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Aim

The motive of this assignment is to make predictions using **Linear Regression**. To make sure you truly understand how the underlying algorithm works, you are to implement it from scratch.

Generating the dataset

Run the cell below to create the dataset. It further splits the available data into training and testing. Please do not edit this cell.

```
! pip install sklearn
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting sklearn
  Downloading sklearn-0.0.post1.tar.gz (3.6 kB)
  Preparing metadata (setup.py) ... done
Building wheels for collected packages: sklearn
  Building wheel for sklearn (setup.py) ... done
  Created wheel for sklearn: filename=sklearn-0.0.post1-py3-none-any.whl size=2955 sha256=cddb18f0f41178b18d40d55186b988e7b3a6a540c
  Stored in directory: /root/.cache/pip/wheels/f8/e0/3d/9d0c2020c44a519b9f02ab4fa6d2a4a996c98d79ab2f569fa1
Successfully built sklearn
Installing collected packages: sklearn
Successfully installed sklearn-0.0.post1
```

```
from sklearn import datasets
from sklearn.model_selection import train_test_split

# Generate the data
X, y = datasets.make_regression(n_samples=100, n_features=1, noise=20, random_state=4)

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1234)
```

```
y
```

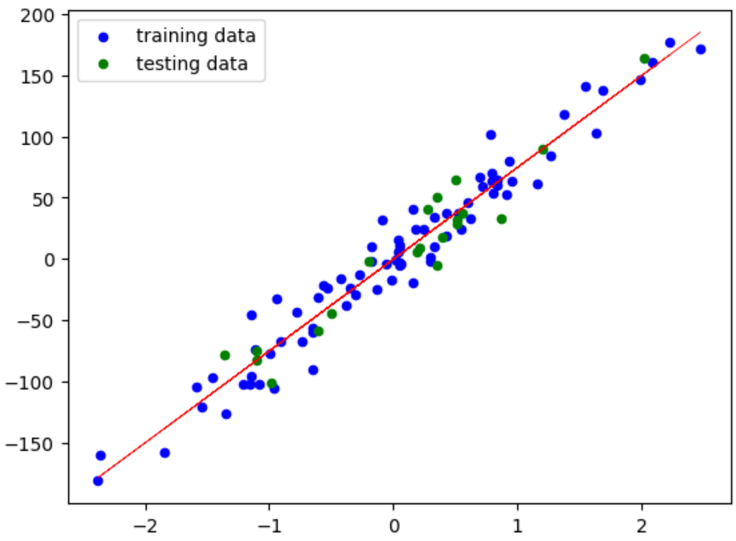
```
array([-126.24922409,   50.92876904,   63.15463302,    6.05472009,
         -5.72954025,   -2.75191769,   58.70355923,   53.81362958,
        -95.34105851,   24.64812471,  -59.41697406,  -73.42349619,
       -104.16266749,   31.80766772,  171.15350154,  -67.75196497,
        141.46769811,  -24.36756973,   -2.11240097,  -32.59583109,
        -29.41505819,  -37.87145989, -101.89829601,   46.41287784,
       -181.34840044,  -31.77399504,   24.13154879,  163.94385144,
         10.77367111,   37.35891532,    0.98036703, -120.88573188,
        138.19938797,    9.20267903,  -16.2068899 ,   33.21708479,
        -45.61698488,   -1.77758908, -105.56283971,    5.26394625,
         89.5978923 ,  146.10300439,  -77.78704394,   -3.80893607,
         60.81195812,  -97.2027103 ,   -1.15989334,  -43.88245964,
         15.74278405,  -24.27446551,  -90.60148118,  -19.07314539,
       -101.79001521,  -56.55140067,   52.1696979 , -158.28468928,
         64.53968736,   84.52102913,   66.43434451,   36.86598297,
         37.43779494,  -82.91713341,  -21.4183161 ,   -5.54348338,
         59.88451573,    8.3784894 ,  -17.17634894, -160.50895428,
       -100.73717846,   80.30335894,   69.64956653,   28.14443518,
          9.7630474 ,   41.12497399,  176.92831393,    9.55981705,
         -4.40463276,  -24.03585202,   19.1701073 ,  102.48327018,
        101.52088195,  -58.51318402,   17.68768961,   63.05366753,
       -102.36728191,   -1.65856494,   64.66264562,  -44.1299115 ,
        117.99658351,   -4.63168152,  -76.71464299,  -67.2815873 ,
        -12.46435171,   24.2973507 ,   31.43120085,   34.44108322,
        -74.76820338,  160.99602125,   40.69772522,   33.43401768])
```

Visualizing the data

Use `matplotlib` to visualize the given data.

```
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from scipy import stats
fig = plt.figure()
ax1 = fig.add_subplot(111)
ax1.scatter(X_train,y_train,s=20,c='b',label="training data")
ax1.scatter(X_test,y_test,s=20,c='g',label="testing data")
plt.legend(loc="upper left")
regressor = LinearRegression()
```

```
regressor.fit(X,y)
y_pred = regressor.predict(X)
plt.plot(X,y_pred,color="red",linewidth="0.3")
plt.show()
```



You should be able to see the linear relations between `y` and the features in vector `X`.

Gradient Descent Review

1. Cost function

   Define the `cost function` to measure the difference between predictions and target outputs. Here, we are working with first degree polynomial, so derivatives are easy to calculate. (Linear function `y = wx +b`)

$$Error = \frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y}_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(y_i - (xw+b))^2$$

where `N` is the number of samples

2. Compute the derivative

$$\frac{\delta Error}{\delta w} = \frac{2}{N}\sum_{i=1}^{N} -x(y_i - (mx+b))$$
$$\frac{\delta Error}{\delta b} = \frac{2}{N}\sum_{i=1}^{N} -(y_i - (mx+b))$$

3. Update current parameters

$$w := w - learning\_rate \cdot \frac{\delta Error}{\delta w}$$
$$b := b - learning\_rate \cdot \frac{\delta Error}{\delta b}$$

4. Repeat until it fits good enough

Model definition

Complete the functions in the class below. Hints provided at appropriate places.

```
import numpy as np

class LinearRegression:

    # The __init__ is called when we make any object of our class. Here, you are to specify the default values for
    # Learning Rate, Number of Iterations, Weights and Biases. It doesn't return anything.
    # Hint: Google what a `self pointer` is and figure out how it can be used here.
    def __init__(self, learning_rate=0.001, n_iters=1000):
        # Your code here
        self.current_W = 0.1
        self.current_b = 0.01
        self.learning_rate = 0.1
```

```
        self.n_iters = 1000

    # The following function would be the heart of the model. This is where the training would happen.
    # You're supposed to iterate and keep on updating the weights and biases according to the steps of Gradient Descent.
    def fit(self, X, y):
        # Gradient Descent code goes here
        n_iters = 1000
        learning_rate = 0.001
        n = float(len(X))
        costs = []
        weights = []
        previous_cost = None
        tol = 1e-6
        X = X.astype(float)

        for i in range(n_iters):
                a = np.multiply(np.array(X),self.current_W)
                y_predicted = a + self.current_b
                current_cost = np.sum((y-y_predicted)**2) / len(y)
                if previous_cost and abs(previous_cost-current_cost) <= tol:
                  break
                previous_cost = current_cost
                costs.append(current_cost)
                weights.append(self.current_W)
                weight_derivative = -(2/n) * np.sum(np.multiply(X,(y - y_predicted)))
                bias_derivative = -(2/n) * np.sum(y - y_predicted)
                self.current_W = self.current_W - (learning_rate * weight_derivative)
                self.current_b = self.current_b - (learning_rate * bias_derivative)


    # This function will be called after our model has been trained and we are predicting on unseen data
    # What is our prediction? Just return that
    def predict(self, X=[],y=[]):
        y = np.array(y)
        d = np.multiply(np.array(X),self.current_W)
        Y_pred = d + self.current_b
        h = Y_pred
        n = h.sum(axis=1)
        return  n
```

Initializing, Training & Predictions

```
# Now, we make an object of our custom class.
regress = LinearRegression()
# Call the fit method on the object to train (pass appropriate part of dataset)
regress.__init__
regress.fit(X_train,y_train)
regress.predict(X_train)

# Now, let's see our what our model predicts
# pass appropriate part of dataset
```

```
     array([1.19528812, 1.1952873 , 1.19530162, 1.19533524, 1.19529412,
            1.19536834, 1.19525891, 1.19528072, 1.19534528, 1.19528256,
            1.19528297, 1.19531396, 1.19525566, 1.19529061, 1.195331  ,
            1.19527435, 1.19523605, 1.19531256, 1.19531699, 1.19526035,
            1.19526639, 1.19529287, 1.19531229, 1.19531391, 1.19523568,
            1.19530947, 1.19532677, 1.19523619, 1.19535918, 1.19534179,
            1.19522396, 1.19526919, 1.19525723, 1.19520884, 1.19529797,
            1.19522053, 1.19527024, 1.19528299, 1.19523888, 1.1953475 ,
            1.19523364, 1.19527763, 1.19524555, 1.19527595, 1.19528289,
            1.19528183, 1.19529776, 1.19537828, 1.19528322, 1.1952189 ,
            1.19524402, 1.19531855, 1.19528249, 1.1952282 , 1.19523741,
            1.19518854, 1.19536302, 1.19526467, 1.19527421, 1.19529412,
            1.19525553, 1.19530536, 1.19528736, 1.19531195, 1.19531776,
            1.1953083 , 1.195242  , 1.19528373, 1.19527894, 1.19529274,
            1.19530237, 1.19530457, 1.1952675 , 1.19525235, 1.19518769,
            1.19528307, 1.19525567, 1.19524334, 1.19531234, 1.19525052])
```

Evaluate the model

Return [Mean Squared Error] & [R2 Score] from the functions below.

```
def mean_squared_error(y_true, y_pred):
    mse = np.sum((y_true - y_pred)**2)/len(y_true)
    return mse
```

```
def r2_score(y_true, y_pred):
    y_mean = np.sum(y_true)/len(y_true)
    r2_score = 1 - np.sum((y_true - y_pred)**2)/np.sum((y_true - y_mean)**2)
    return r2_score

y_pred = regress.predict(X)
mse = mean_squared_error(y,y_pred)
print("MSE:", mse)

accu =  r2_score(y,y_pred)
print("Accuracy:", accu)
```

```
MSE: 290.2612417801377
Accuracy: 0.9482150605235175
```

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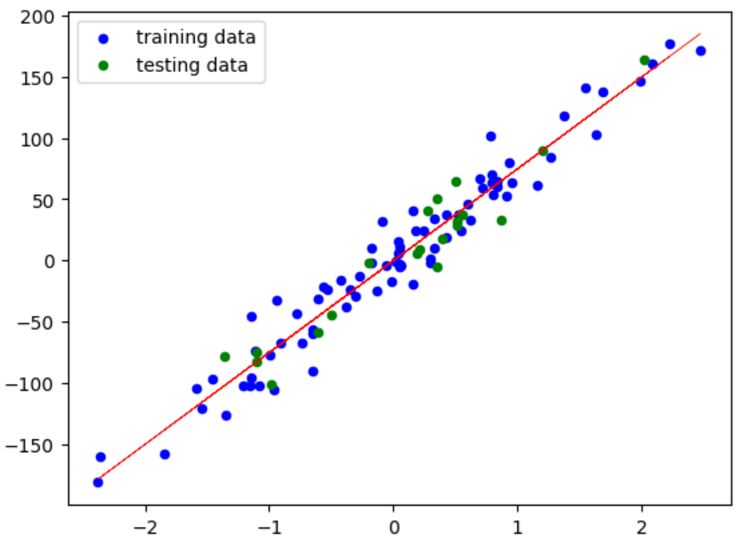

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