ML0101EN-Reg-Simple-Linear-Regression-Co2-py-v1

December 1, 2020

1 Simple Linear Regression

Estimated time needed: **15** minutes

1.1 Objectives

After completing this lab you will be able to:

- Use scikit-learn to implement simple Linear Regression
- Create a model, train,test and use the model

1.1.1 Importing Needed packages

```
[1]: import matplotlib.pyplot as plt
     import pandas as pd
     import pylab as pl
     import numpy as np
     %matplotlib inline
```

1.1.2 Downloading Data

To download the data, we will use !wget to download it from IBM Object Storage.

```
[2]: !wget -O FuelConsumption.csv https://cf-courses-data.s3.us.cloud-object-storage.
     ↪appdomain.cloud/IBMDeveloperSkillsNetwork-ML0101EN-SkillsNetwork/labs/
     ↪Module%202/data/FuelConsumptionCo2.csv
```

```
--2020-12-01 19:50:08--  https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBMDeveloperSkillsNetwork-ML0101EN-
SkillsNetwork/labs/Module%202/data/FuelConsumptionCo2.csv
Resolving cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud (cf-
courses-data.s3.us.cloud-object-storage.appdomain.cloud)… 67.228.254.196
Connecting to cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud (cf-
courses-data.s3.us.cloud-object-storage.appdomain.cloud)|67.228.254.196|:443…
connected.
HTTP request sent, awaiting response… 200 OK
Length: 72629 (71K) [text/csv]
Saving to: 'FuelConsumption.csv'
```

```
FuelConsumption.csv 100%[===================>]   70.93K  --.-KB/s    in 0.06s
```

```
2020-12-01 19:50:08 (1.26 MB/s) - 'FuelConsumption.csv' saved [72629/72629]
```

Did you know? When it comes to Machine Learning, you will likely be working with large datasets. As a business, where can you host your data? IBM is offering a unique opportunity for businesses, with 10 Tb of IBM Cloud Object Storage: Sign up now for free

1.2 Understanding the Data

1.2.1 `FuelConsumption.csv`:

We have downloaded a fuel consumption dataset, **FuelConsumption.csv**, which contains model-specific fuel consumption ratings and estimated carbon dioxide emissions for new light-duty vehicles for retail sale in Canada. Dataset source

- **MODELYEAR** e.g. 2014
- **MAKE** e.g. Acura
- **MODEL** e.g. ILX
- **VEHICLE CLASS** e.g. SUV
- **ENGINE SIZE** e.g. 4.7
- **CYLINDERS** e.g 6
- **TRANSMISSION** e.g. A6
- **FUEL CONSUMPTION in CITY(L/100 km)** e.g. 9.9
- **FUEL CONSUMPTION in HWY (L/100 km)** e.g. 8.9
- **FUEL CONSUMPTION COMB (L/100 km)** e.g. 9.2
- **CO2 EMISSIONS (g/km)** e.g. 182 –> low –> 0

1.3 Reading the data in

```
[3]: df = pd.read_csv("FuelConsumption.csv")

     # take a look at the dataset
     df.head()
```

```
[3]:    MODELYEAR   MAKE        MODEL VEHICLECLASS  ENGINESIZE  CYLINDERS  \
     0      2014  ACURA          ILX      COMPACT         2.0          4
     1      2014  ACURA          ILX      COMPACT         2.4          4
     2      2014  ACURA   ILX HYBRID      COMPACT         1.5          4
     3      2014  ACURA      MDX 4WD  SUV - SMALL         3.5          6
     4      2014  ACURA      RDX AWD  SUV - SMALL         3.5          6

       TRANSMISSION FUELTYPE  FUELCONSUMPTION_CITY  FUELCONSUMPTION_HWY  \
     0          AS5        Z                   9.9                  6.7
     1           M6        Z                  11.2                  7.7
     2          AV7        Z                   6.0                  5.8
     3          AS6        Z                  12.7                  9.1
     4          AS6        Z                  12.1                  8.7
```

```
     FUELCONSUMPTION_COMB  FUELCONSUMPTION_COMB_MPG  CO2EMISSIONS
0                     8.5                        33           196
1                     9.6                        29           221
2                     5.9                        48           136
3                    11.1                        25           255
4                    10.6                        27           244
```

1.3.1 Data Exploration

Lets first have a descriptive exploration on our data.

```python
[4]: # summarize the data
     df.describe()
```

```
[4]:        MODELYEAR    ENGINESIZE    CYLINDERS  FUELCONSUMPTION_CITY  \
     count     1067.0  1067.000000  1067.000000           1067.000000
     mean      2014.0     3.346298     5.794752             13.296532
     std          0.0     1.415895     1.797447              4.101253
     min       2014.0     1.000000     3.000000              4.600000
     25%       2014.0     2.000000     4.000000             10.250000
     50%       2014.0     3.400000     6.000000             12.600000
     75%       2014.0     4.300000     8.000000             15.550000
     max       2014.0     8.400000    12.000000             30.200000

            FUELCONSUMPTION_HWY  FUELCONSUMPTION_COMB  FUELCONSUMPTION_COMB_MPG  \
     count          1067.000000           1067.000000               1067.000000
     mean              9.474602             11.580881                 26.441425
     std               2.794510              3.485595                  7.468702
     min               4.900000              4.700000                 11.000000
     25%               7.500000              9.000000                 21.000000
     50%               8.800000             10.900000                 26.000000
     75%              10.850000             13.350000                 31.000000
     max              20.500000             25.800000                 60.000000

            CO2EMISSIONS
     count   1067.000000
     mean     256.228679
     std       63.372304
     min      108.000000
     25%      207.000000
     50%      251.000000
     75%      294.000000
     max      488.000000
```

Lets select some features to explore more.

```
[5]: cdf = df[['ENGINESIZE','CYLINDERS','FUELCONSUMPTION_COMB','CO2EMISSIONS']]
     cdf.head(9)
```

```
[5]:    ENGINESIZE  CYLINDERS  FUELCONSUMPTION_COMB  CO2EMISSIONS
     0         2.0          4                   8.5           196
     1         2.4          4                   9.6           221
     2         1.5          4                   5.9           136
     3         3.5          6                  11.1           255
     4         3.5          6                  10.6           244
     5         3.5          6                  10.0           230
     6         3.5          6                  10.1           232
     7         3.7          6                  11.1           255
     8         3.7          6                  11.6           267
```
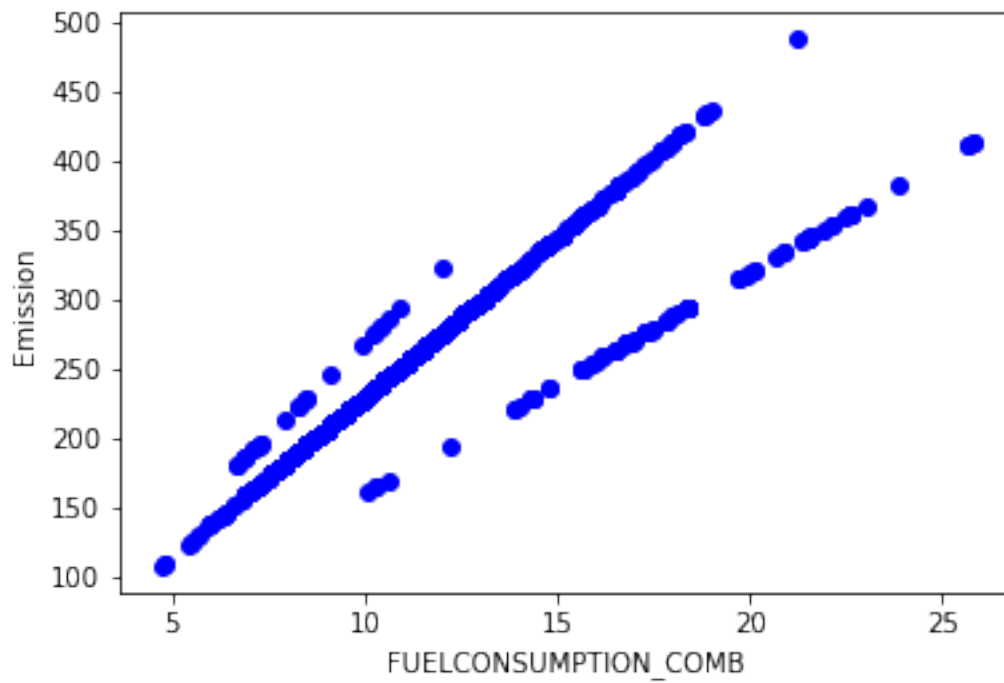
we can plot each of these fearues:

```
[6]: viz = cdf[['CYLINDERS','ENGINESIZE','CO2EMISSIONS','FUELCONSUMPTION_COMB']]
     viz.hist()
     plt.show()
```
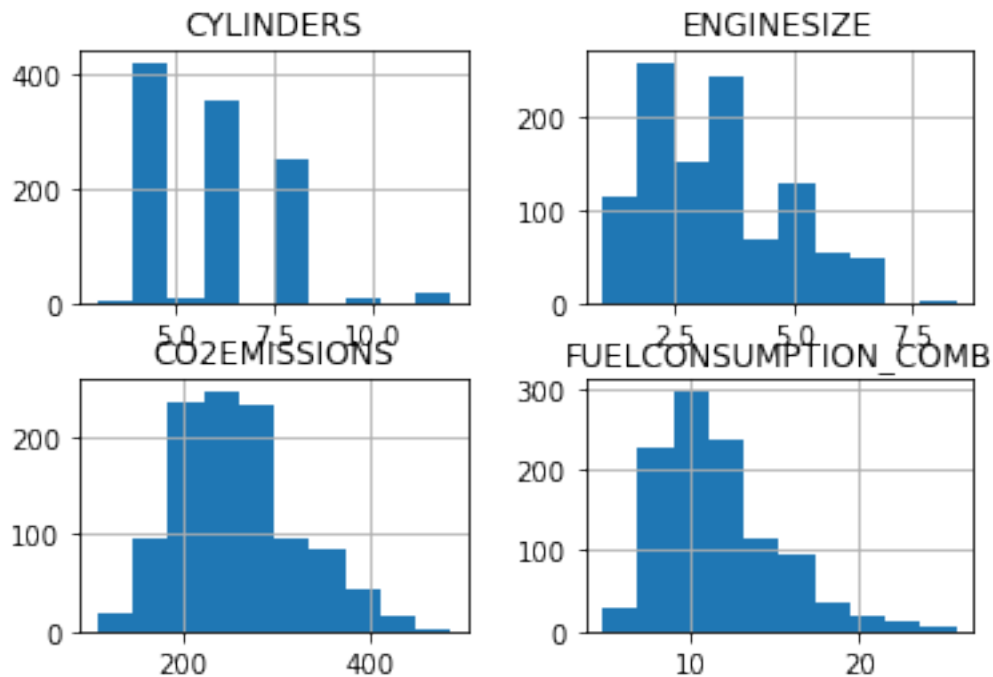

Now, lets plot each of these features vs the Emission, to see how linear is their relation:

```
[7]: plt.scatter(cdf.FUELCONSUMPTION_COMB, cdf.CO2EMISSIONS,  color='blue')
     plt.xlabel("FUELCONSUMPTION_COMB")
     plt.ylabel("Emission")
```
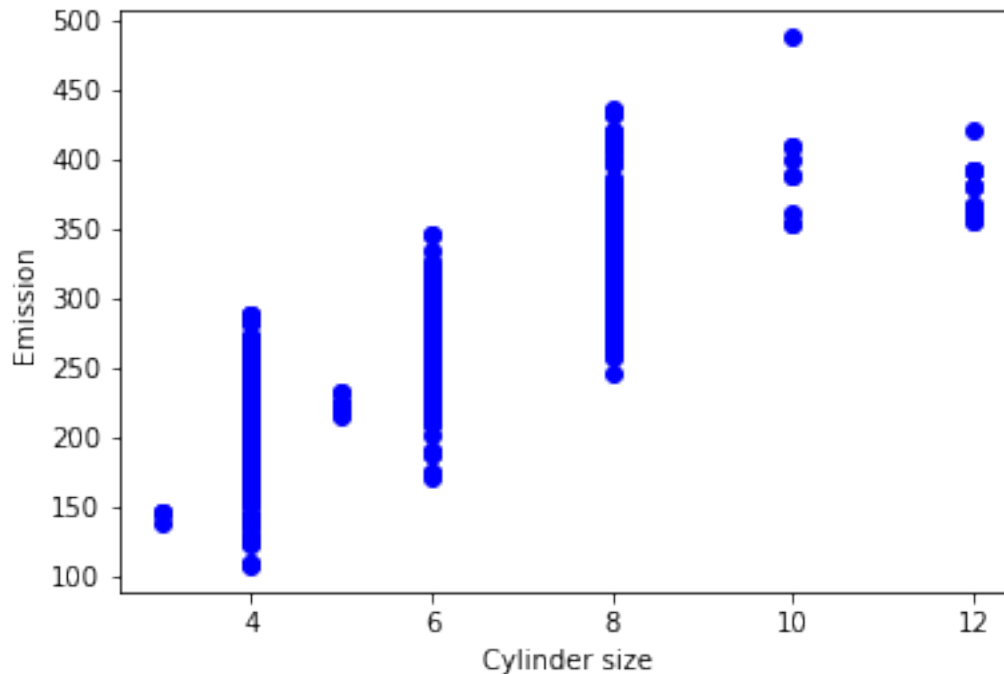
```
plt.show()
```



```
[8]: plt.scatter(cdf.ENGINESIZE, cdf.CO2EMISSIONS,  color='blue')
     plt.xlabel("Engine size")
     plt.ylabel("Emission")
     plt.show()
```
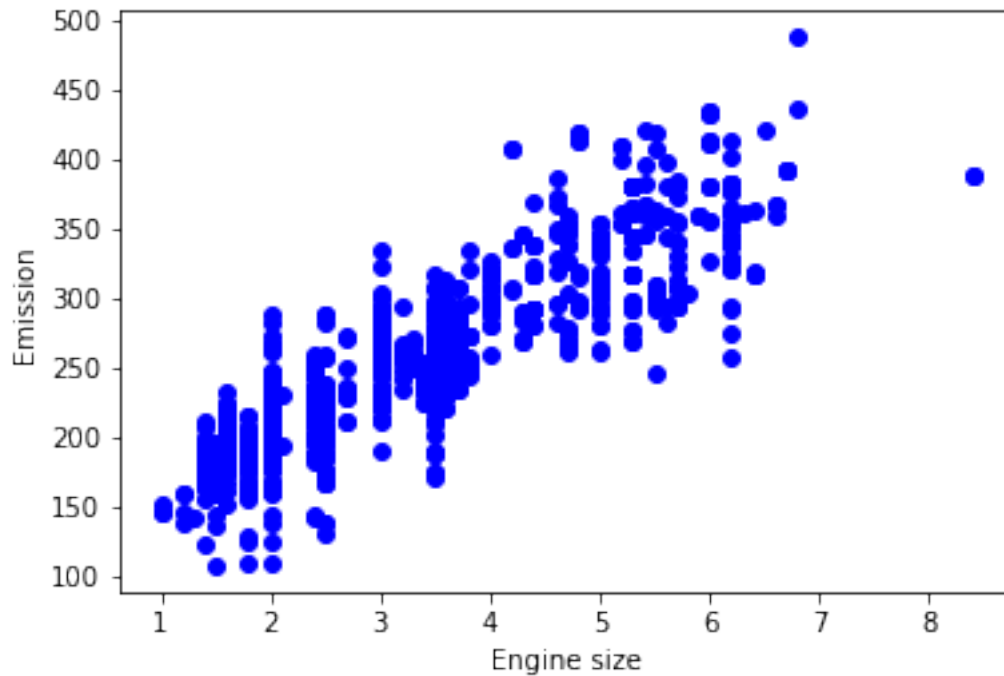
1.4 Practice

plot **CYLINDER** vs the Emission, to see how linear is their relation:

```
[9]: # write your code here
     plt.scatter(cdf.CYLINDERS, cdf.CO2EMISSIONS,  color='blue')
     plt.xlabel("Cylinder size")
     plt.ylabel("Emission")
     plt.show()
```

Double-click **here** for the solution.

Creating train and test dataset Train/Test Split involves splitting the dataset into training and testing sets respectively, which are mutually exclusive. After which, you train with the training set and test with the testing set. This will provide a more accurate evaluation on out-of-sample accuracy because the testing dataset is not part of the dataset that have been used to train the data. It is more realistic for real world problems.

This means that we know the outcome of each data point in this dataset, making it great to test with! And since this data has not been used to train the model, the model has no knowledge of the outcome of these data points. So, in essence, it is truly an out-of-sample testing.

Lets split our dataset into train and test sets, 80% of the entire data for training, and the 20% for testing. We create a mask to select random rows using **np.random.rand()** function:

```
[11]: msk = np.random.rand(len(df)) < 0.8
      train = cdf[msk]
      test = cdf[~msk]
```

1.4.1 Simple Regression Model

Linear Regression fits a linear model with coefficients B = (B1, ..., Bn) to minimize the 'residual sum of squares' between the actual value y in the dataset, and the predicted value yhat using linear approximation.

Train data distribution

```
[12]: plt.scatter(train.ENGINESIZE, train.CO2EMISSIONS,  color='blue')
      plt.xlabel("Engine size")
      plt.ylabel("Emission")
      plt.show()
```
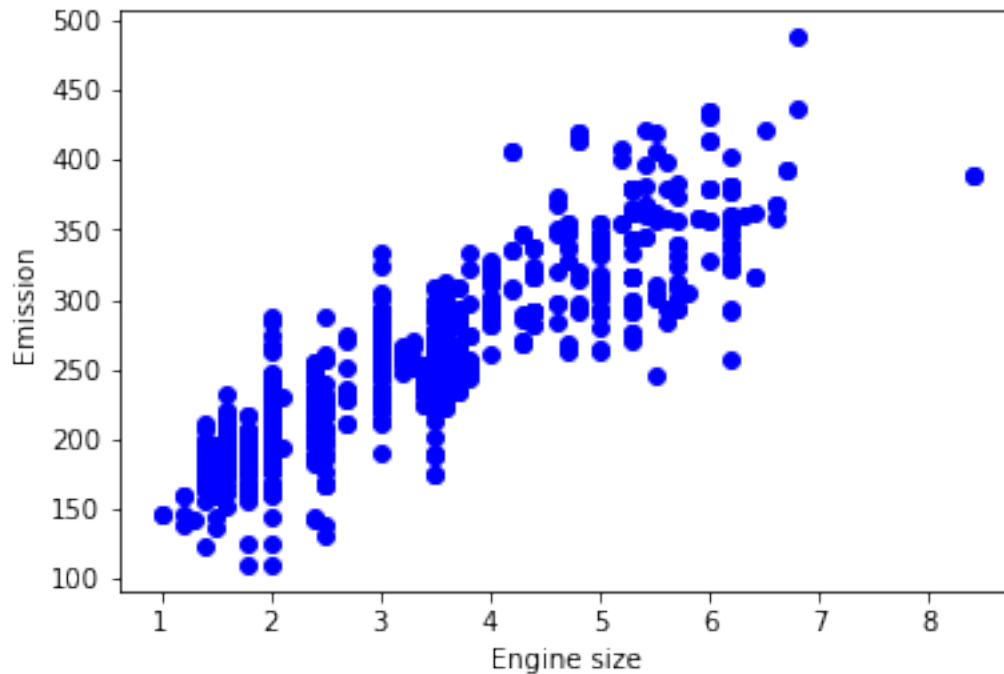

Modeling   Using sklearn package to model data.

```
[13]: from sklearn import linear_model
      regr = linear_model.LinearRegression()
      train_x = np.asanyarray(train[['ENGINESIZE']])
      train_y = np.asanyarray(train[['CO2EMISSIONS']])
      regr.fit (train_x, train_y)
      # The coefficients
      print ('Coefficients: ', regr.coef_)
      print ('Intercept: ',regr.intercept_)
```

```
Coefficients:  [[39.66851149]]
Intercept:  [123.71133926]
```

As mentioned before, **Coefficient** and **Intercept** in the simple linear regression, are the parameters of the fit line. Given that it is a simple linear regression, with only 2 parameters, and knowing that the parameters are the intercept and slope of the line, sklearn can estimate them directly from our data. Notice that all of the data must be available to traverse and calculate the parameters.

Plot outputs   we can plot the fit line over the data:

```
[14]: plt.scatter(train.ENGINESIZE, train.CO2EMISSIONS,  color='blue')
      plt.plot(train_x, regr.coef_[0][0]*train_x + regr.intercept_[0], '-r')
      plt.xlabel("Engine size")
      plt.ylabel("Emission")
```

[14]: Text(0, 0.5, 'Emission')
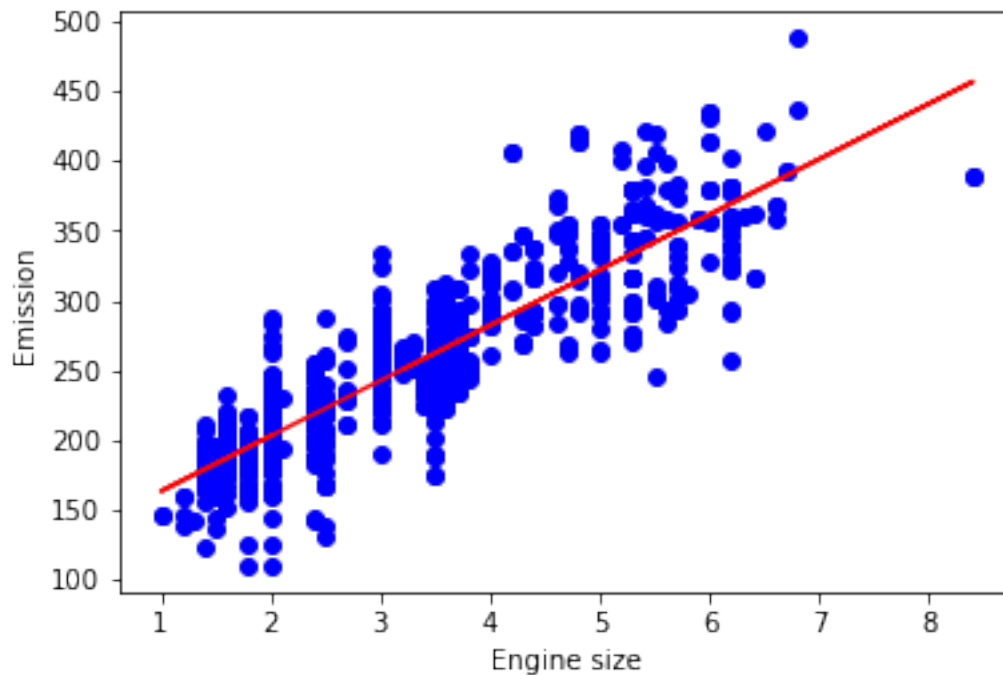
Evaluation   we compare the actual values and predicted values to calculate the accuracy of a regression model. Evaluation metrics provide a key role in the development of a model, as it provides insight to areas that require improvement.

There are different model evaluation metrics, lets use MSE here to calculate the accuracy of our model based on the test set:

```
- Mean absolute error: It is the mean of the absolute value of the errors. This is the easiest
- Mean Squared Error (MSE): Mean Squared Error (MSE) is the mean of the squared error. It's mor
- Root Mean Squared Error (RMSE).
- R-squared is not error, but is a popular metric for accuracy of your model. It represents how
```

```
[15]: from sklearn.metrics import r2_score

      test_x = np.asanyarray(test[['ENGINESIZE']])
      test_y = np.asanyarray(test[['CO2EMISSIONS']])
      test_y_ = regr.predict(test_x)
```

```
print("Mean absolute error: %.2f" % np.mean(np.absolute(test_y_ - test_y)))
print("Residual sum of squares (MSE): %.2f" % np.mean((test_y_ - test_y) ** 2))
print("R2-score: %.2f" % r2_score(test_y , test_y_) )
```

```
Mean absolute error: 24.30
Residual sum of squares (MSE): 997.09
R2-score: 0.74
```

Want to learn more?

IBM SPSS Modeler is a comprehensive analytics platform that has many machine learning algorithms. It has been designed to bring predictive intelligence to decisions made by individuals, by groups, by systems – by your enterprise as a whole. A free trial is available through this course, available here: SPSS Modeler

Also, you can use Watson Studio to run these notebooks faster with bigger datasets. Watson Studio is IBM's leading cloud solution for data scientists, built by data scientists. With Jupyter notebooks, RStudio, Apache Spark and popular libraries pre-packaged in the cloud, Watson Studio enables data scientists to collaborate on their projects without having to install anything. Join the fast-growing community of Watson Studio users today with a free account at Watson Studio

1.4.2 Thank you for completing this lab!

1.5 Author

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1.5.1 Other Contributors

Joseph Santarcangelo

1.6 Change Log

Date (YYYY-MM-DD)	Version	Changed By	Change Description
2020-11-03	2.1	Lakshmi Holla	Changed URL of the csv
2020-08-27	2.0	Lavanya	Moved lab to course repo in GitLab

##