Scikit-learn

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable

What we can achieve using sciket-learn

Classfication
Identifying which category an object belongs to.
Applications: Spam detection, image recognition.

Regression
Predicting a continuous-valued attribute associated with an object.
Applications:Drug response, Stock prices.

Clustering
Automatic grouping of similar objects into sets.
Applications:Customer segmentation, Grouping experiment outcomes.

Model selection
Comparing, validating and choosing parameters and models.
ApplicationsImproved accuracy via parameter tuning.

Preprocessing
Feature extraction and normalization.
Applications: Transforming input data such as text for use with machine learning algorithms.

In [1]:
```python
#Importing required packages.
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [21]:
```python
#Loading dataset
wine = pd.read_csv('winequality-red.csv',sep=';')
wine.head()
```

Out[21]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

In [22]:
```python
#Information about the data columns
wine.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1599 non-null   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1599 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

In [23]:
```python
#checking to see if there's any null variables
wine.isnull().sum()
```

Out[23]:
```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

In [24]:
```python
wine['quality'].unique()
```

Out[24]:
```
array([5, 6, 7, 4, 8, 3], dtype=int64)
```

In [25]:
```python
#Preprocessing Data
bins=(2,6.5,8)
group_names=['Bad','Good']
wine['quality']=pd.cut(wine['quality'],bins=bins,labels=group_names)
wine['quality'].unique()
```

Out[25]:
```
['Bad', 'Good']
Categories (2, object): ['Bad' < 'Good']
```

In [27]:
```python
##Now lets assign a labels to our quality variable We use sklearn
from sklearn.preprocessing import LabelEncoder
label_quality = LabelEncoder()
```

In [28]:
```python
wine['quality'] = label_quality.fit_transform(wine['quality'])

#Bad becomes 0 and good becomes 1
```

In [30]:
```python
wine.head(10)
```

Out[30]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	0
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	0
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	0
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	0
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	0
5	7.4	0.66	0.00	1.8	0.075	13.0	40.0	0.9978	3.51	0.56	9.4	0
6	7.9	0.60	0.06	1.6	0.069	15.0	59.0	0.9964	3.30	0.46	9.4	0
7	7.3	0.65	0.00	1.2	0.065	15.0	21.0	0.9946	3.39	0.47	10.0	1
8	7.8	0.58	0.02	2.0	0.073	9.0	18.0	0.9968	3.36	0.57	9.5	1
9	7.5	0.50	0.36	6.1	0.071	17.0	102.0	0.9978	3.35	0.80	10.5	0

In [31]:
```python
wine['quality'].value_counts()
```

Out[31]:
```
0    1382
1     217
Name: quality, dtype: int64
```

In [36]:
```python
sns.countplot(wine['quality'])
```

```
C:\Users\Sikandar Hayat\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[36]:
```
<AxesSubplot:xlabel='quality', ylabel='count'>
```

In [34]:
```python
#Now seperate the dataset as response variable and feature variabes
X = wine.drop('quality', axis = 1)
y = wine['quality']
```

In [35]:
```python
#Train and Test splitting of data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
```

In [37]:
```python
#Applying Standard scaling to get optimized result
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
```

In [38]:
```python
X_train = sc.fit_transform(X_train)
X_test = sc.fit_transform(X_test)
```

LogisticRegression

In [48]:
```python
# import the class
from sklearn.linear_model import LogisticRegression

# instantiate the model (using the default parameters)
model = LogisticRegression()

# fit the model with data
model.fit(X_train,y_train)

#
model.score(X_test,y_test)
```

Out[48]:
```
0.875
```

In [64]:
```python
#Prediction
y_pred=model.predict(X_test)
len(y_pred)
print(y_pred[200:210])
print(y_test[200:210])
```

```
[0 0 0 0 1 0 0 0 0 0]
727     0
614     0
309     0
78      0
1167    1
1473    0
1385    0
679     0
371     0
584     1
Name: quality, dtype: int32
```

In [67]:
```python
#Let's see how our model performed
print(classification_report(y_test, y_pred))
```

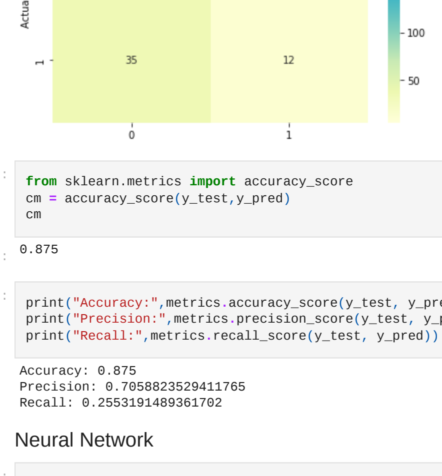
```
              precision    recall  f1-score   support

           0       0.88      0.98      0.93       273
           1       0.71      0.26      0.37        47

    accuracy                           0.88       320
   macro avg       0.80      0.62      0.65       320
weighted avg       0.86      0.88      0.85       320
```

In [74]:
```python
#Confusion matrix for the Logistic Regression
cnf_matrix=confusion_matrix(y_test, y_pred)
cnf_matrix
```

Out[74]:
```
array([[268,   5],
       [ 35,  12]], dtype=int64)
```

In [75]:
```python
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[75]:
```
Text(0.5, 257.44, 'Predicted label')
```



In [71]:
```python
from sklearn.metrics import accuracy_score
cm = accuracy_score(y_test,y_pred)
cm
```

Out[71]:
```
0.875
```

In [76]:
```python
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred))
print("Recall:",metrics.recall_score(y_test, y_pred))
```

```
Accuracy: 0.875
Precision: 0.7058823529411765
Recall: 0.2553191489361702
```

Neural Network

In [90]:
```python
from sklearn.neural_network import MLPClassifier
Model = MLPClassifier(hidden_layer_sizes=(100,200,400,500), max_iter=1000)
```

In [91]:
```python
#Train Neural Network
Model.fit(X_train,y_train)
```

Out[91]:
```
MLPClassifier(hidden_layer_sizes=(100, 200, 400, 500), max_iter=1000)
```

In [92]:
```python
Model.score(X_test,y_test)
```

Out[92]:
```
0.903125
```

In [93]:
```python
#Prediction
y_pred=Model.predict(X_test)
len(y_pred)
print(y_pred[200:210])
print(y_test[200:210])
```

```
[0 0 0 0 1 0 0 0 0 1]
727     0
614     0
309     0
78      0
1167    1
1473    0
1385    0
679     0
371     0
584     1
Name: quality, dtype: int32
```

In [94]:
```python
cnf_matrix=confusion_matrix(y_test, y_pred)
cnf_matrix
```

Out[94]:
```
array([[261,  12],
       [ 19,  28]], dtype=int64)
```

In [95]:
```python
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[95]:
```
Text(0.5, 257.44, 'Predicted label')
```

In [127…
```python
Model_2 = MLPClassifier(hidden_layer_sizes=(100,150,200,500), max_iter=1000,activation='logistic',batch_size=32)# default='relu'
```

In [128…
```python
Model_2.fit(X_train,y_train)
```

Out[128…
```
MLPClassifier(activation='logistic', batch_size=32,
              hidden_layer_sizes=(100, 150, 200, 500), max_iter=1000)
```

In [129…
```python
Model_2.score(X_test,y_test)
```

Out[129…
```
0.86875
```

In [ ]:
```python

```

In [ ]:
```python
# class sklearn.neural_network.MLPClassifier(hidden_layer_sizes=(100,),
#                                             activation='relu', *, solver='adam',
#                                             alpha=0.0001, batch_size='auto',
#                                             learning_rate='constant',
#                                             learning_rate_init=0.001,
#                                             power_t=0.5, max_iter=200,
#                                             shuffle=True, random_state=None,
#                                             tol=0.0001, verbose=False,
#                                             warm_start=False, momentum=0.9,
#                                             nesterovs_momentum=True, early_stopping=False,
#                                             validation_fraction=0.1, beta_1=0.9, beta_2=0.999,
#                                             epsilon=1e-08, n_iter_no_change=10, max_fun=15000)
```

In [130…
```python
Xnew = [[7.4,0.70,0.00,1.9,0.076,11.0,34.0,0.9978,3.51,0.56,9.4]]
Xnew=sc.transform(Xnew)
ynew = Model_2.predict(Xnew)
if(ynew):
    print("Wine is Good")
else:
    print('Wine is bad')
```

```
Wine is bad
```

Save and Load Machine Learning Models in Python with scikit-learn

In [131…
```python
import pickle
```

In [132…
```python
# save the model to disk
filename = 'Wine_Neural_network.sav'
pickle.dump(Model_2, open(filename, 'wb'))
```

In [134…
```python
# some time later...

# load the model from disk
loaded_model = pickle.load(open(filename, 'rb'))
result = loaded_model.score(X_test, y_test)
print(result)
```

```
0.86875
```

In [144…
```python
Xnew = [[7.3,0.65,0.00,1.2,0.065,15.0,21.0,0.9946,3.39,0.47,10.0]]
Xnew=sc.transform(Xnew)
ynew = loaded_model.predict(Xnew)
if(ynew):
    print("Wine is Good")
else:
    print('Wine is bad')
```

```
Wine is bad
```

In [145…
```python
ynew
```

Out[145…
```
array([0])
```

What is Feature Scaling?

Feature Scaling is a method to scale numeric feature in the same scale or range (like:-1 to 1, 0 to 1).
This last step involved in Data Preprocessing and before ML Model training.
It is also called data normalization
We apply feature scaling om independent variable.

Why Feature Scaling?

The Scale of raw feature is different according to its units.
Machine learning algorithms can not understand feature units,understand only number
Ex: if hight 140cm and 8.2feet
Types Of Scaler
Min Max Scaler, Standard Scaler, Max Abs Scaler etc

What is Normalization?

- Normalization rescale the feature in fixed range b/w 0 and 1.
- Normalization also calles as Min-Max Scalling.
- If data doesn't follow normal distribution(Gussian Distribution).

Standardization Vs Normalization ?

- There is no any thumb rule to use Standardization or Normalization for Special Ml algo.
- But mostly Standaridization use clustring analysis,Princpal Component Analysis(PCA).
- Normalization prefer for image processing because pixel intensity b/w 0 to 255,neural network algorith require in scale 0-1,K-Nearest Neighbors.

In [148…
```python
import pandas as pd
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
```

In [151…
```python
df=sns.load_dataset('titanic')
df.head()
```

Out[151…

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	False
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	True
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	True

In [155…
```python
df2=df[['survived','pclass','age','parch']]
df2.head()
```

Out[155…

	survived	pclass	age	parch
0	0	3	22.0	0
1	1	1	38.0	0
2	1	3	26.0	0
3	1	1	35.0	0
4	0	3	35.0	0

In [157…
```python
#checking to see if there's any null variables
df2.isnull().sum()
```

Out[157…
```
survived      0
pclass        0
age         177
parch         0
dtype: int64
```

In [158…
```python
df3=df2.fillna(df2.mean())
```

In [159…
```python
X=df3.drop('survived',axis=1)
Y=df3['survived']
```

In [162…
```python
#Train and Test splitting of data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.2, random_state = 42)
```

In [163…
```python
# Standard Scaler
sc=StandardScaler()
sc.fit(X_train )
```

Out[163…
```
StandardScaler()
```

In [164…
```python
sc.mean_
```

Out[164…
```
array([ 2.33005618, 29.53822538,  0.37921348])
```

In [165…
```python
sc.scale_
```

Out[165…
```
array([ 0.82400502, 12.98541943,  0.79111317])
```

In [169…
```python
X_train.describe()
```

Out[169…

	pclass	age	parch
count	712.000000	712.000000	712.000000
mean	2.330056	29.538225	0.379213
std	0.824584	12.994548	0.791669
min	1.000000	0.420000	0.000000
25%	2.000000	22.000000	0.000000
50%	3.000000	29.699118	0.000000
75%	3.000000	35.000000	0.000000
max	3.000000	80.000000	6.000000

In [176…
```python
X_train_sc=sc.transform(X_train)
X_test_sc=sc.transform(X_test)
```

In [177…
```python
X_train_sc
```

Out[177…
```
array([[-1.61413602,  1.22920747, -0.47934164],
       [-0.40055118, -0.50350514, -0.47934164],
       [ 0.81303367,  0.18957991, -0.47934164],
       ...,
       [ 0.81303367,  0.88266495, -0.47934164],
       [-1.61413602, -1.19659018,  2.04874166],
       [-1.61413602, -0.65752403,  0.78470001]])
```

In [178…
```python
X_train_sc=pd.DataFrame(X_train_sc,columns=['pclass','age','parch'])
X_test_sc=X_train_sc=pd.DataFrame(X_test_sc,columns=['pclass','age','parch'])
```

In [179…
```python
X_test_sc.head()
```

Out[179…

	pclass	age	parch
0	0.813034	0.012390	0.784700
1	-0.400551	0.112570	-0.479342
2	0.813034	-0.734533	-0.479342
3	-0.400551	-1.812666	0.784700
4	0.813034	-1.196590	-0.479342

In [180…
```python
X_train_sc.describe().round(2)
```

Out[180…

	pclass	age	parch
count	179.00	179.00	179.00
mean	-0.13	0.06	0.01
std	1.06	1.00	1.09
min	-1.61	-2.21	-0.48
25%	-1.61	-0.58	-0.48
50%	0.81	0.01	-0.48
75%	0.81	0.50	-0.48
max	0.81	3.19	5.84

In [182…
```python
# Min Max Scaler
mmc=MinMaxScaler()
mmc.fit(X_train )
```

Out[182…
```
MinMaxScaler()
```

In [183…
```python
X_train_mmc=mmc.transform(X_train)
X_test_mmc=mmc.transform(X_test)
```

In [184…
```python
X_train_mmc
```

Out[184…
```
array([[0.        , 0.56647399, 0.        ],
       [0.5       , 0.28373963, 0.        ],
       [1.        , 0.39683338, 0.        ],
       ...,
       [1.        , 0.50992712, 0.        ],
       [0.        , 0.17064589, 0.33333333],
       [0.        , 0.25860769, 0.16666667]])
```

In [185…
```python
X_train_mmc=pd.DataFrame(X_train_mmc,columns=['pclass','age','parch'])
X_test_mmc=X_train_sc=pd.DataFrame(X_test_mmc,columns=['pclass','age','parch'])
```

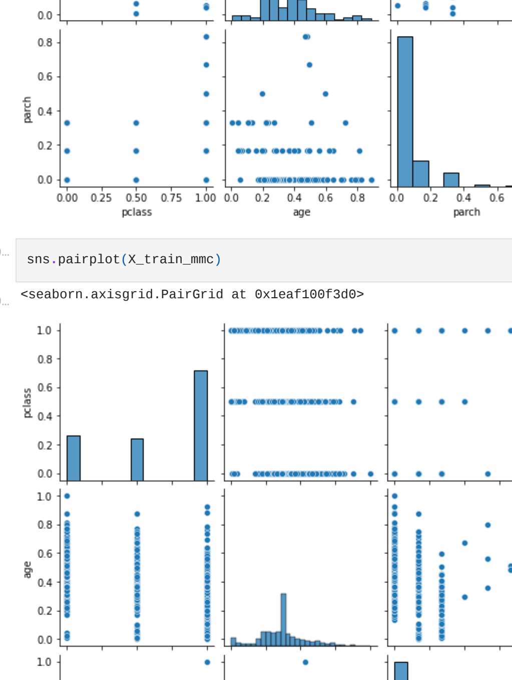
In [186…
```python
X_train_sc.describe().round(2)
```

Out[186…

	pclass	age	parch
count	179.00	179.00	179.00
mean	0.61	0.38	0.07
std	0.44	0.16	0.14
min	0.00	0.01	0.00
25%	0.00	0.27	0.00
50%	1.00	0.37	0.00
75%	1.00	0.45	0.00
max	1.00	0.89	0.83

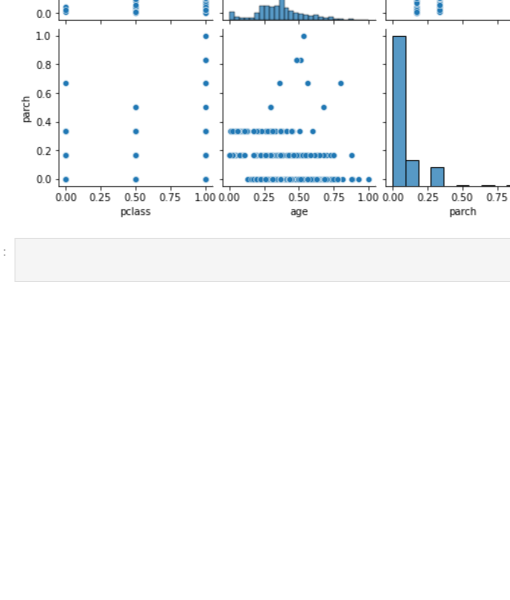
In [187…
```python
sns.pairplot(X_train)
```

Out[187…
```
<seaborn.axisgrid.PairGrid at 0x1eaf64c6910>
```



In [188…
```python
sns.pairplot(X_train_sc)
```

Out[188…
```
<seaborn.axisgrid.PairGrid at 0x1eaebca9b20>
```



In [189…
```python
sns.pairplot(X_train_mmc)
```

Out[189…
```
<seaborn.axisgrid.PairGrid at 0x1eaf100f3d0>
```


In [ ]:
```python

```