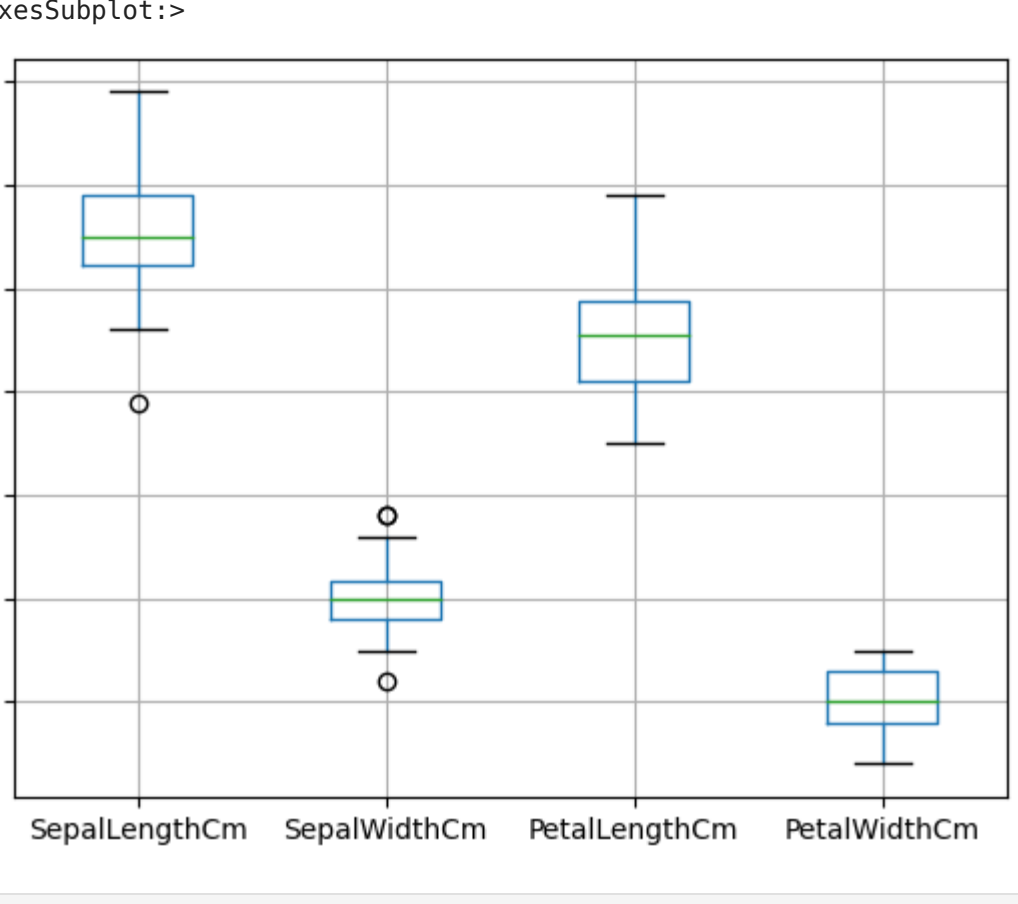
In [16]:
```
# Filtrar por cada uno de los tipos
virginica = df[df["Species"] == "Iris-virginica"]
virginica.head()
```

Out[16]:

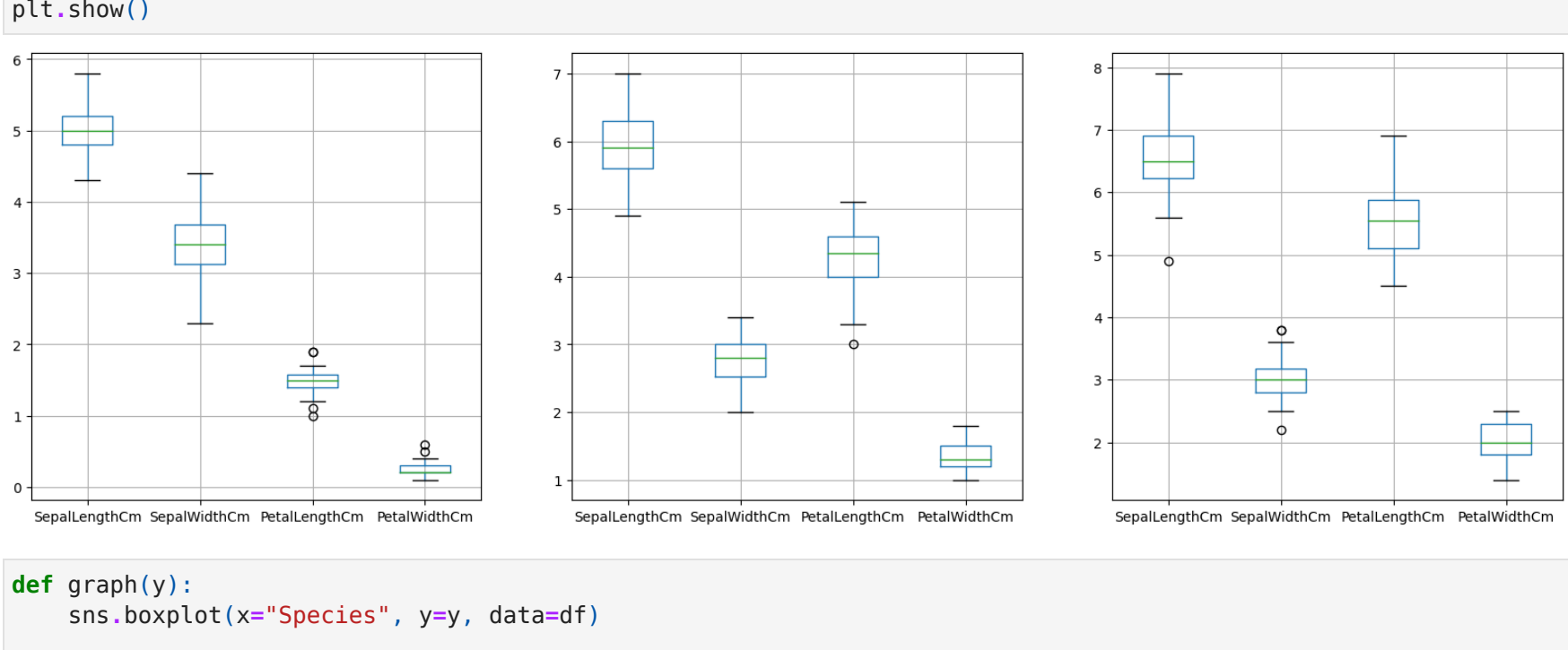
	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
100	101	6.3	3.3	6.0	2.5	Iris-virginica
101	102	5.8	2.7	5.1	1.9	Iris-virginica
102	103	7.1	3.0	5.9	2.1	Iris-virginica
103	104	6.3	2.9	5.6	1.8	Iris-virginica
104	105	6.5	3.0	5.8	2.2	Iris-virginica

In [17]:
```
# boxplot para setosa
virginica.boxplot(column=["SepalLengthCm", "SepalWidthCm", "PetalLengthCm", "PetalWidthCm"])
```

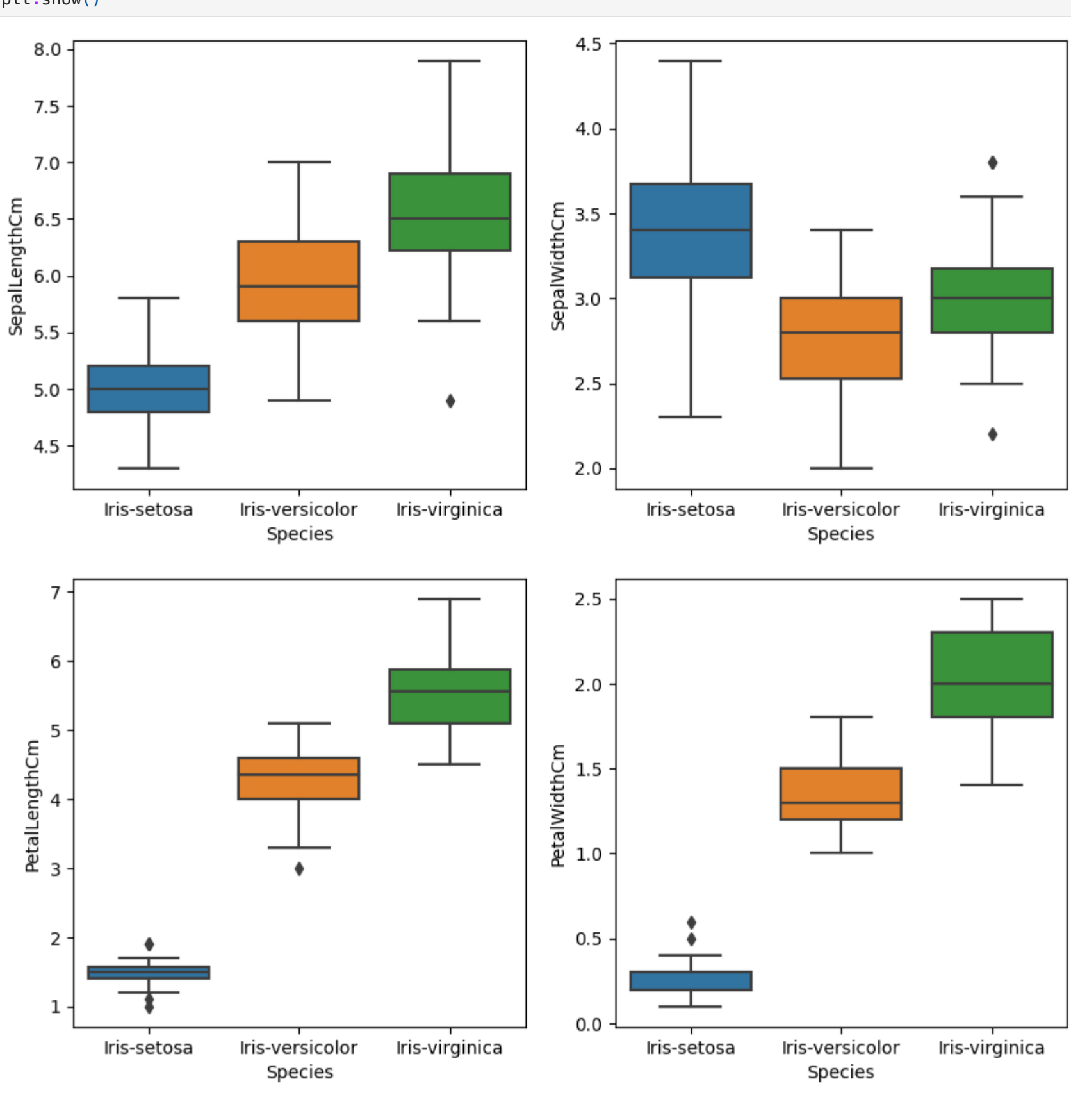
Out[17]: `<AxesSubplot:>`



In [18]:
```
plt.figure(figsize=(20,20))

plt.subplot(3, 3, 1)
setosa.boxplot(column=["SepalLengthCm", "SepalWidthCm", "PetalLengthCm", "PetalWidthCm"])

plt.subplot(3, 3, 2)
versicolor.boxplot(column=["SepalLengthCm", "SepalWidthCm", "PetalLengthCm", "PetalWidthCm"])

plt.subplot(3, 3, 3)
virginica.boxplot(column=["SepalLengthCm", "SepalWidthCm", "PetalLengthCm", "PetalWidthCm"])
plt.show()
```



In [19]:
```
def graph(y):
    sns.boxplot(x="Species", y=y, data=df)

plt.figure(figsize=(10,10))

# Adding the subplot at the specified
# grid position
plt.subplot(221)
graph('SepalLengthCm')

plt.subplot(222)
graph('SepalWidthCm')

plt.subplot(223)
graph('PetalLengthCm')

plt.subplot(224)
graph('PetalWidthCm')

plt.show()
```



Conclusiones:

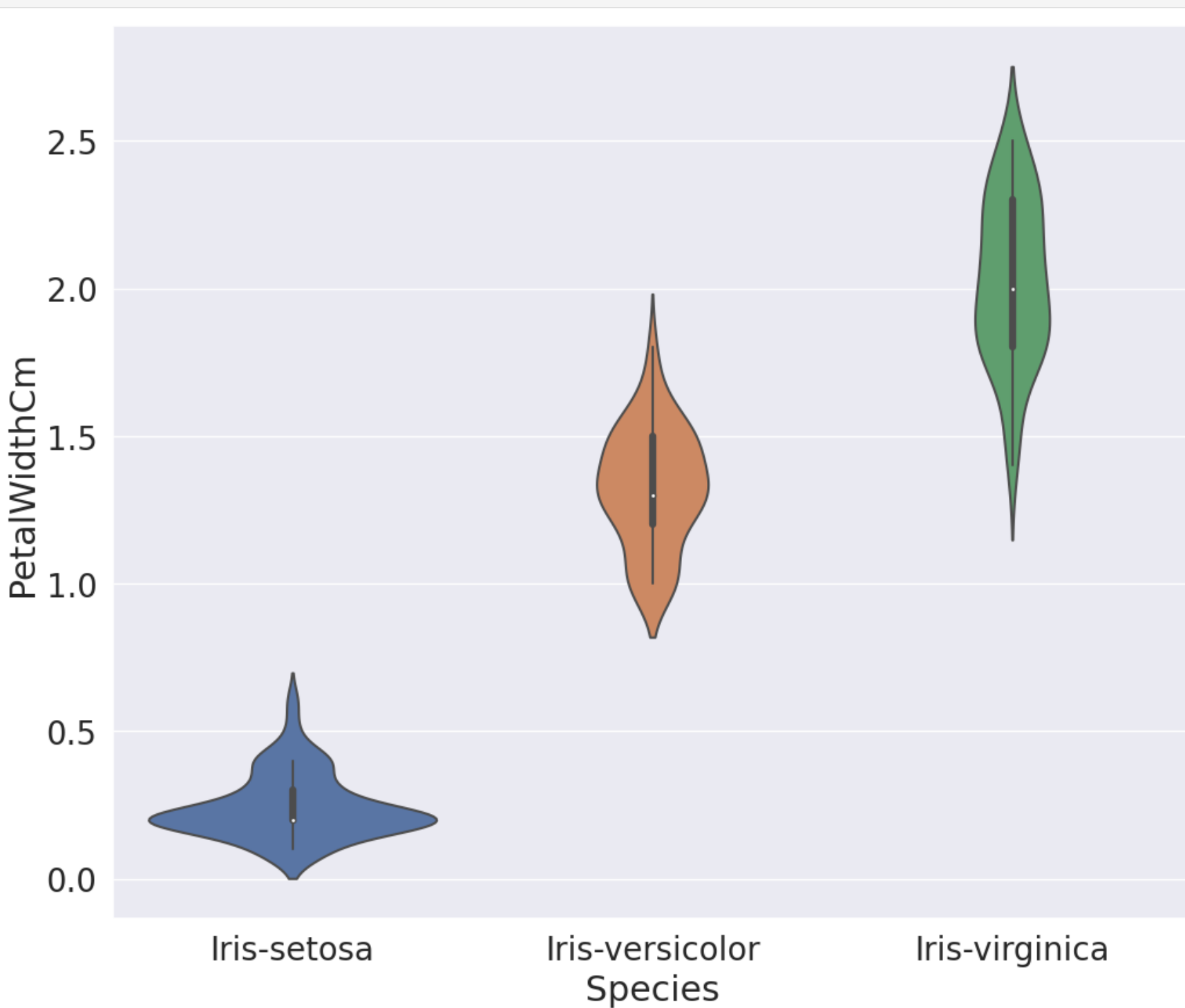
- Observamos que en el caso del Sépalo en virgínica presenta outliers, mientras que en las otras dos especies no.
- En el caso del Pétalo setosa y versicolor presentan outliers para la longitud del pétalo, y en el caso de setosa también para la anchura.
- en el caso de setosa el tamaño del pétalo y también en la longitud del sépalo presenta menor tamaño que las otras dos especies. Y la variabilidad de los datos también es menor en estos casos. Mientras que en la anchura del sépalo la variabilidad es mucho mayor que el de las otras dos especies.

Violin plot

Pétalo

In [20]:
```
sns.set(font_scale=1.8, rc={'figure.figsize':(12, 10)})
sns.violinplot(x="Species", y="PetalLengthCm", data=df, size=6)
plt.show()
```


```
In [21]: sns.set(font_scale=1.8, rc={'figure.figsize':(12, 10)})
sns.violinplot(x="Species", y="PetalWidthCm", data=df, size=6)
plt.show()
```



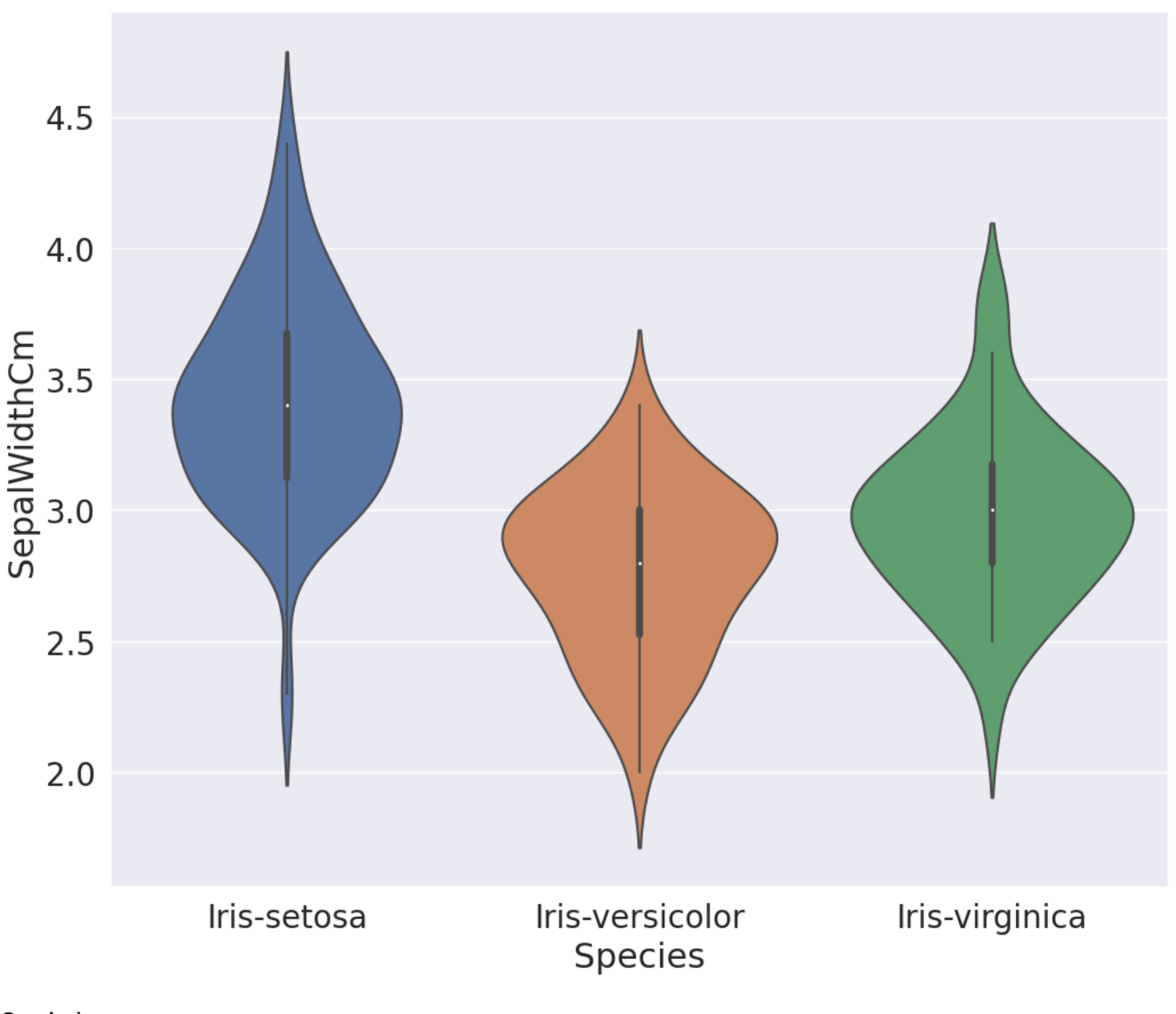
Conclusiones:

En el caso, de vígінica presenta más variabilidad de los datos y estan más homogéneos, que en caso sobretodo de setosa que sería lo opuesto.

Sépalo

```
In [22]: sns.set(font_scale=1.8, rc={'figure.figsize':(12, 10)})
sns.violinplot(x="Species", y="SepalLengthCm", data=df, size=6)
plt.show()
```


```
In [23]: sns.set(font_scale=1.8, rc={'figure.figsize':(12, 10)})
sns.violinplot(x="Species", y="SepalWidthCm", data=df, size=6)
plt.show()
```



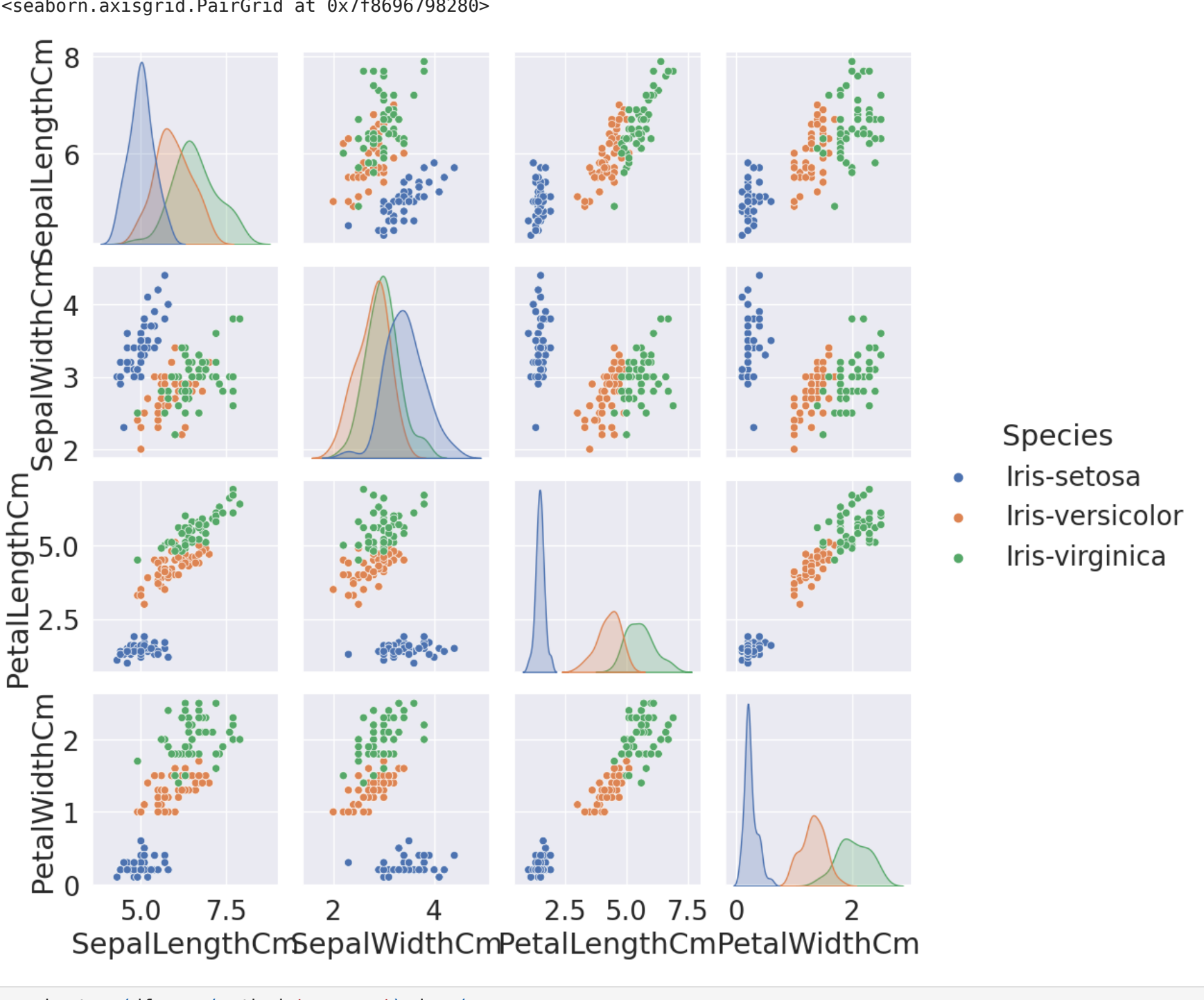
Conclusiones:

En el caso de la longitud en virgínica presentan más variabilidad pero en anchura es en setosa, los valores se encuentran concentrados en ambas especies.

Análisis de correlación

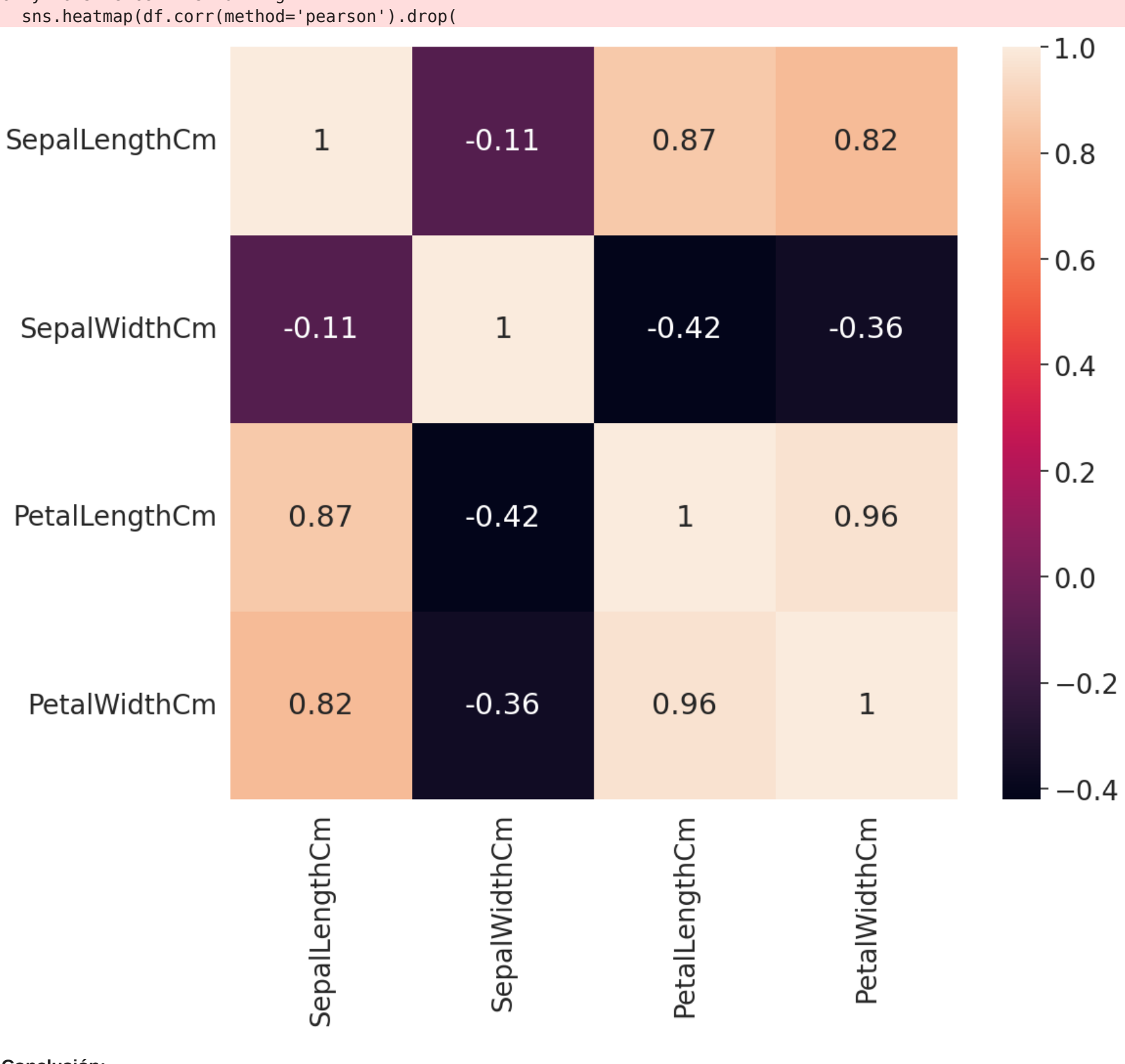
```
In [24]: sns.pairplot(df.drop(['Id'], axis = 1),
             hue='Species')
```

```
Out[24]: <seaborn.axisgrid.PairGrid at 0x7f8696798280>
```




```
In [25]: sns.heatmap(df.corr(method='pearson').drop(
  ['Id'], axis=1).drop(['Id'], axis=0),
            annot = True);

plt.show()
```

```
/tmp/ipykernel_8436/64058618.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(df.corr(method='pearson').drop(
```



Conclusión:

- Presentan correlación entre el Pétalo y la longitud del Sépalo, pero no con la anchura.
- También se observa correlación entre la anchura y longitud del Pétalo, pero no entre la anchura y longitud del sépalo

-5- Observo la información que tengo

y hago algunas transformaciones, si lo necesito

Generalmente uso .value_counts() para obtener información de la salida

Modifico si me interesa la información

EN ESTE CASO:

-Necesito transformar la salida en información para poder ser utilizada

```
In [26]: # Nombre de las columnas
df.columns
```

```
Out[26]: Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

```
In [27]: # NombreDataFrame.NombreColumna.value_counts()
# Nos permite saber cuantos tipos diferentes de salida tenemos
# y su repetición en esa columna
df.Species.value_counts()
```

```
Out[27]: Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: Species, dtype: int64
```

```
In [28]: # UNA OPCIÓN:

# usamos .map() para transformar el texto en números
# existen mas formas de hacerlo.

# 'target_names': array(['setosa', 'versicolor', 'virginica'], dtype='<U10'),

df.Species = df.Species.map({'Iris-setosa': 0, 'Iris-versicolor': 1, 'Iris-virginica': 2 })
df.head()
```

Out[28]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	0
1	2	4.9	3.0	1.4	0.2	0
2	3	4.7	3.2	1.3	0.2	0
3	4	4.6	3.1	1.5	0.2	0
4	5	5.0	3.6	1.4	0.2	0

```
In [29]: # .tolist() me permite transformar esa información en una lista
print(np.array(df.Species.tolist()))
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
```

```
In [30]: # Otra opción

# Procesar el df modificar las columnas Setosa, versicolor, virgínica
#df.loc[df["Species"] == "Iris-setosa", "Species"] = 0

#df.loc[df["Species"] == "Iris-versicolor", "Species"] = 1

#df.loc[df["Species"] == "Iris-virginica", "Species"] = 2

#df["Species"] = df[['Species']].astype('int')
#print(df)
```

```
In [31]: #print(np.array(df.Species.tolist()))
```

```
In [32]: # usando get_dummies

#y = pd.get_dummies(df['Species'])
# print(y)
```

```
In [33]: df.describe()
```

Out[33]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
count	150.000000	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667	1.000000
std	43.445368	0.828066	0.433594	1.764420	0.763161	0.819232
min	1.000000	4.300000	2.000000	1.000000	0.100000	0.000000
25%	38.250000	5.100000	2.800000	1.600000	0.300000	0.000000
50%	75.500000	5.800000	3.000000	4.350000	1.300000	1.000000
75%	112.750000	6.400000	3.300000	5.100000	1.800000	2.000000
max	150.000000	7.900000	4.400000	6.900000	2.500000	2.000000

No hace falta escalar los datos ya que no hay mucha distancia entre el mínimo y el máximo

-6- Establezco X, y

```
In [34]: #df.head(2)
df.head(2)
```

Out[34]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	0
1	2	4.9	3.0	1.4	0.2	0

```
In [35]: # drop me permite borrar, axis=1 le indico que las columnas.
X = df.drop(["Id", "Species"], axis = 1)
X.head()
```

Out[35]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
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 [36]: # y, la salida, sólamente la columna "Species"
# Comentar en el caso de get_dummies
y = df["Species"]
y
```

```
Out[36]: 0      0
1      0
2      0
3      0
4      0
      ..
145    2
146    2
147    2
148    2
149    2
Name: Species, Length: 150, dtype: int64
```

```
In [37]: # Algunas veces necesario para que no devuelvan errores posteriormente.
X = X.values
X
```

```
Out[37]: array([[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],
       [5.4, 3.9, 1.7, 0.4],
       [4.6, 3.4, 1.4, 0.3],
       [5. , 3.4, 1.5, 0.2],
       [4.4, 2.9, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5.4, 3.7, 1.5, 0.2],
       [4.8, 3.4, 1.6, 0.2],
       [4.8, 3. , 1.4, 0.1],
       [4.3, 3. , 1.1, 0.1],
       [5.8, 4. , 1.2, 0.2],
       [5.7, 4.4, 1.5, 0.4],
       [5.4, 3.9, 1.3, 0.4],
       [5.1, 3.5, 1.4, 0.3],
       [5.7, 3.8, 1.7, 0.3],
       [5.1, 3.8, 1.5, 0.3],
       [5.4, 3.4, 1.7, 0.2],
       [5.1, 3.7, 1.5, 0.4],
       [4.6, 3.6, 1. , 0.2],
       [5.1, 3.3, 1.7, 0.5],
       [4.8, 3.4, 1.9, 0.2],
       [5. , 3. , 1.6, 0.2],
       [5. , 3.4, 1.6, 0.4],
       [5.2, 3.5, 1.5, 0.2],
       [5.2, 3.4, 1.4, 0.2],
       [4.7, 3.2, 1.6, 0.2],
       [4.8, 3.1, 1.6, 0.2],
       [5.4, 3.4, 1.5, 0.4],
       [5.2, 4.1, 1.5, 0.1],
       [5.5, 4.2, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5. , 3.2, 1.2, 0.2],
       [5.5, 3.5, 1.3, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [4.4, 3. , 1.3, 0.2],
       [5.1, 3.4, 1.5, 0.2],
       [5. , 3.5, 1.3, 0.3],
       [4.5, 2.3, 1.3, 0.3],
       [4.4, 3.2, 1.3, 0.2],
       [5. , 3.5, 1.6, 0.6],
       [5.1, 3.8, 1.9, 0.4],
       [4.8, 3. , 1.4, 0.3],
       [5.1, 3.8, 1.6, 0.2],
       [4.6, 3.2, 1.4, 0.2],
       [5.3, 3.7, 1.5, 0.2],
       [5. , 3.3, 1.4, 0.2],
       [7. , 3.2, 4.7, 1.4],
       [6.4, 3.2, 4.5, 1.5],
       [6.9, 3.1, 4.9, 1.5],
       [5.5, 2.3, 4. , 1.3],
       [6.5, 2.8, 4.6, 1.5],
       [5.7, 2.8, 4.5, 1.3],
       [6.3, 3.3, 4.7, 1.6],
       [4.9, 2.4, 3.3, 1. ],
       [6.6, 2.9, 4.6, 1.3],
       [5.2, 2.7, 3.9, 1.4],
       [5. , 2. , 3.5, 1. ],
       [5.9, 3. , 4.2, 1.5],
       [6. , 2.2, 4. , 1. ],
       [6.1, 2.9, 4.7, 1.4],
       [5.6, 2.9, 3.6, 1.3],
       [6.7, 3.1, 4.4, 1.4],
       [5.6, 3. , 4.5, 1.5],
       [5.8, 2.7, 4.1, 1. ],
       [6.2, 2.2, 4.5, 1.5],
       [5.6, 2.5, 3.9, 1.1],
       [5.9, 3.2, 4.8, 1.8],
       [6.1, 2.8, 4. , 1.3],
       [6.3, 2.5, 4.9, 1.5],
       [6.1, 2.8, 4.7, 1.2],
       [6.4, 2.9, 4.3, 1.3],
       [6.6, 3. , 4.4, 1.4],
       [6.8, 2.8, 4.8, 1.4],
       [6.7, 3. , 5. , 1.7],
       [6. , 2.9, 4.5, 1.5],
       [5.7, 2.6, 3.5, 1. ],
       [5.5, 2.4, 3.8, 1.1],
       [5.5, 2.4, 3.7, 1. ],
       [5.8, 2.7, 3.9, 1.2],
       [6. , 2.7, 5.1, 1.6],
       [5.4, 3. , 4.5, 1.5],
       [6. , 3.4, 4.5, 1.6],
       [6.7, 3.1, 4.7, 1.5],
       [6.3, 2.3, 4.4, 1.3],
       [5.6, 3. , 4.1, 1.3],
       [5.5, 2.5, 4. , 1.3],
       [5.5, 2.6, 4.4, 1.2],
       [6.1, 3. , 4.6, 1.4],
       [5.8, 2.6, 4. , 1.2],
       [5. , 2.3, 3.3, 1. ],
       [5.6, 2.7, 4.2, 1.3],
       [5.7, 3. , 4.2, 1.2],
       [5.7, 2.9, 4.2, 1.3],
       [6.2, 2.9, 4.3, 1.3],
       [5.1, 2.5, 3. , 1.1],
       [5.7, 2.8, 4.1, 1.3],
       [6.3, 3.3, 6. , 2.5],
       [5.8, 2.7, 5.1, 1.9],
       [7.1, 3. , 5.9, 2.1],
       [6.3, 2.9, 5.6, 1.8],
       [6.5, 3. , 5.8, 2.2],
       [7.6, 3. , 6.6, 2.1],
       [4.9, 2.5, 4.5, 1.7],
       [7.3, 2.9, 6.3, 1.8],
       [6.7, 2.5, 5.8, 1.8],
       [7.2, 3.6, 6.1, 2.5],
       [6.5, 3.2, 5.1, 2. ],
       [6.4, 2.7, 5.3, 1.9],
       [6.8, 3. , 5.5, 2.1],
       [5.7, 2.5, 5. , 2. ],
       [5.8, 2.8, 5.1, 2.4],
       [6.4, 3.2, 5.3, 2.3],
       [6.5, 3. , 5.5, 1.8],
       [7.7, 3.8, 6.7, 2.2],
       [7.7, 2.6, 6.9, 2.3],
       [6. , 2.2, 5. , 1.5],
       [6.9, 3.2, 5.7, 2.3],
       [5.6, 2.8, 4.9, 2. ],
       [7.7, 2.8, 6.7, 2. ],
       [6.3, 2.7, 4.9, 1.8],
       [6.7, 3.3, 5.7, 2.1],
       [7.2, 3.2, 6. , 1.8],
       [6.2, 2.8, 4.8, 1.8],
       [6.1, 3. , 4.9, 1.8],
       [6.4, 2.8, 5.6, 2.1],
       [7.2, 3. , 5.8, 1.6],
       [7.4, 2.8, 6.1, 1.9],
       [7.9, 3.8, 6.4, 2. ],
       [6.4, 2.8, 5.6, 2.2],
       [6.3, 2.8, 5.1, 1.5],
       [6.1, 2.6, 5.6, 1.4],
       [7.7, 3. , 6.1, 2.3],
       [6.3, 3.4, 5.6, 2.4],
       [6.4, 3.1, 5.5, 1.8],
       [6. , 3. , 4.8, 1.8],
       [6.9, 3.1, 5.4, 2.1],
       [6.7, 3.1, 5.6, 2.4],
       [6.9, 3.1, 5.1, 2.3],
       [5.8, 2.7, 5.1, 1.9],
       [6.8, 3.2, 5.9, 2.3],
       [6.7, 3.3, 5.7, 2.5],
       [6.7, 3. , 5.2, 2.3],
       [6.3, 2.5, 5. , 1.9],
       [6.5, 3. , 5.2, 2. ],
       [6.2, 3.4, 5.4, 2.3],
       [5.9, 3. , 5.1, 1.8]])
```

```
In [38]: y = y.values
y
```

```
Out[38]: array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

-7- Divido mi set de datos en: train, test

(set de entranamiento y set de test)

```
In [39]: from sklearn.model_selection import train_test_split
```

```
In [40]: X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
# test_size por defecto es 0, osea 75%-25%
```

-8- Utilizando algoritmos realizo una 1ª predicción

Lo 1º será decidir si estamos ante un problema de regresión, clasificación o clustering

en este caso, Clasificación Multivariable (salida 0-1-2)

DecisionTreeClassifier

```
In [41]: from sklearn.tree import DecisionTreeClassifier
```

```
In [42]: # 1-nuestro clasificador (clf) será DecisionTreeClassifier
clf = DecisionTreeClassifier()
# 2-Entreno con los datos que indico entre paréntesis.
clf.fit(X_train, y_train)
# 3-Realizo la predición
y_pred = clf.predict(X_test)
# imprimo esa predicción
y_pred
```

```
Out[42]: array([2, 1, 0, 2, 0, 2, 0, 1, 1, 1, 2, 1, 1, 1, 1, 0, 1, 1, 0, 0, 2, 1,
       0, 0, 2, 0, 0, 1, 1, 0, 2, 1, 0, 2, 2, 1, 0, 2])
```

-9- Evalúo el modelo

```
In [43]: from sklearn.metrics import confusion_matrix
cm_dtc = confusion_matrix(y_test, y_pred)
cm_dtc
```

```
Out[43]: array([[13,  0,  0],
       [ 0, 15,  1],
       [ 0,  0,  9]])
```

```
In [44]: # Una posible forma para ello es accuracy_score
# existen muchas otras, pero por el momento es suficiente
from sklearn.metrics import accuracy_score
```

```
In [45]: # me dice que % de coincidencias hay
acc_dtc = accuracy_score(y_test, y_pred)
acc_dtc
```

```
Out[45]: 0.9736842105263158
```

0.9736 indica que el 97.36% de los datos han sido predecidos correctamente

Si usamos el get_dummies nos muestra 1??

-10- Repetimos el procedimiento para otro algoritmo

(En este caso)

En la práctica crearíamos una función para hacerlo todo de un solo paso

RandomForestClassifier

```
In [46]: from sklearn.ensemble import RandomForestClassifier
```

```
In [47]: clf = RandomForestClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
y_pred
```

```
Out[47]: array([2, 1, 0, 2, 0, 2, 0, 1, 1, 1, 2, 1, 1, 1, 1, 0, 1, 1, 0, 0, 2, 1,
       0, 0, 2, 0, 0, 1, 1, 0, 2, 1, 0, 2, 2, 1, 0, 2])
```

```
In [48]: cm_rfc = confusion_matrix(y_test, y_pred)
cm_rfc
```

```
Out[48]: array([[13,  0,  0],
       [ 0, 15,  1],
       [ 0,  0,  9]])
```

```
In [49]: acc_rfc = accuracy_score(y_test, y_pred)
acc_rfc
```

```
Out[49]: 0.9736842105263158
```

Logistic Regression

```
In [50]: from sklearn.linear_model import LogisticRegression

algoritmo = LogisticRegression()
```

```
In [51]: algoritmo.fit(X_train, y_train)
```

```
Out[51]: LogisticRegression()
```

```
In [52]: y_pred = algoritmo.predict(X_test)
y_pred
```

```
Out[52]: array([2, 1, 0, 2, 0, 2, 0, 1, 1, 1, 2, 1, 1, 1, 1, 0, 1, 1, 0, 0, 2, 1,
       0, 0, 2, 0, 0, 1, 1, 0, 2, 1, 0, 2, 2, 1, 0, 2])
```

```
In [53]: cm_lr = confusion_matrix(y_test, y_pred)
cm_lr
```

```
Out[53]: array([[13,  0,  0],
       [ 0, 15,  1],
       [ 0,  0,  9]])
```

```
In [54]: acc_lr = accuracy_score(y_test, y_pred)
acc_lr
```

```
Out[54]: 0.9736842105263158
```

KNN

```
In [55]: #Defino el algoritmo a utilizar
from sklearn.neighbors import KNeighborsClassifier

algoritmo = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p=2)
```

```
In [56]: algoritmo.fit(X_train, y_train)
```

```
Out[56]: KNeighborsClassifier()
```

```
In [57]: y_pred = algoritmo.predict(X_test)
y_pred
```

```
Out[57]: array([2, 1, 0, 2, 0, 2, 0, 1, 1, 1, 2, 1, 1, 1, 1, 0, 1, 1, 0, 0, 2, 1,
       0, 0, 2, 0, 0, 1, 1, 0, 2, 1, 0, 2, 2, 1, 0, 2])
```

```
In [58]: cm_knn = confusion_matrix(y_test, y_pred)
cm_knn
```

```
Out[58]: array([[13,  0,  0],
       [ 0, 15,  1],
       [ 0,  0,  9]])
```

```
In [59]: acc_knn = accuracy_score(y_test, y_pred)
acc_knn
```

```
Out[59]: 0.9736842105263158
```

Support Vector Machine (SVM)

```
In [60]: #Import svm model
from sklearn import svm

#Create a svm Classifier
algoritmo = svm.SVC(kernel='linear') # Linear Kernel
```

```
In [61]: algoritmo.fit(X_train, y_train)
```

```
Out[61]: SVC(kernel='linear')
```

```
In [62]: y_pred = algoritmo.predict(X_test)
y_pred
```

```
Out[62]: array([2, 1, 0, 2, 0, 2, 0, 1, 1, 1, 2, 1, 1, 1, 1, 0, 1, 1, 0, 0, 2, 1,
       0, 0, 2, 0, 0, 1, 1, 0, 2, 1, 0, 2, 2, 1, 0, 2])
```

```
In [63]: cm_svm = confusion_matrix(y_test, y_pred)
cm_svm
```

```
Out[63]: array([[13,  0,  0],
       [ 0, 15,  1],
       [ 0,  0,  9]])
```

```
In [64]: acc_svm = accuracy_score(y_test, y_pred)
acc_svm
```

```
Out[64]: 0.9736842105263158
```

Naives Bayes

```
In [65]: from sklearn.naive_bayes import GaussianNB

gnb = GaussianNB()

gnb.fit(X_train, y_train)
```

```
Out[65]: GaussianNB()
```

```
In [66]: y_pred = gnb.predict(X_test)
y_pred
```

```
Out[66]: array([2, 1, 0, 2, 0, 2, 0, 1, 1, 1, 2, 1, 1, 1, 1, 0, 1, 1, 0, 0, 2, 1,
       0, 0, 2, 0, 0, 1, 1, 0, 2, 1, 0, 2, 2, 1, 0, 1])
```

```
In [67]: cm_nb = confusion_matrix(y_test, y_pred)
cm_nb
```

```
Out[67]: array([[13,  0,  0],
       [ 0, 16,  0],
       [ 0,  0,  9]])
```

In [68]:
```
acc_nb = accuracy_score(y_test, y_pred)
acc_nb
```

Out[68]: `1.0`

Conclusión del mejor modelo

In [69]:
```
def test_model():
    models = {}
    models['Decission tree'] = acc_dtc
    models['Random Forest'] = acc_rfc
    models['Logistic Regression'] = acc_lr
    models['KNN'] = acc_knn
    models['Support Vector Machine'] = acc_svm
    models['Naives bayes']= acc_nb
    for key, value in models.items():
        if max(models.values()) == value:
            return key, value
```

In [70]:
```
test_model()
```

Out[70]: `('Naives bayes', 1.0)`

En este caso sale Naives Bayes

Realizamos la predicción

Realizamos la seguiente transformación que habrá que tenerlo encuenta para el resultado:

{'Iris-setosa': 0, 'Iris-versicolor': 1, 'Iris-virginica': 2 }

SepalLengthCm = 1.2

SepalWidthCm = 0.6

PetalLengthCm = 5.6

PetalWidthCm = 1.5

In [72]:
```
test = gnb.predict([[1.2, 0.6, 5.6, 1.5]])
```

In [73]:
```
result = {'Iris-setosa': 0, 'Iris-versicolor': 1, 'Iris-virginica': 2 }

for key, value in result.items():
    if value == test[0]:
        print("Es de tipo: ", key)
```

```
Es de tipo:  Iris-virginica
```

Es de tipo Virgínica

Creado por:

Isabel Maniega