Regressão

November 10, 2023

[ ]:
```
#import de todas as bibliotecas necessárias
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

[ ]:
```
# Leitura do DataFrame
wine = pd.read_csv('winequalityN.csv')
#visualização das primeiras linhas do DataFrame
wine.head()
```

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

   chlorides  free sulfur dioxide  total sulfur dioxide  density    pH  \
0      0.045                 45.0                 170.0   1.0010  3.00
1      0.049                 14.0                 132.0   0.9940  3.30
2      0.050                 30.0                  97.0   0.9951  3.26
3      0.058                 47.0                 186.0   0.9956  3.19
4      0.058                 47.0                 186.0   0.9956  3.19

   sulphates  alcohol  quality
0       0.45      8.8        6
1       0.49      9.5        6
2       0.44     10.1        6
3       0.40      9.9        6
4       0.40      9.9        6
```

[ ]:
```
wine.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6497 entries, 0 to 6496
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   type                  6497 non-null   object
 1   fixed acidity         6487 non-null   float64
 2   volatile acidity      6489 non-null   float64
 3   citric acid           6494 non-null   float64
 4   residual sugar        6495 non-null   float64
 5   chlorides             6495 non-null   float64
 6   free sulfur dioxide   6497 non-null   float64
 7   total sulfur dioxide  6497 non-null   float64
 8   density               6497 non-null   float64
 9   pH                    6488 non-null   float64
 10  sulphates             6493 non-null   float64
 11  alcohol               6497 non-null   float64
 12  quality               6497 non-null   int64
dtypes: float64(11), int64(1), object(1)
memory usage: 660.0+ KB
```

[ ]:

```
# Verificando se há valores nulos no DataFrame, retornando a soma de valores␣
  ↪nulos por coluna
wine.dropna(inplace=True)
wine.isnull().sum()
```

[ ]:

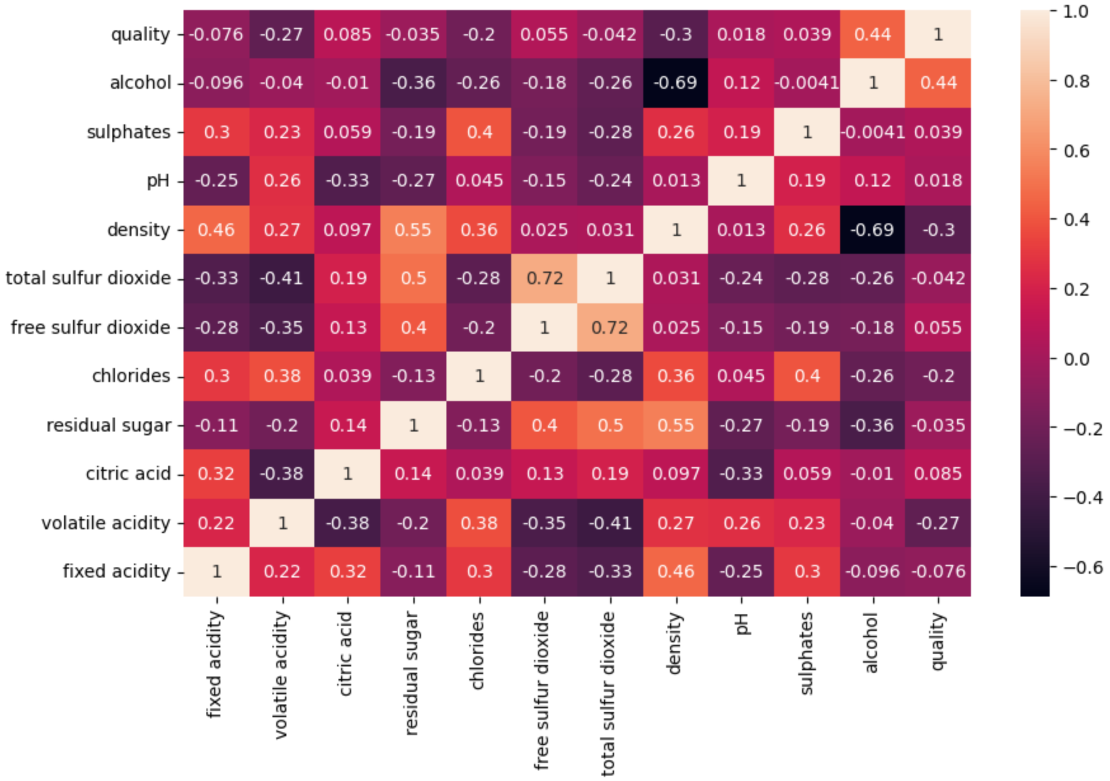
```
type                    0
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol   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

[ ]:

```
# Excluir colunas não numéricas
numeric_wine = wine.select_dtypes(exclude=['object'])

# Calcular correlação para as colunas numéricas
correlation_matrix = numeric_wine.corr()
```

```
# Plotar a matriz de correlação
plt.figure(figsize=(10,6))
sns.heatmap(correlation_matrix, annot=True)
plt.ylim(0, 12)
plt.show()
```



```
[ ]: #excluindo colunas com strings
     wine = wine.drop(['type'], axis=1)
     #separação dos dados em treino e teste
     x_values = wine.drop(['alcohol'],axis=1).values
     y_values = wine['alcohol'].values

     x_train, x_test, y_train, y_test = train_test_split(x_values, y_values,␣
      ↪test_size=0.2, random_state=42)

      # normalização
     pipe = Pipeline([('scaler', StandardScaler())])
     x_train = pipe.fit_transform(x_train)
     x_test = pipe.transform(x_test)

     # regressão (treinamento)
```

```
my_model = LinearRegression()
my_model.fit(x_train, y_train)
print(my_model.score(x_test, y_test)) # r2 squared
```

```
0.822867726346168
```

[ ]:

```
 #regressão (teste)
test_pred = my_model.predict(x_test)
train_pred = my_model.predict(x_train)


#função para avaliar o modelo
def print_evaluate(real, predicted):
  mae = metrics.mean_absolute_error(real, predicted)
  mse = metrics.mean_squared_error(real, predicted)
  rmse = np.sqrt(metrics.mean_squared_error(real, predicted))
  r2_square = metrics.r2_score(real, predicted)

  print('MAE:', mae)
  print('MSE:', mse)
  print('RMSE:', rmse)
  print('R2 Square', r2_square)
  print('__________________________________')

print("Dados de teste:")
print_evaluate(y_test, test_pred)
print("\nDados de treinamento:")
print_evaluate(y_train, train_pred)
```

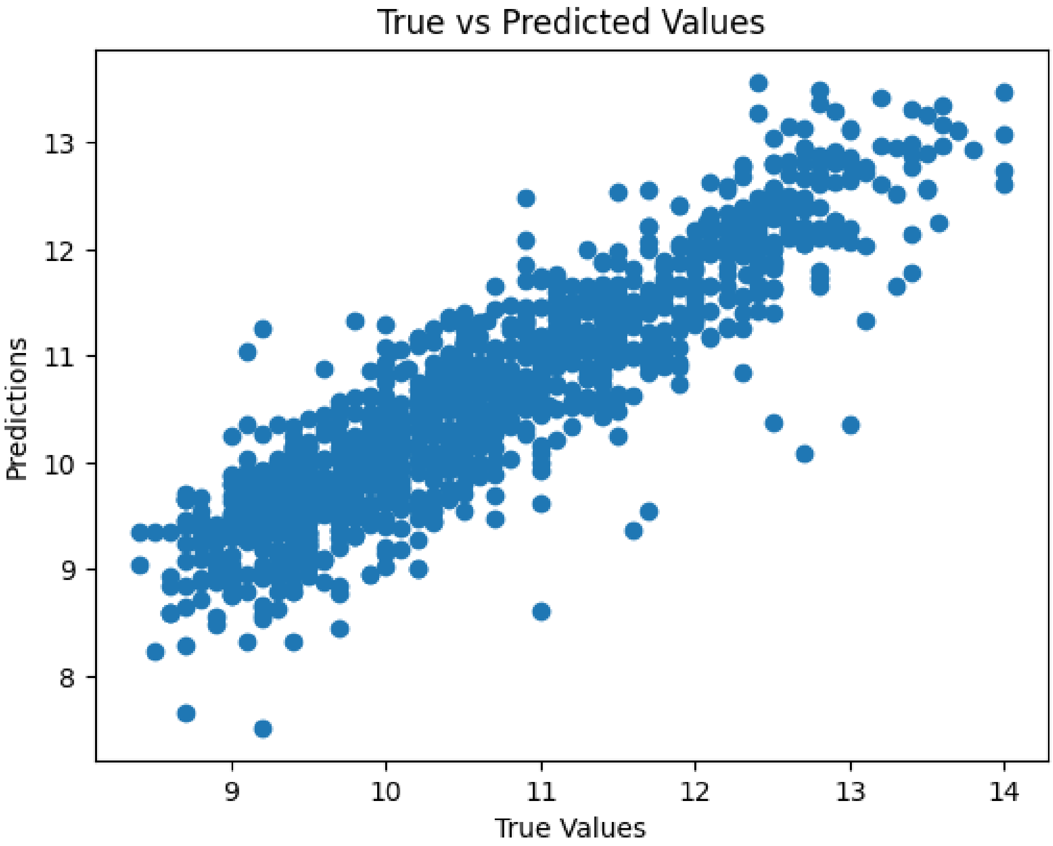
```
Dados de teste:
MAE: 0.3989843612973598
MSE: 0.26681814760634337
RMSE: 0.5165444294601805
R2 Square 0.822867726346168
__________________________________

Dados de treinamento:
MAE: 0.3902429824443842
MSE: 0.2907334124101731
RMSE: 0.5391970070486047
R2 Square 0.7923181301457404
__________________________________
```

[ ]:

```
# Plotando os resultados
plt.scatter(y_test, test_pred)
plt.xlabel('True Values')
plt.ylabel('Predictions')
plt.title('True vs Predicted Values')
plt.show()


print(my_model.intercept_, my_model.coef_, my_model.score(x_test, y_test))
```



```
10.469660863957882 [ 0.67997065  0.26082324  0.06907571  0.93566117 -0.00667731
-0.00666862
 -0.23469732 -1.72110406  0.45068922  0.19007688  0.12494332] 0.822867726346168
```