Iris Data Classification

January 27, 2024

[3]:
```
from sklearn import datasets
import pandas as pd
import numpy as np

iris = datasets.load_iris() #Loading the dataset
iris.keys()

dict_keys = (['data', 'target', 'frame', 'target_names', 'DESCR',␣
↪'feature_names', 'filename', 'data_module'])
```

[4]:
```
iris = pd.DataFrame(
    data= np.c_[iris['data'], iris['target']],
    columns= iris['feature_names'] + ['target']
    )
```

[5]:
```
iris.head(10)
```

[5]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0.0
1	4.9	3.0	1.4	0.2	0.0
2	4.7	3.2	1.3	0.2	0.0
3	4.6	3.1	1.5	0.2	0.0
4	5.0	3.6	1.4	0.2	0.0
5	5.4	3.9	1.7	0.4	0.0
6	4.6	3.4	1.4	0.3	0.0
7	5.0	3.4	1.5	0.2	0.0
8	4.4	2.9	1.4	0.2	
9	4.9	3.1	1.5	0.1	

```
8     0.0
9     0.0
```

[6]:
```
species = []

for i in range(len(iris['target'])):
    if iris['target'][i] == 0:
        species.append("setosa")
    elif iris['target'][i] == 1:
        species.append('versicolor')
    else:
        species.append('virginica')


iris['species'] = species
```

[7]:
```
iris.groupby('species').size()
```

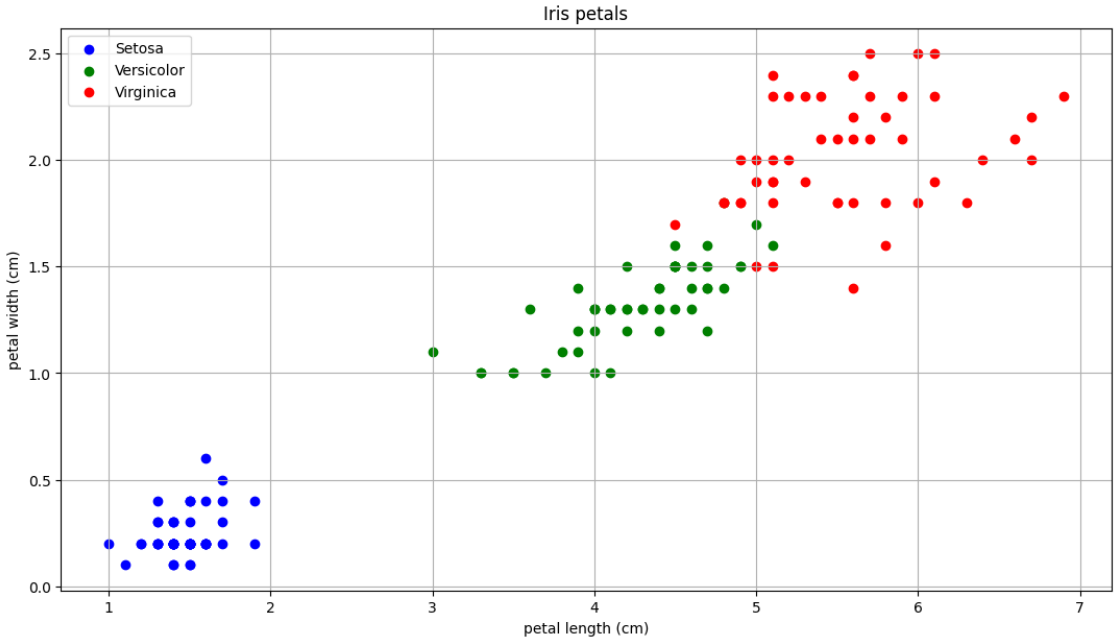
[7]:
```
species
setosa        50
versicolor    50
virginica     50
dtype: int64
```

[8]:
```
iris.describe()
```

[8]:
```
       sepal length (cm)  sepal width (cm)  petal length (cm)  \
count         150.000000        150.000000         150.000000
mean            5.843333          3.057333           3.758000
std             0.828066          0.435866           1.765298
min             4.300000          2.000000           1.000000
25%             5.100000          2.800000           1.600000
50%             5.800000          3.000000           4.350000
75%             6.400000          3.300000           5.100000
max             7.900000          4.400000           6.900000

       petal width (cm)      target
count        150.000000  150.000000
mean           1.199333    1.000000
std            0.762238    0.819232
min            0.100000    0.000000
25%            0.300000    0.000000
50%            1.300000    1.000000
75%            1.800000    2.000000
max            2.500000    2.000000
```

[9]:
```
import matplotlib.pyplot as plt

setosa = iris[iris.species == "setosa"]
versicolor = iris[iris.species=='versicolor']
virginica = iris[iris.species=='virginica']

fig, ax = plt.subplots()
fig.set_size_inches(13, 7) # adjusting the length and width of plot

# lables and scatter points
ax.scatter(setosa['petal length (cm)'], setosa['petal width (cm)'],␣
 ↪label="Setosa", facecolor="blue")
ax.scatter(versicolor['petal length (cm)'], versicolor['petal width (cm)'],␣
 ↪label="Versicolor", facecolor="green")
ax.scatter(virginica['petal length (cm)'], virginica['petal width (cm)'],␣
 ↪label="Virginica", facecolor="red")


ax.set_xlabel("petal length (cm)")
ax.set_ylabel("petal width (cm)")
ax.grid()
ax.set_title("Iris petals")
ax.legend()
```

[9]: <matplotlib.legend.Legend at 0x254479ff390>



[10]:
```
from sklearn.model_selection import train_test_split

# Droping the target and species since we only need the measurements
X = iris.drop(['target','species'], axis=1)

# converting into numpy array and assigning petal length and petal width
X = X.to_numpy()[:, (2,3)]
y = iris['target']

# Splitting into train and test
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.5,␣
 ↪random_state=42)
```

[11]:
```
from sklearn.linear_model import LogisticRegression

log_reg = LogisticRegression()
log_reg.fit(X_train,y_train)
```

[11]:
```
LogisticRegression()
```

[12]:
```
training_prediction = log_reg.predict(X_train)
training_prediction
```

[12]:
```
array([1., 2., 1., 0., 1., 2., 0., 0., 1., 2., 0., 2., 0., 0., 2., 1., 2.,
       2., 2., 2., 1., 0., 0., 1., 2., 0., 0., 0., 1., 2., 0., 2., 2., 0.,
       1., 1., 2., 1., 2., 0., 2., 1., 2., 1., 1., 1., 0., 1., 1., 0., 1.,
       2., 2., 0., 1., 2., 2., 0., 2., 0., 1., 2., 2., 1., 2., 1., 1., 2.,
       2., 0., 1., 1., 0., 1., 2.])
```

[13]:
```
test_prediction = log_reg.predict(X_test)
test_prediction
```

[13]:
```
array([1., 0., 2., 1., 1., 0., 1., 2., 1., 1., 2., 0., 0., 0., 0., 1., 2.,
       1., 1., 2., 0., 2., 0., 2., 2., 2., 2., 2., 0., 0., 0., 0., 1., 0.,
       0., 2., 1., 0., 0., 0., 2., 1., 1., 0., 0., 1., 2., 2., 1., 2., 1.,
       2., 1., 0., 2., 1., 0., 0., 0., 1., 2., 0., 0., 0., 1., 0., 1., 2.,
       0., 1., 2., 0., 2., 2., 1.])
```

[14]:
```
from sklearn import metrics

print("Precision, Recall, Confusion matrix, in training\n")

# Precision Recall scores
print(metrics.classification_report(y_train, training_prediction, digits=3))

# Confusion matrix
print(metrics.confusion_matrix(y_train, training_prediction))
```

```
Precision, Recall, Confusion matrix, in training

              precision    recall  f1-score   support

         0.0      1.000     1.000     1.000        21
         1.0      0.923     0.889     0.906        27
         2.0      0.893     0.926     0.909        27

    accuracy                          0.933        75
   macro avg      0.939     0.938     0.938        75
weighted avg      0.934     0.933     0.933        75

[[21  0  0]
 [ 0 24  3]
 [ 0  2 25]]
```

[15]:
```
print("Precision, Recall, Confusion matrix, in testing\n")

# Precision Recall scores
print(metrics.classification_report(y_test, test_prediction, digits=3))

# Confusion matrix
print(metrics.confusion_matrix(y_test, test_prediction))
```

```
Precision, Recall, Confusion matrix, in testing

              precision    recall  f1-score   support

         0.0      1.000     1.000     1.000        29
         1.0      1.000     1.000     1.000        23
         2.0      1.000     1.000     1.000        23

    accuracy                          1.000        75
   macro avg      1.000     1.000     1.000        75
weighted avg      1.000     1.000     1.000        75

[[29  0  0]
 [ 0 23  0]
 [ 0  0 23]]
```

[ ]:
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