nn-mlp

June 26, 2023

[1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import (
    accuracy_score,
    classification_report,
    ConfusionMatrixDisplay
)
from sklearn.neural_network import MLPClassifier
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```python
white_wines = pd.read_csv("./data/winequality-white.csv", sep=";")
```

[3]:
```python
white_wines.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4898 entries, 0 to 4897
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   fixed acidity         4898 non-null   float64
 1   volatile acidity      4898 non-null   float64
 2   citric acid           4898 non-null   float64
 3   residual sugar        4898 non-null   float64
 4   chlorides             4898 non-null   float64
 5   free sulfur dioxide   4898 non-null   float64
 6   total sulfur dioxide  4898 non-null   float64
 7   density               4898 non-null   float64
 8   pH                    4898 non-null   float64
 9   sulphates             4898 non-null   float64
 10  alcohol               4898 non-null   float64
 11  quality               4898 non-null   int64
dtypes: float64(11), int64(1)
memory usage: 459.3 KB
```

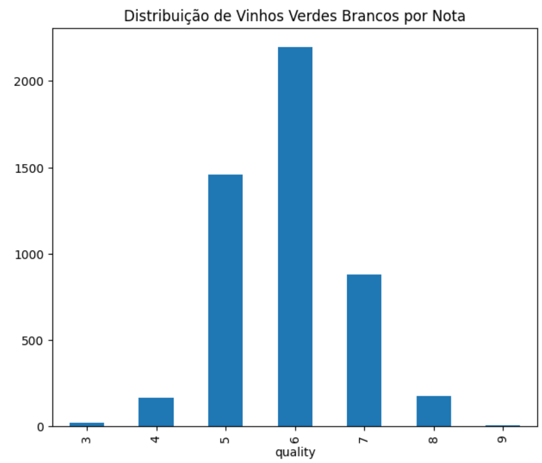
A base não possui dados nulos ou faltantes

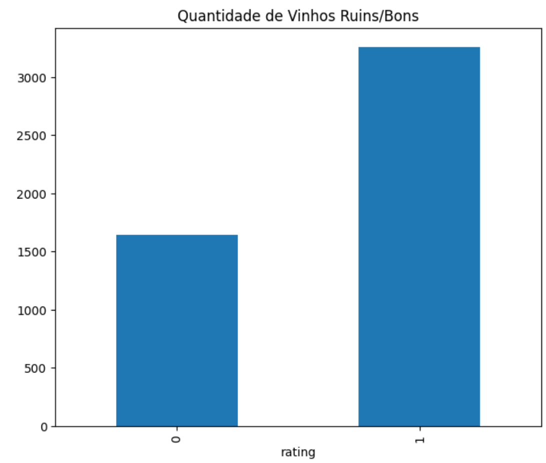
[4]:
```
white_wines['rating'] = [0 if quality < 6 else 1 for quality in␣
↪white_wines['quality']]
white_wines.head()
```

[4]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.0              0.27         0.36            20.7      0.045
1            6.3              0.30         0.34             1.6      0.049
2            8.1              0.28         0.40             6.9      0.050
3            7.2              0.23         0.32             8.5      0.058
4            7.2              0.23         0.32             8.5      0.058

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 45.0                 170.0   1.0010  3.00       0.45
1                 14.0                 132.0   0.9940  3.30       0.49
2                 30.0                  97.0   0.9951  3.26       0.44
3                 47.0                 186.0   0.9956  3.19       0.40
4                 47.0                 186.0   0.9956  3.19       0.40

   alcohol  quality  rating
0      8.8        6       1
1      9.5        6       1
2     10.1        6       1
3      9.9        6       1
4      9.9        6       1
```

[5]:
```
fig, axs = plt.subplots(1, 2, figsize=(16,6))
ax = plt.subplot(121)
white_wines.quality.value_counts().sort_index(ascending=True).plot.bar()
ax.set_title("Distribuição de Vinhos Verdes Brancos por Nota")
ax = plt.subplot(122)
white_wines.rating.value_counts().sort_index(ascending=True).plot.bar()
ax.set_title("Quantidade de Vinhos Ruins/Bons")
```

[5]:
```
Text(0.5, 1.0, 'Quantidade de Vinhos Ruins/Bons')
```





[6]:
```
white_wines.describe()
```

[6]:

	fixed acidity	volatile acidity	citric acid	residual sugar
count	4898.000000	4898.000000	4898.000000	4898.000000
mean	6.854788	0.278241	0.334192	6.391415
std	0.843868	0.100795	0.121020	5.072058
min	3.800000	0.080000	0.000000	0.600000
25%	6.300000	0.210000	0.270000	1.700000
50%	6.800000	0.260000	0.320000	5.200000
75%	7.300000	0.320000	0.390000	9.900000
max	14.200000	1.100000	1.660000	65.800000

	chlorides	free sulfur dioxide	total sulfur dioxide	density
count	4898.000000	4898.000000	4898.000000	4898.000000
mean	0.045772	35.308085	138.360657	0.994027
std	0.021848	17.007137	42.498065	0.002991
min	0.009000	2.000000	9.000000	0.987110
25%	0.036000	23.000000	108.000000	0.991723
50%	0.043000	34.000000	134.000000	0.993740
75%	0.050000	46.000000	167.000000	0.996100
max	0.346000	289.000000	440.000000	1.038980

	pH	sulphates	alcohol	quality	rating
count	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000
mean	3.188267	0.489847	10.514267	5.877909	0.665169
std	0.151001	0.114126	1.230621	0.885639	0.471979
min	2.720000	0.220000	8.000000	3.000000	0.000000
25%	3.090000	0.410000	9.500000	5.000000	0.000000
50%	3.180000	0.470000	10.400000	6.000000	1.000000
75%	3.280000	0.550000	11.400000	6.000000	1.000000
max	3.820000	1.080000	14.200000	9.000000	1.000000

Variável

Tipo

Valor Médio

Desvio Padrão

fixed acidity

Contínua

6.854788

0.843868

volatile acidity

Contínua

0.278241

0.100795

citric acid

Contínua

0.334192

0.121020

residual sugar

Contínua

6.391415

5.072058

chlorides

Contínua

0.045772

0.021848

free sulfur dioxide

Contínua

35.308085

17.007137

total sulfur dioxide

Contínua

138.360657

42.498065

density

Contínua

0.994027

0.002991

pH

Contínua

3.188267

0.151001

sulphates

Contínua

0.489847

0.114126

alcohol

Contínua

10.514267

1.230621

quality

Categórica

—

—

rating

Categórica

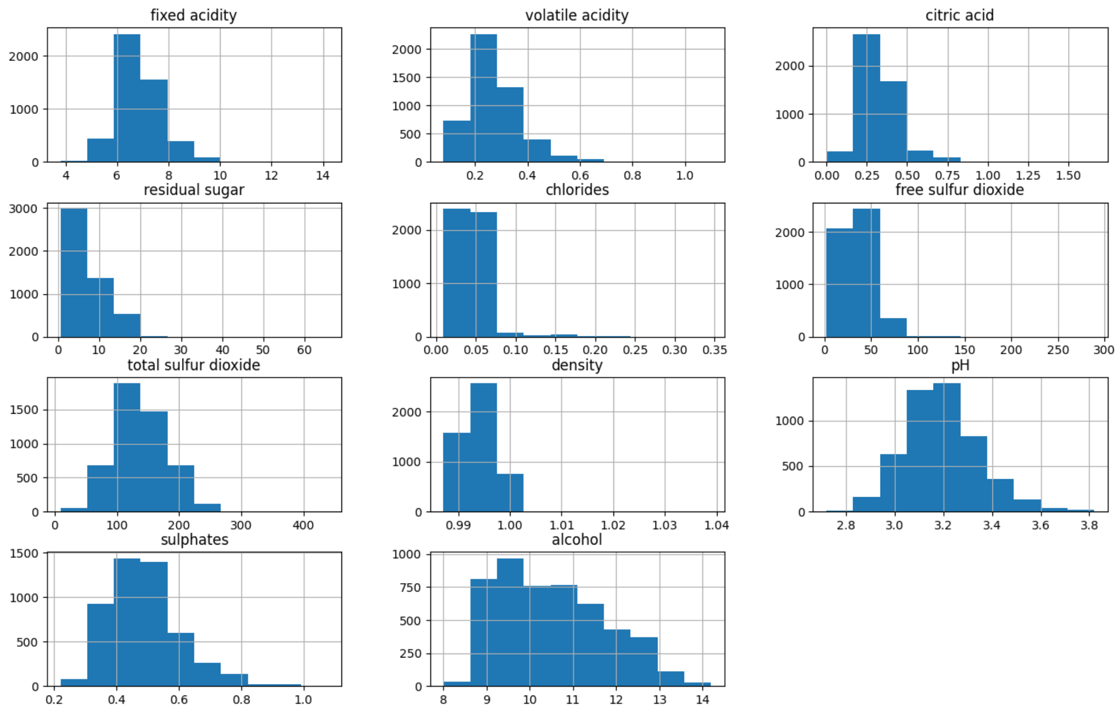
—

—

[7]:
```
features = white_wines.columns.drop(labels=['quality', 'rating'])
features
```

[7]:
```
Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'pH', 'sulphates', 'alcohol'],
      dtype='object')
```

[8]:
```
_ = white_wines[features].hist(figsize=(16, 10))
```




```
[9]: X = white_wines[features]
     y = white_wines['rating']

     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
      ↪random_state=42, stratify=y)

     scaler = StandardScaler()

     scaler = scaler.fit(X_train)
     X_train_scaled = scaler.transform(X_train)
     X_test_scaled = scaler.transform(X_test)
```

```
[10]: mlp = MLPClassifier(hidden_layer_sizes=(50,30),
                          activation="tanh",
                          solver='adam',
                          max_iter=10000,
                          alpha=0.05,
                          learning_rate='adaptive')
```

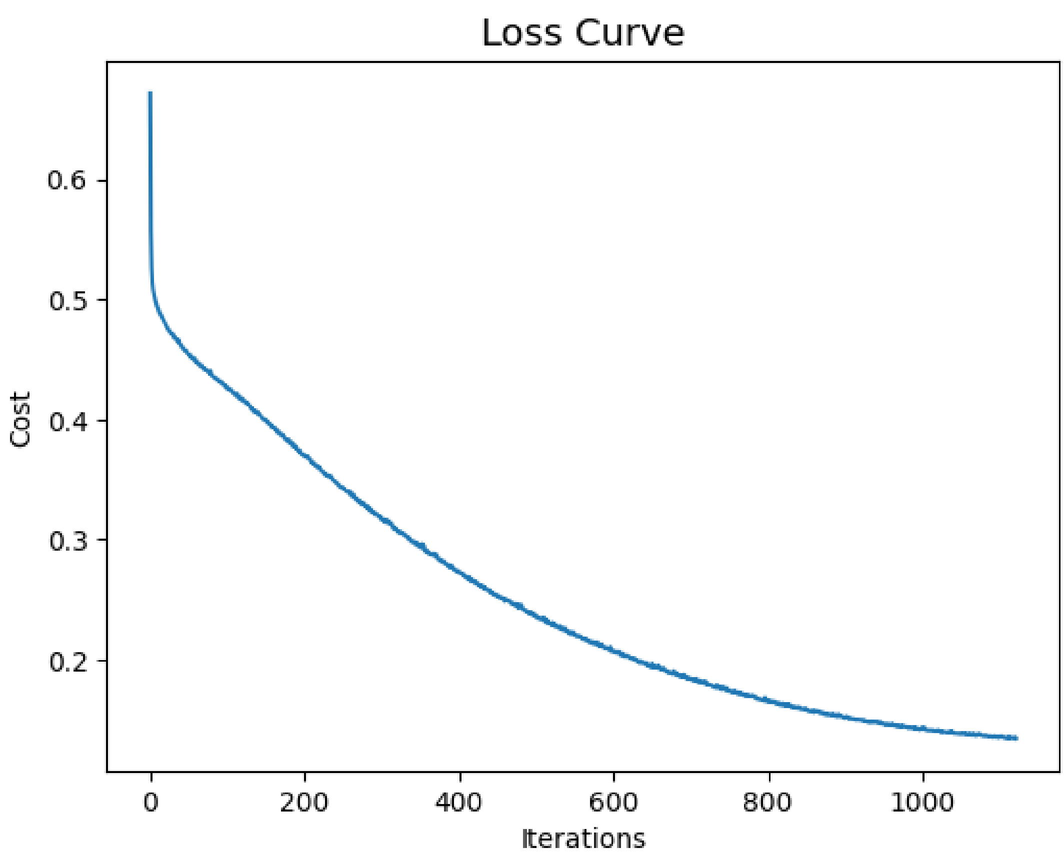
```
[11]: mlp.fit(X_train_scaled, y_train)
```

```
[11]: MLPClassifier(activation='tanh', alpha=0.05, hidden_layer_sizes=(50, 30),
                    learning_rate='adaptive', max_iter=10000)
```

[12]:
```python
y_pred = mlp.predict(X_test_scaled)

print('Accuracy: {:.2f}'.format(accuracy_score(y_test, y_pred)))
```

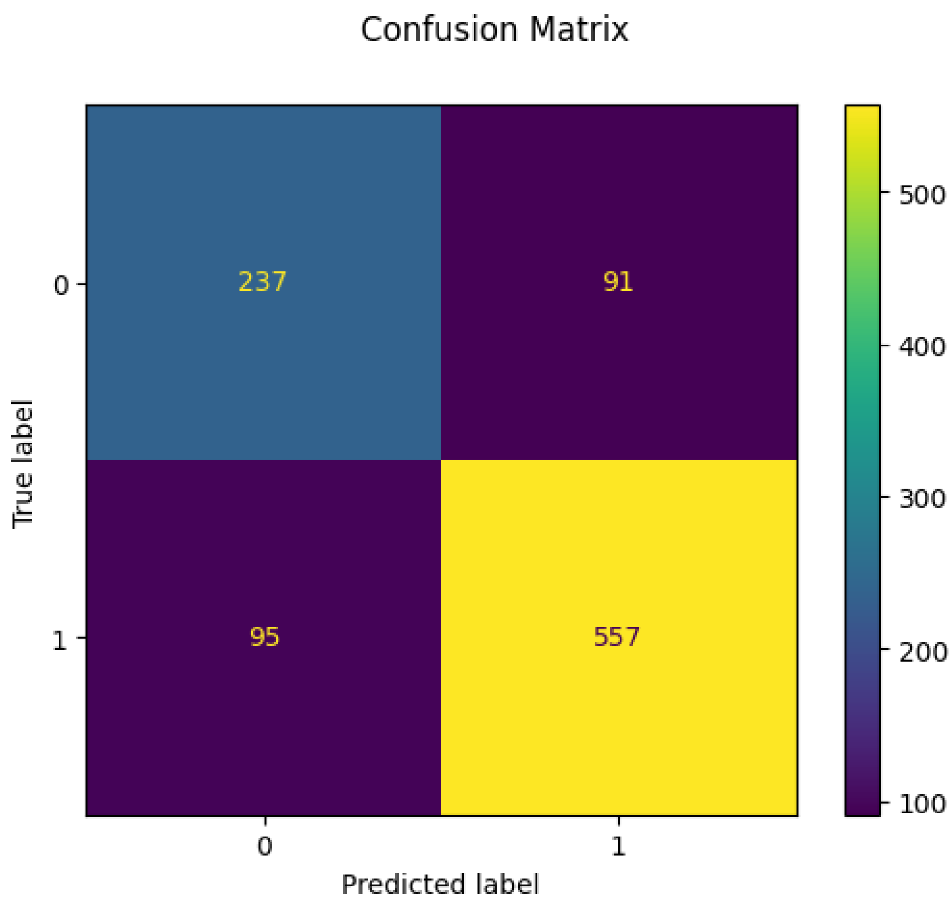
```
Accuracy: 0.81
```

[13]:
```python
plt.plot(mlp.loss_curve_)
plt.title("Loss Curve", fontsize=14)
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.show()
```



[14]:
```python
disp = ConfusionMatrixDisplay.from_predictions(y_test, mlp.
    ↪predict(X_test_scaled))
disp.figure_.suptitle("Confusion Matrix")
print(f"Confusion matrix:\n{disp.confusion_matrix}")
```

```
Confusion matrix:
[[237  91]
 [ 95 557]]
```



[15]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.71      0.72      0.72       328
           1       0.86      0.85      0.86       652

    accuracy                           0.81       980
   macro avg       0.79      0.79      0.79       980
weighted avg       0.81      0.81      0.81       980
```

[36]:
```
y_hat = mlp.predict_proba(X_train_scaled)
fig, ax = plt.subplots(1, 1, figsize=(8, 6))
sns.distplot(y_hat[y_train.values == 1, 1], label="Good", ax=ax)
ax.set_xlim([0, 1])
sns.distplot(y_hat[y_train == 0, 1], label="Bad", ax=ax)
ax.legend();
ax.axvline(0.5, color="red", ls=":", lw=3)
```

[36]: <matplotlib.lines.Line2D at 0x1c76de6c520>