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

November 12, 2018

#
Simple Linear Regression

About this Notebook In this notebook, we learn how to use scikit-learn to implement simple linear regression. We download a dataset that is related to fuel consumption and Carbon dioxide emission of cars. Then, we split our data into training and test sets, create a model using training set, evaluate your model using test set, and finally use model to predict unknown value.

0.0.1 Importing Needed packages

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

0.0.2 Downloading Data

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

```
In [2]: !wget -O FuelConsumption.csv https://s3-api.us-geo.objectstorage.softlayer.net/cf-course
        print('File Downloaded!')
```

```
--2018-11-11 23:38:47--  https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/Cogni
Resolving s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.net).
Connecting to s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.n
HTTP request sent, awaiting response... 200 OK
Length: 72629 (71K) [text/csv]
Saving to: FuelConsumption.csv

FuelConsumption.csv 100%[===================>]  70.93K  --.-KB/s   in 0.02s

2018-11-11 23:38:48 (3.15 MB/s) - FuelConsumption.csv saved [72629/72629]

File Downloaded!
```

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0.1 Understanding the Data

0.1.1 `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

0.2 Reading the data in

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

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

```
Out[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
```

0.2.1 Data Exploration

Lets first have a descriptive exploration on our data.

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

Out[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.

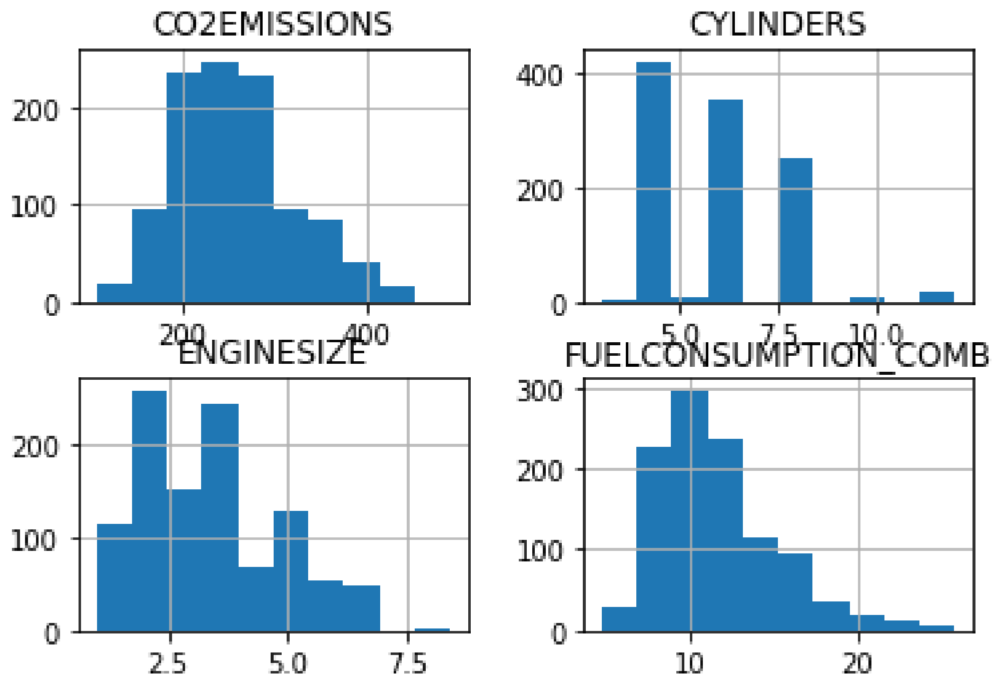
In [5]:
```
cdf = df[['ENGINESIZE','CYLINDERS','FUELCONSUMPTION_COMB','CO2EMISSIONS']]
cdf.head(9)
```

Out[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

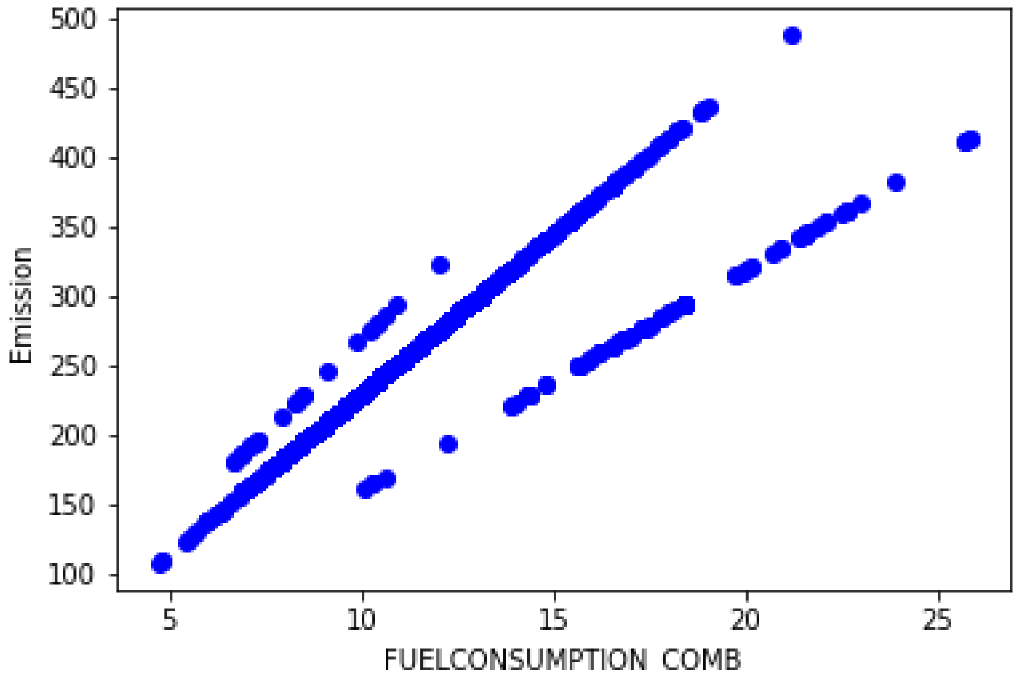
we can plot each of these features:

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

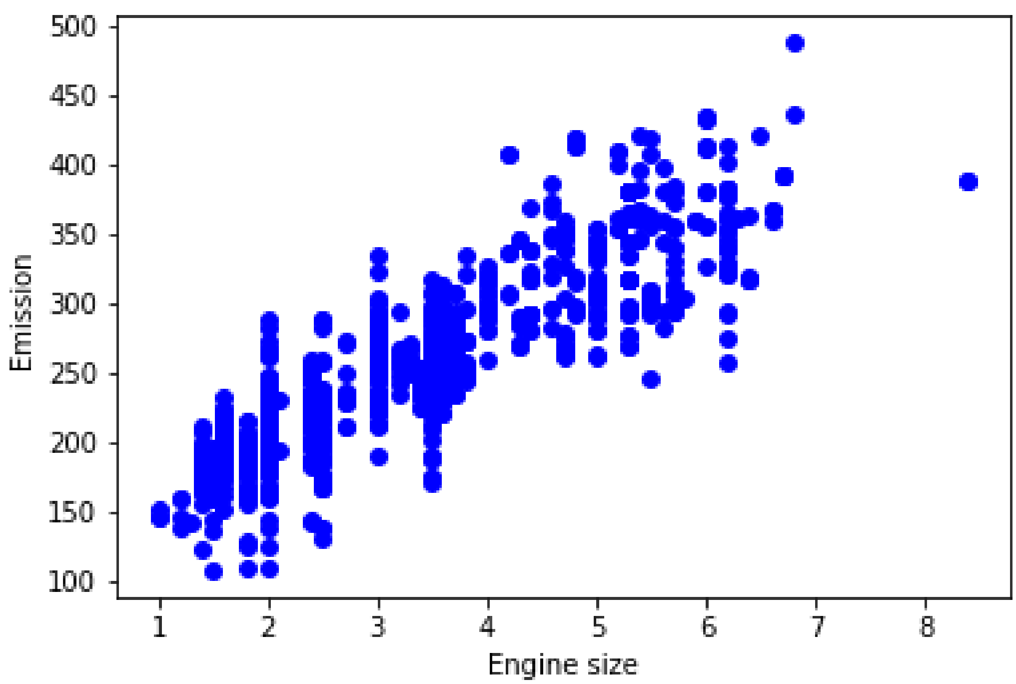


Now, lets plot each of these features vs the Emission, to see how linear is their relation:

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



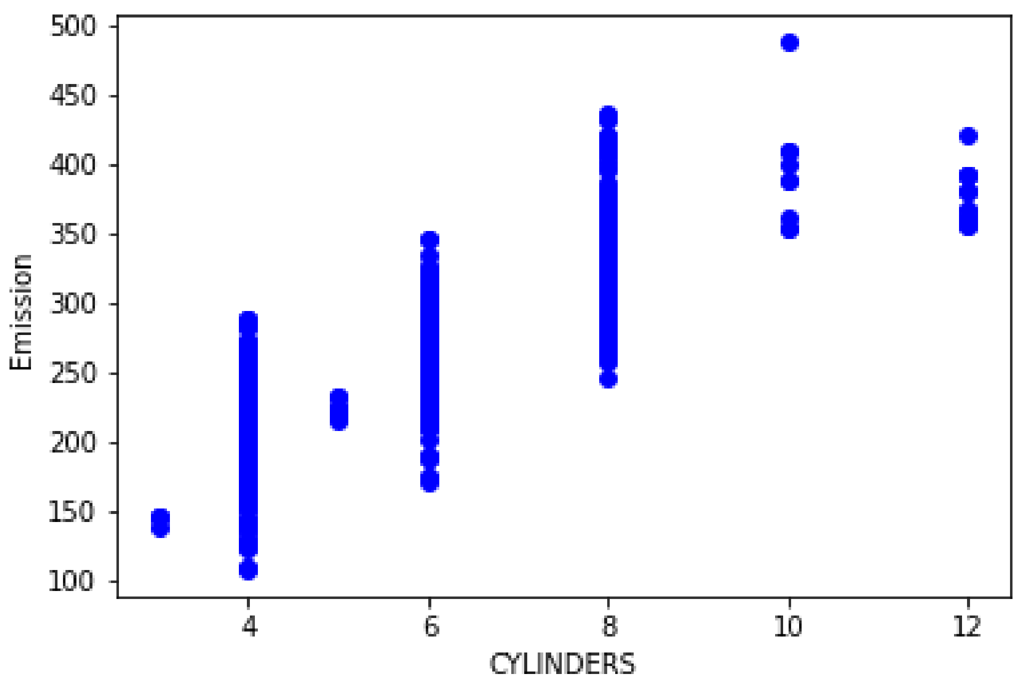
In [8]:
```
plt.scatter(cdf.ENGINESIZE, cdf.CO2EMISSIONS,  color='blue')
plt.xlabel("Engine size")
plt.ylabel("Emission")
plt.show()
```



0.3 Practice

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

```
In [10]: # write your code here
         plt.scatter(cdf.CYLINDERS, cdf.CO2EMISSIONS,  color='blue')
         plt.xlabel("CYLINDERS")
         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:

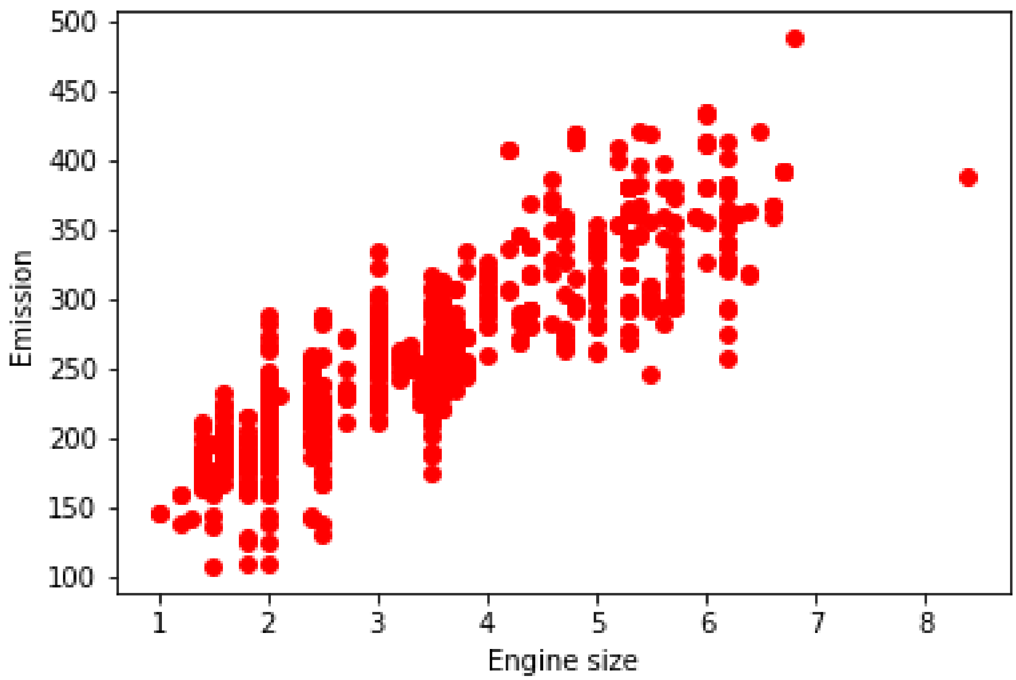
```
In [11]: msk = np.random.rand(len(df)) < 0.8
         train = cdf[msk]
         test = cdf[~msk]
```

0.3.1 Simple Regression Model

Linear Regression fits a linear model with coefficients $\theta = (\theta_1, ..., \theta_n)$ to minimize the 'residual sum of squares' between the independent x in the dataset, and the dependent y by the linear approximation.

Train data distribution

```
In [13]: plt.scatter(train.ENGINESIZE, train.CO2EMISSIONS,  color='red')
         plt.xlabel("Engine size")
         plt.ylabel("Emission")
         plt.show()
```



Modeling Using sklearn package to model data.

```
In [18]: from sklearn import linear_model as lm
         #regr = linear_model.LinearRegression()
         regr = lm.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_)
```

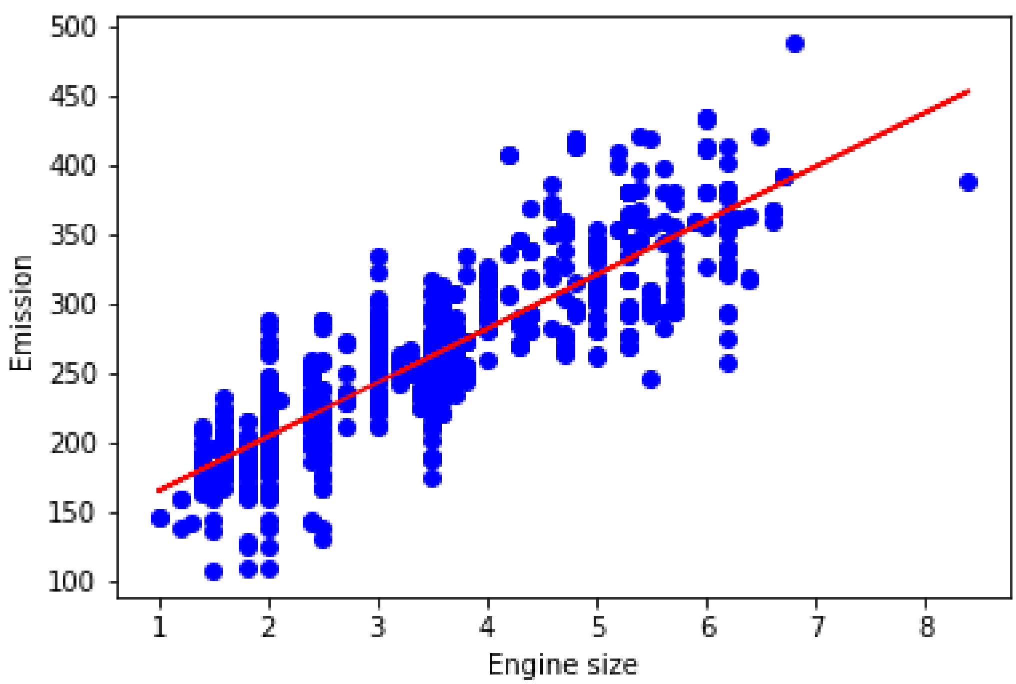
```
Coefficients:  [[38.90535622]]
Intercept:  [126.41328789]
```

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:

```
In [15]: 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")
```

```
Out[15]: 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:

```
<li> Mean absolute error: It is the mean of the absolute value of the errors. This is the easies
<li> Mean Squared Error (MSE): Mean Squared Error (MSE) is the mean of the squared error. Its mo
<li> Root Mean Squared Error (RMSE): This is the square root of the Mean Square Error. </li>
<li> R-squared is not error, but is a popular metric for accuracy of your model. It represents h
```

```
In [16]: from sklearn.metrics import r2_score

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

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

```
Mean absolute error: 23.09
Residual sum of squares (MSE): 835.17
R2-score: 0.72
```

0.4 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

0.4.1 Thanks for completing this lesson!

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