University of Missouri-Kansas City School of Computing and Engineering



ICP: ICP-09

Course Name: Big Data Analytics and Applications

Course ID: COMP-SCI 5542

Semester /Session: Spring 2022

Student ID: Student Name

16334245 Mustavi Islam

16321217 Keenan Flynn

Description of the Problem:

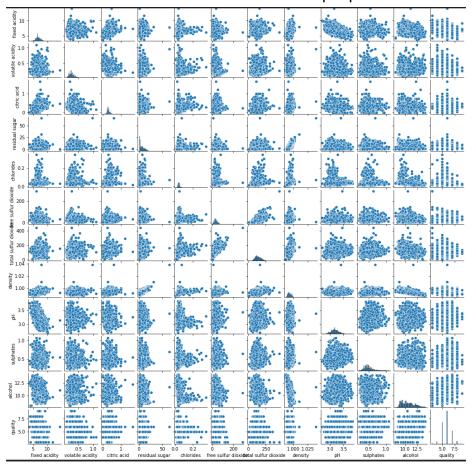
In this ICP, we used a machine learning model to solve a regression problem. Regression can be used to predict values where the output is continuous. This differs from classification where the output is a distinct number of classes.

We chose a dataset that describes chemical components of wine, which we downloaded from the UCI repository. This dataset has 12 attributes and can be downloaded here.

Description of Solution:

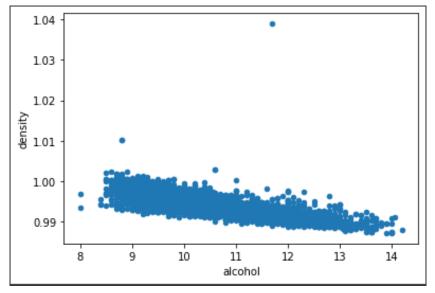
We took several steps to create a Regression model.

- 1. Preprocessing
 - a. After reading and getting basic statistical information from the data with .info() and .describe() methods, we used a Seaborn pairplot to get correlation graphs between all of the attributes. Because there are no class labels, there is no specific variable that we want to predict. We will choose to make a regression model between 2 variables that are correlated based on what we see from the pairplot.

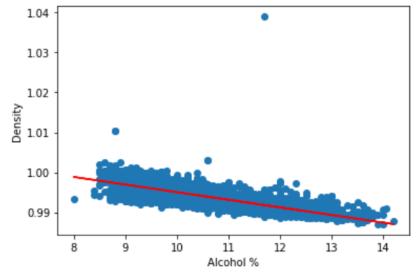


2. Regression model

a. From the above pairplot, we see that Alcohol % and density are closely correlated. Let's take a closer look.



- b. We can see that alcohol decreases linearly with density. We can model this with a LinearRegression() object from Sci-Kit Learn. Before we use this model, we split the data into testing and training subsets so that we evaluate with metrics later on.
- c. We fit the regression model with the training data. To draw the line on the map, we use this model to predict values at every point and then plot. The output looks like this.



d. To get the slope and y intercept, we use the intercept_ and coef_ calls from the LinearRegression() object. The values seen in this model are small due to the nature of the 2 attributes: alcohol and density being small. The slope is the change in the y value divided by the change of the x value. The intercept is the predicted value when x = 0. With these 2 values you can predict values for any x value.

The Y intercept for this Linear Regression is: 1.0141
The Slope for this Linear Regression is: -0.00190612

3. Evaluation

- a. Regression models use different metrics than classification models. These metrics include MAE, MSE, RMSE, and R2.
- b. Mean Square Error is the average of the square of all true values minus the square of all predicted values.

$$oxed{ ext{MSE} = rac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2}$$

mse: 2.902e-06

c. Mean Absolute Error is the absolute value of the prediction minus the true value averaged.

$$ext{MAE} = rac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$

mae: 1.370e-03

d. Root Mean Square Error is the root of the MSE.

$$ext{RMSD} = \sqrt{rac{\sum_{i=1}^{N}\left(x_i - \hat{x}_i
ight)^2}{N}}$$

rmse: 1.703e-03

e. R2 a score that is 1 minus the sum of square residuals over the total sum of squares.

$$R^2 = 1 - rac{RSS}{TSS}$$

Challenges:

Challenges that we faced in this model relate to the creation of the LinearRegression() object. We could not insert the data straight into the model as it was giving us an error. We needed to reshape this data so that it became a 1 dimensional array.

Learning Outcomes

- 1. Learn how to implement a Sci-Kit Learn Regression model.
- 2. Learn how to evaluate a regression model.
- 3. Learn how to use a pairplot to graph many attributes at once.
- 4. Learn how to get the y-intercept and slope of a linear regression.

Resources:

https://archive.ics.uci.edu/ml/machine-learning-databases/wine-quality/

Video Link:

https://youtu.be/j-R40i2Psv0

Screenshots:

[1] import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns

* Data Exploration

** white_wine = pd.read_csv('winequality-white.csv', delimiter=';') white_wine.head()

E

** fixed volatile citric residual sugar chlorides free sulfur dioxide density pH sulphates alcohol quality

**0 7.0 0.27 0.36 20.7 0.045 45.0 170.0 1.0010 3.00 0.45 8.8 6

**1 6.3 0.30 0.34 1.6 0.049 14.0 132.0 0.9940 3.30 0.49 9.5 6

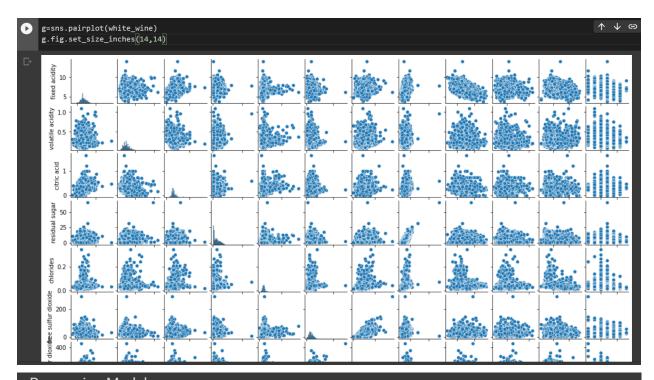
**2 8.1 0.28 0.40 6.9 0.050 30.0 97.0 0.9951 3.26 0.44 10.1 6

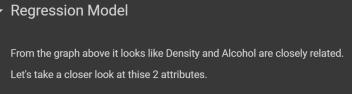
**3 7.2 0.23 0.32 8.5 0.058 47.0 186.0 0.9956 3.19 0.40 9.9 6

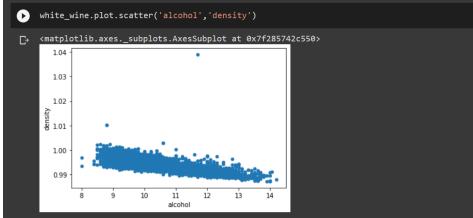
**4 7.2 0.23 0.32 8.5 0.058 47.0 186.0 0.9956 3.19 0.40 9.9 6

white_wine.info() C→ <class 'pandas.core.frame.DataFrame'> RangeIndex: 4898 entries, 0 to 4897 Data columns (total 12 columns): # Column Non-Null Count Dtype 4898 non-null 0 fixed acidity float64 4898 non-null volatile acidity float64 citric acid 4898 non-null float64 residual sugar 4898 non-null float64 chlorides 4898 non-null float64 free sulfur dioxide 4898 non-null total sulfur dioxide 4898 non-null float64 6 float64 density 4898 non-null float64 8 pН 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

[6] white_wine.describe()													
		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	quali
	count	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.0000
	mean	6.854788	0.278241	0.334192	6.391415	0.045772	35.308085	138.360657	0.994027	3.188267	0.489847	10.514267	5.8779
	std	0.843868	0.100795	0.121020	5.072058	0.021848	17.007137	42.498065	0.002991	0.151001	0.114126	1.230621	0.8856
	min	3.800000	0.080000	0.000000	0.600000	0.009000	2.000000	9.000000	0.987110	2.720000	0.220000	8.000000	3.0000
	25%	6.300000	0.210000	0.270000	1.700000	0.036000	23.000000	108.000000	0.991723	3.090000	0.410000	9.500000	5.0000
	50%	6.800000	0.260000	0.320000	5.200000	0.043000	34.000000	134.000000	0.993740	3.180000	0.470000	10.400000	6.0000
	75%	7.300000	0.320000	0.390000	9.900000	0.050000	46.000000	167.000000	0.996100	3.280000	0.550000	11.400000	6.0000
	max	14.200000	1.100000	1.660000	65.800000	0.346000	289.000000	440.000000	1.038980	3.820000	1.080000	14.200000	9.0000
	7.												







We extract those attributes below. Density will be our Y variable and Alcohol will be our X variable.

We need to split the data so that we can evaluate the model later on.

```
from sklearn.model_selection import train_test_split
train, test = train_test_split(white_wine, test_size = 0.2, random_state = 42)

density_train = train['density']
density_test = test['density']

alcohol_train = train['alcohol']
alcohol_test = test['alcohol']
```

We need to reshape the data so that it can fit into the Linear Regressor

```
[ ] Y_train = density_train.values.reshape(-1, 1)
    X_train = alcohol_train.values.reshape(-1, 1)

Y_test = density_test.values.reshape(-1, 1)
    X_test = alcohol_test.values.reshape(-1, 1)
```

We can use a linear regressor from Sci-Kit Learn to draw the regression line

```
from sklearn.linear_model import LinearRegression

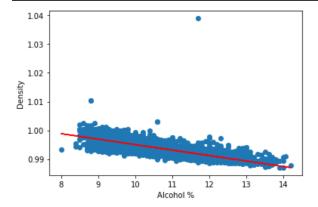
#Create Linear regression object
linear_regressor = LinearRegression()
linear_regressor.fit(X_train, Y_train)

#Predict the values
Y_pred = linear_regressor.predict(X_train)

#Scatter plot the original values
plt.scatter(X_train, Y_train)

#Line plot on the predicted values
plt.plot(X_train, Y_pred, color='red')

plt.xlabel('Alcohol %')
plt.ylabel('Density')
plt.show()
```



```
Print out the y intercept and the slope
 y_int = linear_regressor.intercept_[0]
      print(f'The Y intercept for this Linear Regression is: {y_int:.6}')
      slope = linear_regressor.coef_[0][0]
      print(f'The Slope for this Linear Regression is: {slope:.6}')
 The Y intercept for this Linear Regression is: 1.0141
     The Slope for this Linear Regression is: -0.00190612

    Evaluation of Model

  Get predictions for the evaluation
   Y_pred_test = linear_regressor.predict(X_test)
                                                                     + Code — + Text

    Mean Square Error

  [ ] from sklearn.metrics import mean_squared_error print('mse:', "{:.3e}".format(mean_squared_error(Y_test,Y_pred_test)))
▼ Mean Absolute Error
  [ ] from sklearn.metrics import mean_absolute_error print('mae:', "{:.3e}".format(mean_absolute_error(Y_test,Y_pred_test)))
       mae: 1.370e-03
▼ Root Mean Square Error
   [ ] from sklearn.metrics import mean_squared_error
        print('rmse:', "{:.3e}".format(mean_squared_error(Y_test,Y_pred_test, squared=False)))
 ▼ R2 Score
  [ ] from sklearn.metrics import r2_score
       print('r2:', "{:.3}".format(r2_score(Y_test,Y_pred_test)))
        r2: 0.645
```