Andrew Vu - CS156_HW3

March 7, 2022

1 CS156 (Introduction to AI), Spring 2022

2 Homework 3 submission

2.0.1 Roster Name: Andrew Vu

2.0.2 Student ID: 015055911

2.0.3 Email address: andrew.k.vu@sjsu.edu

Any special notes or anything you would like to communicate to me about this homework submission goes in here.

2.1 References and sources

List all your references and sources here. This includes all sites/discussion boards/blogs/posts/etc. where you grabbed some code examples.

- regression boston file from files section

2.2 Solution

Load libraries and set random number generator seed

[234]:
```
import numpy as np
import pandas as pd
from sklearn import datasets
from sklearn import linear_model
from sklearn import preprocessing
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
import seaborn as sns
```

[235]:
```
np.random.seed(42)
```

Code the solution

2.3 1. Load Dataset

[236]:
```
concrete_file = pd.read_csv(r'C:\Users\Andrew\CS156 Jupyter␣
↪Files\hw3usefulfiles\homework3_input_data.csv')
```

[237]:
```
df = pd.DataFrame(concrete_file, columns=concrete_file.columns)
df.head()
feature_names = ['cement', 'slag', 'flyash', 'water', 'superplasticizer',␣
↪'coarseaggregate', 'fineaggregate', 'age']
X = df[feature_names]
Y = df['csMPa']
#print(df.head())
#print(X)
```

[238]:
```
print(df.columns)
df.describe()
```

```
Index(['cement', 'slag', 'flyash', 'water', 'superplasticizer',
       'coarseaggregate', 'fineaggregate', 'age', 'csMPa'],
      dtype='object')
```

[238]:

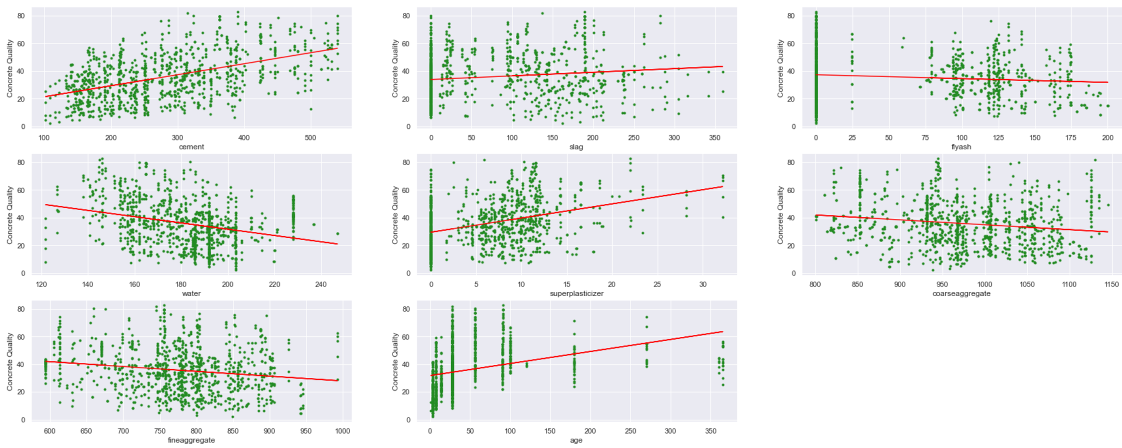
	cement	slag	flyash	water	superplasticizer
count	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000
mean	281.167864	73.895825	54.188350	181.567282	6.204660
std	104.506364	86.279342	63.997004	21.354219	5.973841
min	102.000000	0.000000	0.000000	121.800000	0.000000
25%	192.375000	0.000000	0.000000	164.900000	0.000000
50%	272.900000	22.000000	0.000000	185.000000	6.400000
75%	350.000000	142.950000	118.300000	192.000000	10.200000
max	540.000000	359.400000	200.100000	247.000000	32.200000

	coarseaggregate	fineaggregate	age	csMPa
count	1030.000000	1030.000000	1030.000000	1030.000000
mean	972.918932	773.580485	45.662136	35.817961
std	77.753954	80.175980	63.169912	16.705742
min	801.000000	594.000000	1.000000	2.330000
25%	932.000000	730.950000	7.000000	23.710000
50%	968.000000	779.500000	28.000000	34.445000
75%	1029.400000	824.000000	56.000000	46.135000
max	1145.000000	992.600000	365.000000	82.600000

2.4 2. Plot Independent vs. Dependent Var

[239]:
```
plt.figure(figsize=(30,20))
for i, col in enumerate(df.columns[0:8]):
    plt.subplot(5, 3, i+1)
    x = df[col]
    y = df['csMPa']
```

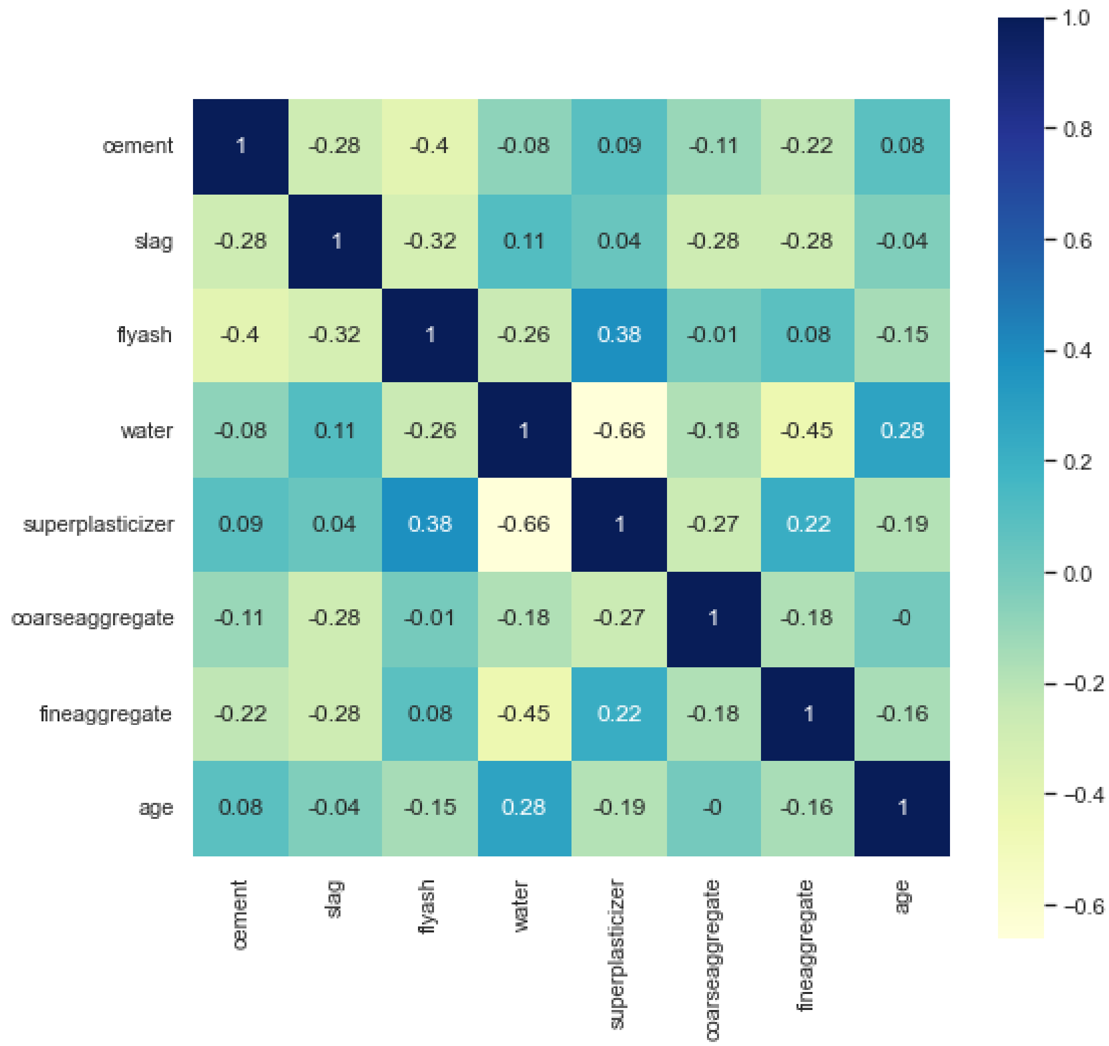
```
    plt.plot(x, y, '.', color="forestgreen")
    # create linear regression line:
    #plt.plot(np.unique(x), np.poly1d(np.polyfit(x, y, 1))(np.
↪unique(x)),color="red")
    m, b = np.polyfit(x, y, 1)
    plt.plot(x, m*x + b, color="red")
    plt.xlabel(col)
    plt.ylabel('Concrete Quality')
```



2.5 3. Correlation Matrix of Independent Vars

[240]:
```
features = df[feature_names]
sns.set(rc={'figure.figsize': (8.5,8.5)})
sns.heatmap(features.corr().round(2), square=True, cmap='YlGnBu', annot=True)
```

[240]: <AxesSubplot:>



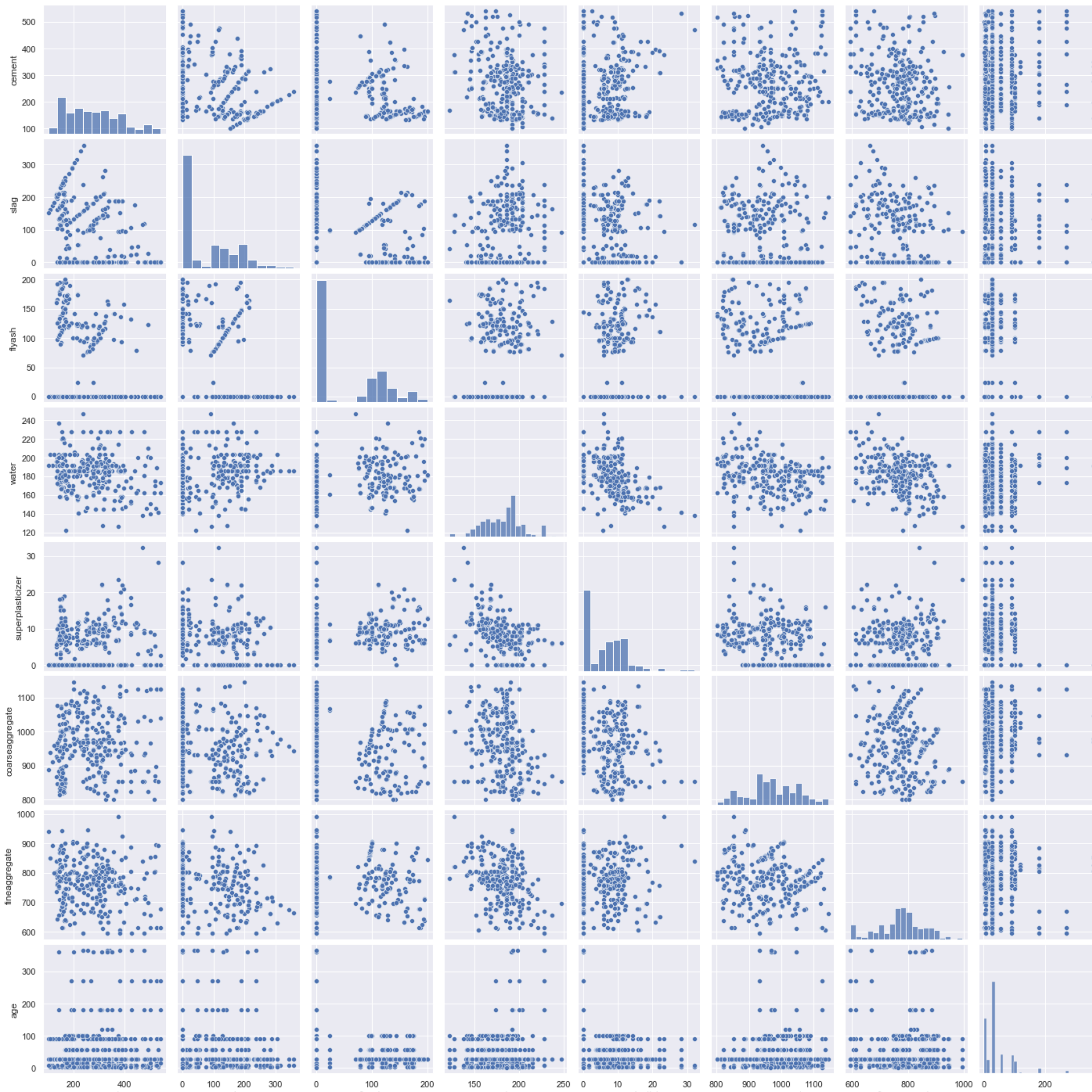
2.6 4. Training and Test Datasets

[241]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,␣
↪random_state=0)
X_train.shape, Y_train.shape, X_test.shape, Y_test.shape
```

[241]: ((824, 8), (824,), (206, 8), (206,))

[242]:
```
train_df = pd.DataFrame(X_train, columns=feature_names)
train_df['csMPa'] = Y_train
sns.pairplot(train_df, vars = feature_names)
```

[242]: <seaborn.axisgrid.PairGrid at 0x20ee9487070>



2.7 5. Train linear regression model to predict csMPa values

[243]:
```
model = linear_model.LinearRegression().fit(X_train, Y_train)
```

2.8 6. Report mean squared error and coefficient of determination for test data

[244]:
```
# The coefficients:
print('Coefficients: \n', model.coef_)

Y_test_pred = model.predict(X_test)
# print("this is y test")
# print(Y_test)
```

```
# print("this is y test pred")
# print(Y_test_pred)

# The mean squared error:
print('Mean squared error: %.2f' % mean_squared_error(Y_test, Y_test_pred))

# The coefficient of determination (1 is perfect prediction):
print('Coefficient of determination: %.2f' % r2_score(Y_test, Y_test_pred))
```

```
Coefficients:
 [ 0.11923772  0.10881555  0.0911555  -0.14527714  0.31551104  0.02225423
  0.02248514  0.11520355]
Mean squared error: 95.62
Coefficient of determination: 0.64
```

[245]:
```
pred_df = pd.DataFrame({'Actual': Y_test, 'Predicted':Y_test_pred})
pred_df.head()
```

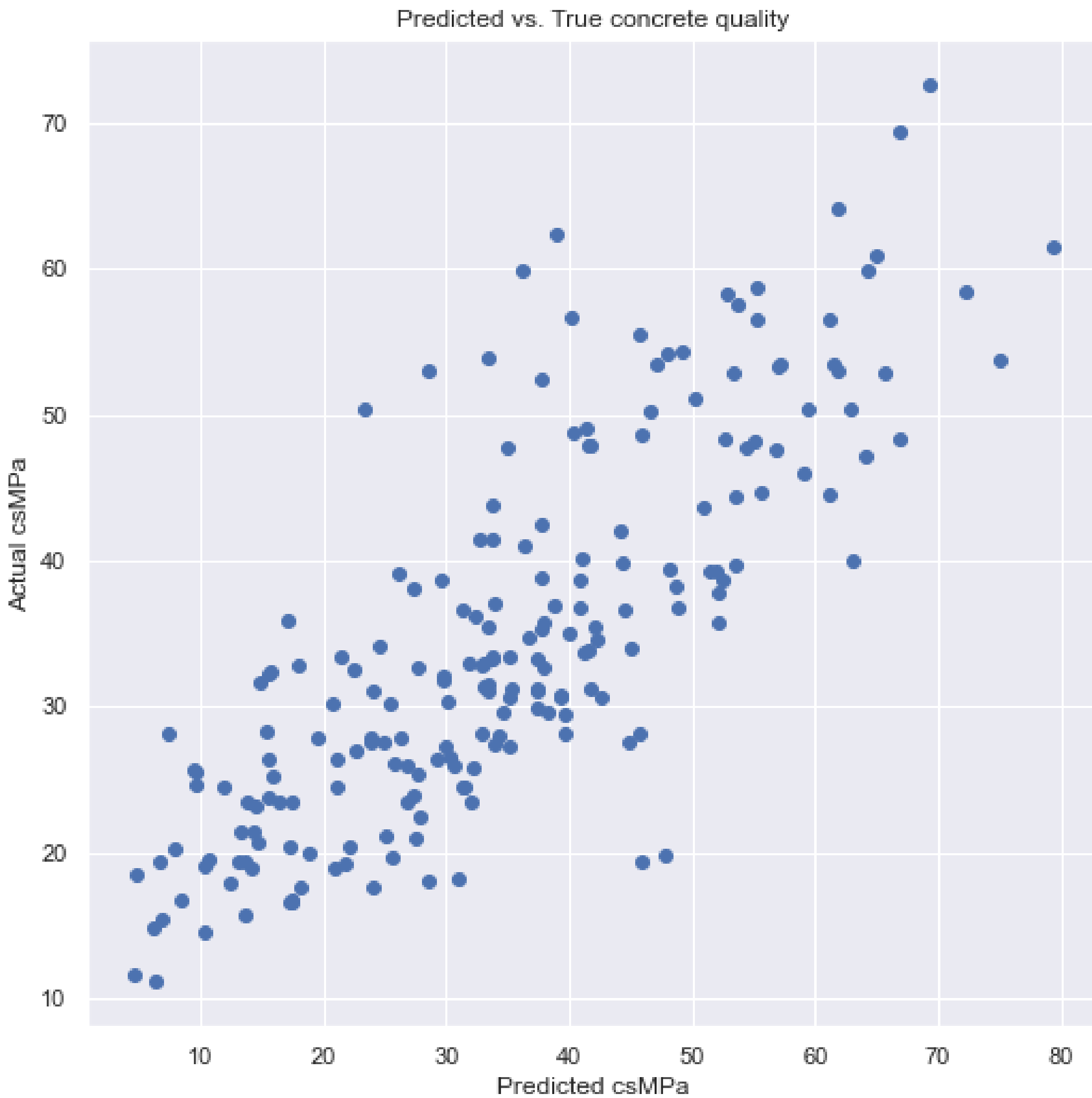
[245]:

	Actual	Predicted
747	26.06	39.161683
718	10.35	14.619856
175	79.30	61.440067
828	74.99	53.777042
713	9.69	24.668431

2.9 7. Plot predicted vs. actual csMPa values

[246]:
```
plt.scatter(Y_test,Y_test_pred)
plt.title('Predicted vs. True concrete quality')
plt.xlabel('Predicted csMPa')
plt.ylabel('Actual csMPa')
```

[246]: Text(0, 0.5, 'Actual csMPa')


Predicted vs. True concrete quality
Actual csMPa
Predicted csMPa
10
20
30
40
50
60
70
80