exercises-uci-iris-dataset-classification

March 13, 2022

1 Exercises - UCI Iris Dataset - Classification

Exercises with UCI Iris Dataset.

Original page https://archive.ics.uci.edu/ml/datasets/iris

New beta version UCI website https://archive-beta.ics.uci.edu/ml/datasets/iris

1.1 Packages import

[1]:
```
import requests # web requests
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib as plt # data visualization
import seaborn as sb # data visualization
import graphviz # grahp visualization
from sklearn.model_selection import StratifiedShuffleSplit # dataset subsetting
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder # mange categorical data
from sklearn.linear_model import LogisticRegression
from sklearn import tree as skl_tree # Decision tree models
from sklearn import metrics # results evaluation
```

2 Data preprocessing and exploration

2.1 Data import - (One shoot execution)

Let's use the original website.

Next steps are "one shoot execution", you should execute it only the first time, once did it you can go directly to *Starting points* that youll'find along the code.

First we want to make a web request to download the dataset description and save it locally.

[5]:
```
# Dataset description url
description_url = 'https://archive.ics.uci.edu/ml/machine-learning-databases/
↪iris/iris.names'

requestDatasetDescription = requests.get(description_url, allow_redirects=True)
if requestDatasetDescription.status_code != 200:
```

```python
    print(f"Request status: {requestDatasetDescription.status_code}")
else:
    open('Datasets/Iris/Py_IrisDatasetDescription.txt', 'wb').
 ↪write(requestDatasetDescription.content)
```

[6]:
```python
# Read the dataset description
DatasetDescription = open('Datasets/Iris/Py_IrisDatasetDescription.txt', 'r')
```

[7]:
```python
print(DatasetDescription.read())
```

```
1. Title: Iris Plants Database
        Updated Sept 21 by C.Blake - Added discrepency information

2. Sources:
     (a) Creator: R.A. Fisher
     (b) Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
     (c) Date: July, 1988

3. Past Usage:
   - Publications: too many to mention!!!  Here are a few.
   1. Fisher,R.A. "The use of multiple measurements in taxonomic problems"
      Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions
      to Mathematical Statistics" (John Wiley, NY, 1950).
   2. Duda,R.O., & Hart,P.E. (1973) Pattern Classification and Scene Analysis.
      (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.
   3. Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System
      Structure and Classification Rule for Recognition in Partially Exposed
      Environments".  IEEE Transactions on Pattern Analysis and Machine
      Intelligence, Vol. PAMI-2, No. 1, 67-71.
      -- Results:
         -- very low misclassification rates (0% for the setosa class)
   4. Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE
      Transactions on Information Theory, May 1972, 431-433.
      -- Results:
         -- very low misclassification rates again
   5. See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al's AUTOCLASS II
      conceptual clustering system finds 3 classes in the data.

4. Relevant Information:
   --- This is perhaps the best known database to be found in the pattern
       recognition literature.  Fisher's paper is a classic in the field
       and is referenced frequently to this day.  (See Duda & Hart, for
       example.)  The data set contains 3 classes of 50 instances each,
       where each class refers to a type of iris plant.  One class is
       linearly separable from the other 2; the latter are NOT linearly
       separable from each other.
   --- Predicted attribute: class of iris plant.
```

```
   --- This is an exceedingly simple domain.
   --- This data differs from the data presented in Fishers article
        (identified by Steve Chadwick,  spchadwick@espeedaz.net )
        The 35th sample should be: 4.9,3.1,1.5,0.2,"Iris-setosa"
        where the error is in the fourth feature.
        The 38th sample: 4.9,3.6,1.4,0.1,"Iris-setosa"
        where the errors are in the second and third features.

5. Number of Instances: 150 (50 in each of three classes)

6. Number of Attributes: 4 numeric, predictive attributes and the class

7. 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

8. Missing Attribute Values: None

Summary Statistics:
                 Min  Max   Mean    SD   Class Correlation
   sepal length: 4.3  7.9   5.84  0.83    0.7826
    sepal width: 2.0  4.4   3.05  0.43   -0.4194
   petal length: 1.0  6.9   3.76  1.76    0.9490  (high!)
    petal width: 0.1  2.5   1.20  0.76    0.9565  (high!)

9. Class Distribution: 33.3% for each of 3 classes.
```

Let's import the dataset directly with *pandas* and save it in a comfortable python format

[9]:
```
IrisDF = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/
 ↪iris/iris.data', header=None)

IrisDF.to_pickle("Datasets/Iris/IrisDF.pkl")
```

2.2 Starting point - read data

Once downloaded the dataset the first time, you can restart from here reading the saved pandas DF object

[2]:
```
IrisDF = pd.read_pickle("Datasets/Iris/IrisDF.pkl")
type(IrisDF)
```

[2]: pandas.core.frame.DataFrame

2.3 Data exploration

[3]:
```
print(IrisDF.shape)
IrisDF.head()
```

```
(150, 5)
```

[3]:

	0	1	2	3	4
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]:
```
print(IrisDF.describe())
```

```
                0           1           2           3
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
```

Let's add colunmns description

[3]:
```
IrisDF.columns = ['Sepal_Length', 'Sepal_Width','Petal_Length', 'Petal_Width',␣
 ↪'Species' ]
print(IrisDF.describe())
```

```
       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
```

categorical data exploration

[7]:
```
print(IrisDF.groupby('Species').size())
```

```
Species
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
dtype: int64
```

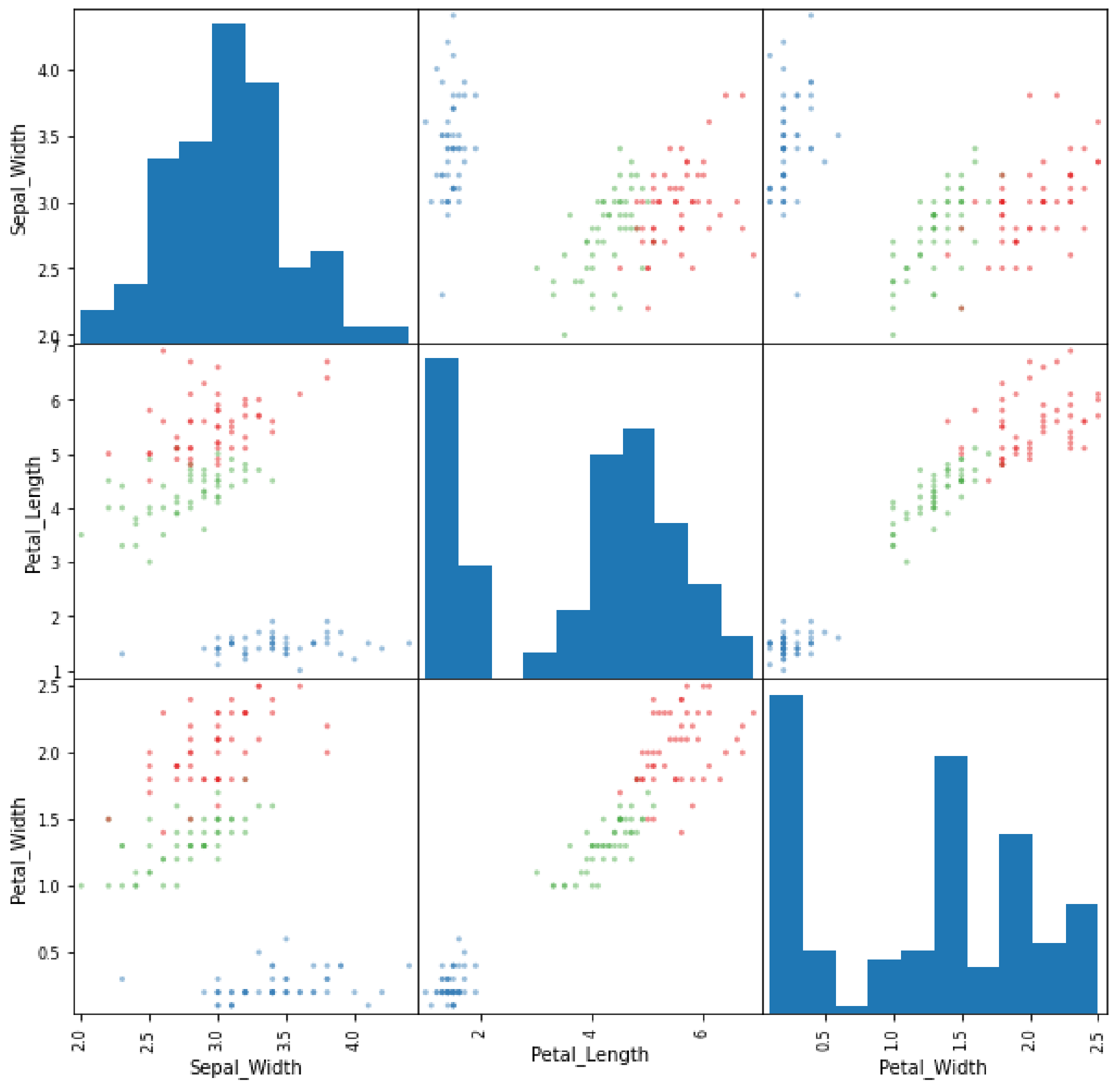
Let's have a graphical global exploration

[8]:
```python
colors_palette = {'Iris-setosa': '#377eb8', \
                  'Iris-versicolor': '#4eae4b',\
                  'Iris-virginica': '#e41a1c'}

colors = [colors_palette[c] for c in IrisDF.loc[ : , 'Species']]
```

[9]:
```python
pd.plotting.scatter_matrix(IrisDF.iloc[: , 1: ], color=colors, figsize=(10,10))
```

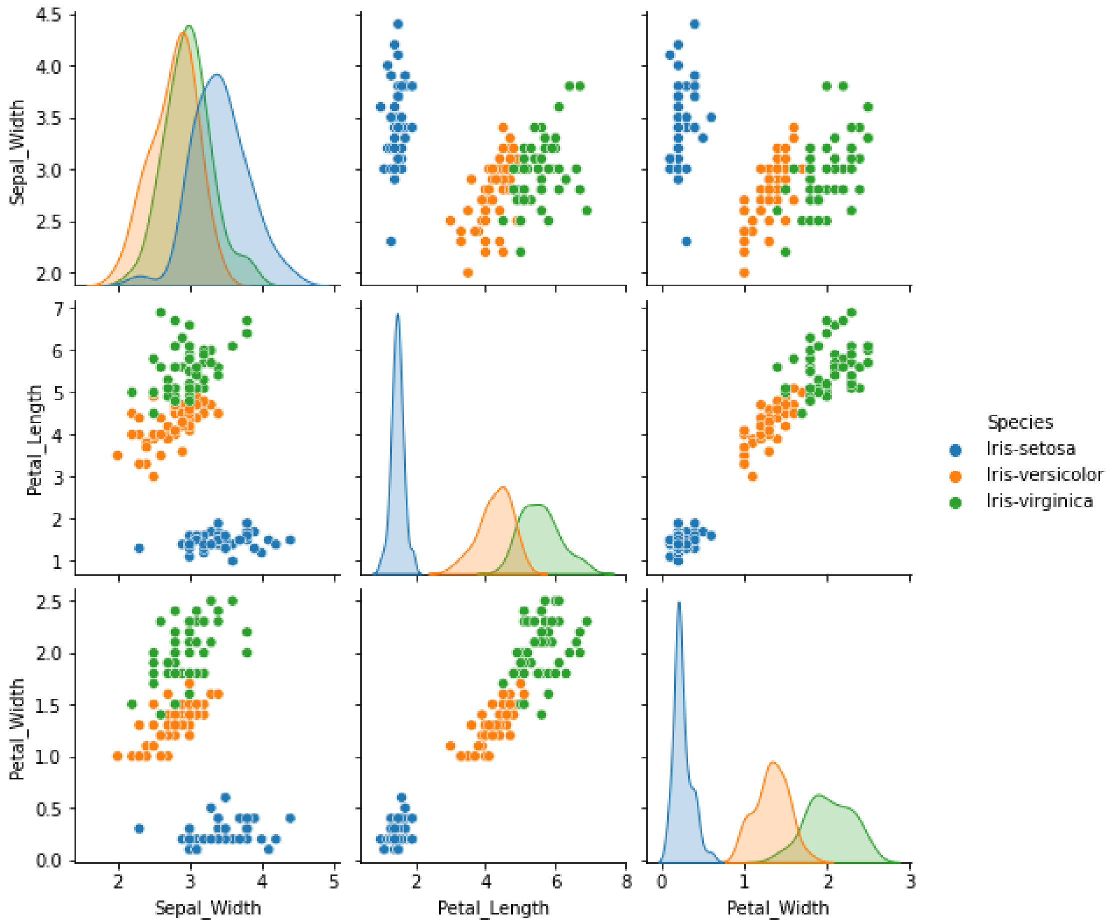
[9]:
```
array([[<AxesSubplot:xlabel='Sepal_Width', ylabel='Sepal_Width'>,
        <AxesSubplot:xlabel='Petal_Length', ylabel='Sepal_Width'>,
        <AxesSubplot:xlabel='Petal_Width', ylabel='Sepal_Width'>],
       [<AxesSubplot:xlabel='Sepal_Width', ylabel='Petal_Length'>,
        <AxesSubplot:xlabel='Petal_Length', ylabel='Petal_Length'>,
        <AxesSubplot:xlabel='Petal_Width', ylabel='Petal_Length'>],
       [<AxesSubplot:xlabel='Sepal_Width', ylabel='Petal_Width'>,
        <AxesSubplot:xlabel='Petal_Length', ylabel='Petal_Width'>,
        <AxesSubplot:xlabel='Petal_Width', ylabel='Petal_Width'>]],
      dtype=object)
```



Let's try using seaborn

[10]:
```
sb.pairplot(IrisDF.iloc[: , 1: ], hue="Species" )
```

[10]: <seaborn.axisgrid.PairGrid at 0x7f7dbf9eb5b0>



2.4 Training and Test subsetting

Let's create traing and test subset with variable Species propotrional to the original dataset

[6]:
```
split_3_7 = StratifiedShuffleSplit(n_splits=1, test_size=0.7, random_state=22)

for train_index, test_index in split_3_7.split(IrisDF, IrisDF['Species']):
    proportional_train = IrisDF.loc[train_index]
    proportional_test = IrisDF.loc[test_index]
```

[7]:
```
proportional_train['Species'].value_counts()/len(proportional_train)
```

[7]:
```
Iris-virginica     0.333333
Iris-versicolor    0.333333
Iris-setosa        0.333333
Name: Species, dtype: float64
```

[8]:
```
proportional_test['Species'].value_counts()/len(proportional_test)
```

[8]:
```
Iris-virginica     0.333333
Iris-setosa        0.333333
Iris-versicolor    0.333333
Name: Species, dtype: float64
```

[9]:
```
proportional_train.describe()
```

[9]:

	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width
count	45.000000	45.000000	45.000000	45.000000
mean	5.877778	2.991111	3.820000	1.182222
std	0.931980	0.456181	1.869565	0.772331
min	4.300000	2.200000	1.000000	0.100000
25%	5.000000	2.700000	1.500000	0.200000
50%	5.800000	3.000000	4.500000	1.300000
75%	6.500000	3.200000	5.100000	1.800000
max	7.700000	4.200000	6.900000	2.500000

[11]:
```
proportional_test.describe()
```

[11]:

	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width
count	105.000000	105.000000	105.000000	105.000000
mean	5.828571	3.080952	3.732381	1.205714
std	0.783694	0.422924	1.726017	0.762817
min	4.400000	2.000000	1.200000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.300000	1.300000
75%	6.400000	3.400000	5.100000	1.800000
max	7.900000	4.400000	6.700000	2.500000

3 Models application

3.1 Preprocessing - Standardization

A lot of ML models suppose that the data are distributed as a Gaussian with zero mean and unit variance. So we need to standardize the data to achive better results.

StandardScaler Scikit Learn package makes a simple naive rescaling that could be a good choice in this case. It simply remove the mean and divide for the standard deviation each feature

3.1.1 Digression on standardization

There are different opinions on when and how apply standardization. We can find 3 main opinions:

- Standardize the entire dataset before splitting
- Standardize the dataset after splitting using the mean ad standard deviation of the training subset also for the test subset
- Standardize the dataset after splitting using the mean ad standard deviation of the training subset only for the training subset and the mean ad standard deviation of the test subset only for the test subset

I've an unpopular opinon: there are no a priori a real good or bad choice, except for some particular situations.

Anyway I have a preference for the third choice.

So let's try to explain the reasons for the third choice wich probably most of the people consider a bad choice.

In most of the cases the statistic behind the model is demostrated supposing tha the data are distributed as a Gaussian with zero mean and unit variance, so make the conditions for this supposition both in the training and in the testing of the model shouldn't be considered a bad idea. We are testing the model in the conditions on wich the teorical bases have been constructed.

Clearly we must not forget that the "real world dataset" will tend to be a Gaussian with zero mean and unit variance but our dataset will ever bee to small to be exactly that. Aniway we have no reasons to consider the addition of a non random noise (firsth and second options) a better choice.

I'm planning to make some empirical test in future to have a feedback on my opinion, for the moment let's apply also the second choice wich is the most common.

[12]:
```
scaled_prop_train = proportional_train
scaled_prop_test_T = proportional_test
scaled_prop_test_FT = proportional_test

scaler1 = StandardScaler()
scaler2 = StandardScaler()



scaled_prop_train.iloc[:, 0:4] = scaler1.fit_transform(scaled_prop_train.iloc[:
 ↪, 0:4])
scaled_prop_test_T.iloc[:, 0:4] = scaler1.transform(scaled_prop_test_T.iloc[:,␣
 ↪0:4])
scaled_prop_test_FT.iloc[:, 0:4] = scaler2.fit_transform(scaled_prop_test_FT.
 ↪iloc[:, 0:4])
```

[13]:
```
scaled_prop_test_T.describe()
```

[13]:

	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width
count	1.050000e+02	1.050000e+02	1.050000e+02	1.050000e+02
mean	3.595008e-17	3.172066e-18	4.229421e-18	-3.595008e-17
std	1.004796e+00	1.004796e+00	1.004796e+00	1.004796e+00
min	-1.831612e+00	-2.568163e+00	-1.474219e+00	-1.456466e+00
25%	-9.341223e-01	-6.674960e-01	-1.241360e+00	-1.193023e+00
50%	-3.663225e-02	-1.923294e-01	3.304380e-01	1.241948e-01
75%	7.326450e-01	7.580039e-01	7.961559e-01	7.828035e-01
max	2.655838e+00	3.133837e+00	1.727592e+00	1.704856e+00

[14]:
```
scaled_prop_test_FT.describe()
```

[14]:
```
       Sepal_Length   Sepal_Width  Petal_Length   Petal_Width
count  1.050000e+02  1.050000e+02  1.050000e+02  1.050000e+02
mean   3.595008e-17  3.172066e-18  4.229421e-18 -3.595008e-17
std    1.004796e+00  1.004796e+00  1.004796e+00  1.004796e+00
min   -1.831612e+00 -2.568163e+00 -1.474219e+00 -1.456466e+00
25%   -9.341223e-01 -6.674960e-01 -1.241360e+00 -1.193023e+00
50%   -3.663225e-02 -1.923294e-01  3.304380e-01  1.241948e-01
75%    7.326450e-01  7.580039e-01  7.961559e-01  7.828035e-01
max    2.655838e+00  3.133837e+00  1.727592e+00  1.704856e+00
```

[15]:
```python
scaled_prop_train.describe()
```

[15]:
```
       Sepal_Length   Sepal_Width  Petal_Length   Petal_Width
count  4.500000e+01  4.500000e+01  4.500000e+01  4.500000e+01
mean  -4.798631e-16  1.148772e-16  3.219647e-16 -4.096260e-16
std    1.011300e+00  1.011300e+00  1.011300e+00  1.011300e+00
min   -1.712062e+00 -1.753801e+00 -1.525417e+00 -1.417075e+00
25%   -9.524850e-01 -6.453593e-01 -1.254953e+00 -1.286134e+00
50%   -8.439740e-02  1.970563e-02  3.678310e-01  1.542197e-01
75%    6.751792e-01  4.630823e-01  6.923877e-01  8.089260e-01
max    1.977311e+00  2.679966e+00  1.666058e+00  1.725515e+00
```

[16]:
```python
print(scaler1.mean_)
print(scaler1.var_)
print(scaler2.mean_)
print(scaler2.var_)
```

```
[5.87777778 2.99111111 3.82       1.18222222]
[0.84928395 0.20347654 3.4176     0.58323951]
[-0.05339427  0.19916761 -0.04739559  0.03076081]
[0.71628167 0.87067037 0.86340151 0.9881846 ]
```

3.2 Multinomial logistic regression (softmax regression)

Let's use scikit-learn package.

We need to specify that has to be multinomial classification and we need to specify a solver wich allows softmax regression.

In this case we have few feature and apparently all important so we can reduce the impact of the regularization term.

[20]:
```python
# C parameter is the invers of the parameter applied to the regularization term
softmax_regressionM_Slbfgs_C10 = LogisticRegression(multi_class='multinomial', ␣
↪solver='lbfgs', C=100)

#encode categorical data
labels = scaled_prop_train.iloc[:,4].to_numpy()
label_encoder = LabelEncoder()
```

```
label_encoded_labels = label_encoder.fit_transform(labels)

# training
softmax_regressionM_Slbfgs_C10.fit(scaled_prop_train.iloc[:,0:4],␣
 ↪label_encoded_labels)

# prediction
softmax_regressionM_Slbfgs_C10_predictionT = softmax_regressionM_Slbfgs_C10.
 ↪predict(scaled_prop_test_T.iloc[:,0:4])
softmax_regressionM_Slbfgs_C10_predictionFT = softmax_regressionM_Slbfgs_C10.
 ↪predict(scaled_prop_test_FT.iloc[:,0:4])

test_labels = scaled_prop_test_T.iloc[:,4].to_numpy()
test_labels_encoded = label_encoder.transform(test_labels)

# results evaluation
print(f"The accuracy of the scikit-learn implementation of Softmax Regression␣
 ↪with lbfgs solver and 100 as C parameter on test dataset standardize on␣
 ↪traning data is \
{metrics.accuracy_score(softmax_regressionM_Slbfgs_C10_predictionT,␣
 ↪test_labels_encoded)}" )
print(f"The accuracy of the scikit-learn implementation of Softmax Regression␣
 ↪with lbfgs solver and 100 as C parameter on test dataset standardize on test␣
 ↪data is \
{metrics.accuracy_score(softmax_regressionM_Slbfgs_C10_predictionFT,␣
 ↪test_labels_encoded)}" )
```

```
The accuracy of the scikit-learn implementation of Softmax Regression with lbfgs
solver and 100 as C parameter on test dataset standardize on traning data is
0.9809523809523809
The accuracy of the scikit-learn implementation of Softmax Regression with lbfgs
solver and 100 as C parameter on test dataset standardize on test data is
0.9809523809523809
```

Looks good :)

3.3 Decision tree (Herarchical model)

Let's use scikit-learn package. Take in consideration that scikit-learn DecisionTreeClassifier is based on CART algorithm (Classification And Regression Trees). Let's try it with defatul values, wich means split down to the deepest possibile split using gini index (node "purity" check).

[7]:
```
default_tree = skl_tree.DecisionTreeClassifier()

# There is no need of standardization for Decision trees so let's use non␣
 ↪standardized subsets.
labels = proportional_train.iloc[:,4].to_numpy()
label_encoder = LabelEncoder()
```

```
label_encoded_labels = label_encoder.fit_transform(labels)

default_tree.fit(proportional_train.iloc[:, 0:4], label_encoded_labels)
default_tree_prediction = default_tree.predict(proportional_test.iloc[:, 0:4])

test_labels = proportional_test.iloc[:,4].to_numpy()
test_labels_encoded = label_encoder.transform(test_labels)


print (f"The accuracy of the scikit-learn implementation of Decision Tree with␣
 ↪default parameters is \
{metrics.accuracy_score(default_tree_prediction, test_labels_encoded)}")
```

```
The accuracy of the scikit-learn implementation of Decision Tree with default
parameters is 0.9619047619047619
```

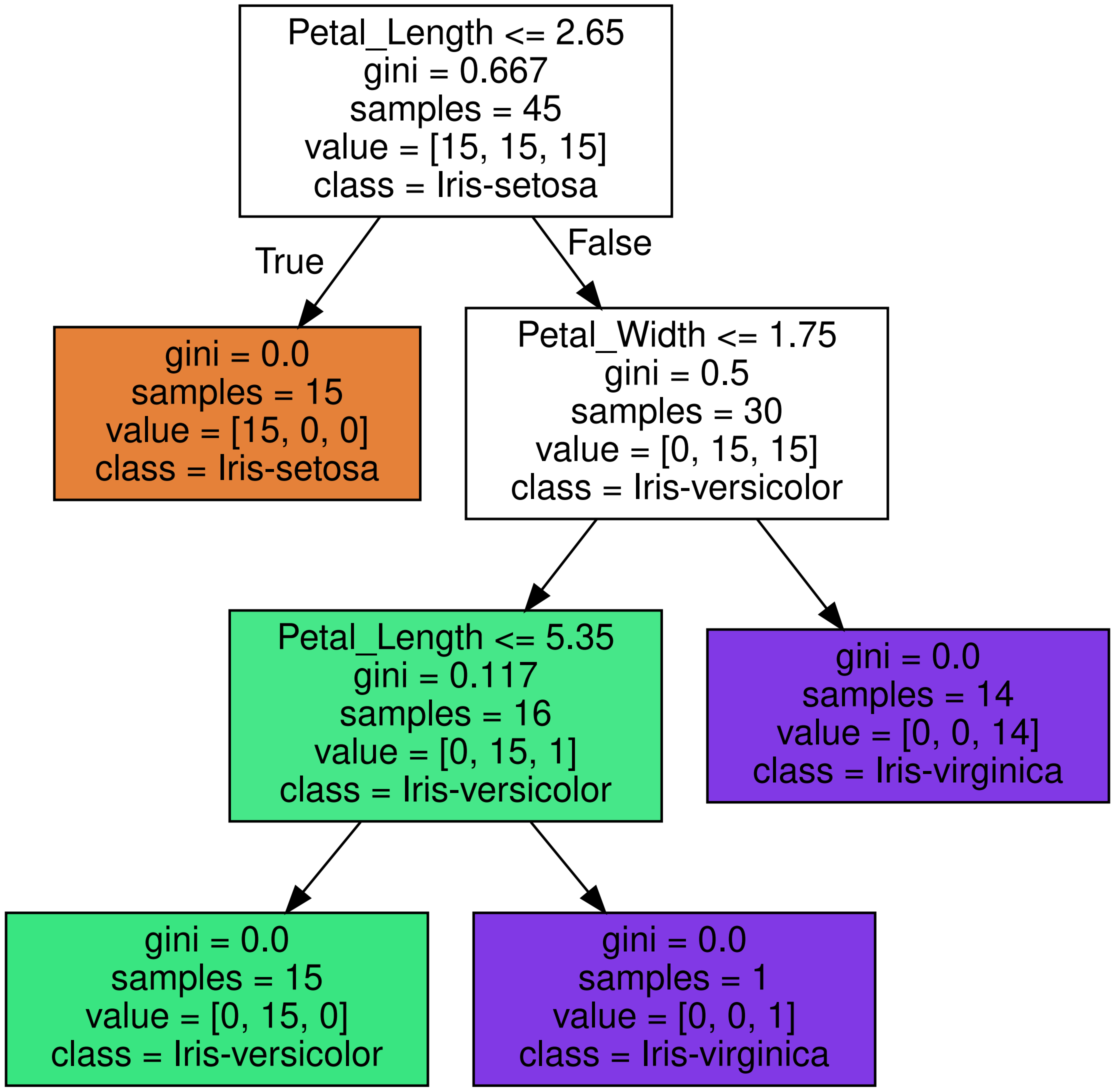
still good

we can also have a graphical visualization of the decision tree

[8]:
```
default_tree_graph = skl_tree.export_graphviz(default_tree, \
                                              feature_names = IrisDF.
 ↪columns[0:4], \
                                              class_names = label_encoder.
 ↪inverse_transform([0,1,2]), \
                                              filled = True)

image_graph = graphviz.Source(default_tree_graph)
image_graph
```

[8]:


Petal_Length <= 2.65
gini = 0.667
samples = 45
value = [15, 15, 15]
class = Iris-setosa
True
False
gini = 0.0
samples = 15
value = [15, 0, 0]
class = Iris-setosa
Petal_Width <= 1.75
gini = 0.5
samples = 30
value = [0, 15, 15]
class = Iris-versicolor
Petal_Length <= 5.35
gini = 0.117
samples = 16
value = [0, 15, 1]
class = Iris-versicolor
gini = 0.0
samples = 14
value = [0, 0, 14]
class = Iris-virginica
gini = 0.0
samples = 15
value = [0, 15, 0]
class = Iris-versicolor
gini = 0.0
samples = 1
value = [0, 0, 1]
class = Iris-virginica

```
[ ]:
```