Linear Regression from scratch in Python

Importing the libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_diabetes
from sklearn.model_selection import train_test_split

# Step 1: Load the diabetes dataset
diabetes = load_diabetes()
diabetes_df = pd.DataFrame(data=diabetes.data, columns=diabetes.feature_names)
diabetes_df['target'] = diabetes.target

diabetes_df.head()
```

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	target
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.019908	-0.017646	151.0
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.068330	-0.092204	75.0
2	0.085299	0.050680	0.044451	-0.005671	-0.045599	-0.034194	-0.032356	-0.002592	0.002864	-0.025930	141.0
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.022692	-0.009362	206.0
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.031991	-0.046641	135.0

Splitting the Data into X and y

```
# splitting the data into X and y
X = diabetes_df.iloc[:, :-1]
y = diabetes_df.iloc[:, -1]
```

Shuffling the data

```
# shuffling the data
def shuffle(X, y):
    np.random.seed(67)
    randomize = np.arange(len(X))
    np.random.shuffle(randomize)
    X = X.iloc[randomize]
    y = y.iloc[randomize]
    return X, y

X, y = shuffle(X, y)
```

```
# make sure that the labels and features are still matching after shuffling the data.
print(pd.DataFrame(X.head()))
print(pd.DataFrame(y.head()))
```

```
          age       sex       bmi        bp        s1        s2        s3  \
295 -0.052738  0.050680  0.039062 -0.040099 -0.005697 -0.012900  0.011824
114  0.023546 -0.044642  0.110198  0.063187  0.013567 -0.032942 -0.024993
197  0.048974  0.050680  0.003494  0.070073 -0.008449  0.013404 -0.054446
255  0.001751 -0.044642 -0.065486 -0.005671 -0.007073 -0.019476  0.041277
429 -0.041840 -0.044642 -0.033151 -0.022885  0.046589  0.041587  0.056003

           s4        s5        s6
295 -0.039493  0.016305  0.003064
114  0.020655  0.099240  0.023775
197  0.034309  0.013316  0.036201
255 -0.039493 -0.003304  0.007207
429 -0.024733 -0.025952 -0.038357
     target
295    85.0
114   258.0
197   129.0
255   153.0
429    94.0
```

Splitting the data into train , dev and test

```
# Step 2: Split the dataset into train, dev, and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
X_dev, X_test, y_dev, y_test = train_test_split(X_test, y_test, test_size=0.5, random_state=42)
```

Choosing the best feature

```
from sklearn.ensemble import RandomForestRegressor

# choosing the best feature for the model
def bestFeature(X_train, y_train, X_dev, y_dev):
    # initialize the best feature and its corresponding RMSE
    best_feature = None
    # initialize the best RMSE to infinity
    best_rmse = float('inf')

    # loop over all features
    for feature in X_train.columns:
        # train the model on the current feature
        model = RandomForestRegressor()
        model.fit(X_train[feature].values.reshape(-1, 1), y_train)
        # compute the RMSE on the dev set
        y_pred = model.predict(X_dev[feature].values.reshape(-1, 1))
        rmse = np.sqrt(np.mean((y_pred - y_dev) ** 2))
        mse = np.mean((y_pred - y_dev) ** 2)
        # print each feature's MSE and RMSE
        print("RMSE and MSE for feature {}: \t{}, \t{}".format(feature, rmse, mse))
        # get the best feature
        if rmse < best_rmse:
            best_rmse = rmse
            best_feature = feature

    return best_feature, best_rmse
```

```
best_feature, best_score = bestFeature(X_train, y_train, X_dev, y_dev)
best_feature, best_score
```

```
RMSE and MSE for feature age:   74.11909245767413,      5493.639866749247
RMSE and MSE for feature sex:   71.68464103816397,      5138.687760770422
RMSE and MSE for feature bmi:   69.44534268362493,      4822.655620446098
RMSE and MSE for feature bp:    70.2122539986217,       4929.7606115669705
RMSE and MSE for feature s1:    79.48067459889481,      6317.177634695403
RMSE and MSE for feature s2:    83.47639166380381,      6968.3079652087745
RMSE and MSE for feature s3:    75.06332038001686,      5634.502066473055
RMSE and MSE for feature s4:    62.618756692648326,     3921.1086897330892
RMSE and MSE for feature s5:    70.46098911210943,      4964.750986656803
RMSE and MSE for feature s6:    67.18398922534259,      4513.688408230949
('s4', 62.618756692648326)
```

```
theta = np.array([0.0, 0.0])
```

```
def compute_cost(Y_pred, Y_true):
    m = len(Y_true)
    cost = (1/2*m) * np.sum(np.square(Y_pred - Y_true)) # MSE
    return cost


def univariate_linear_regression(theta, input):
    pred = theta[0] + theta[1] * input
    return pred
```

The univariate_linear_regression function implements a simple linear regression model with a single feature, where theta is the vector of weights, theta[0] is the intercept and theta[1] is the slope. The input feature input is multiplied by the slope and added to the intercept to obtain the predicted output pred.

```
def gradient_descent(theta, X, Y_true, Y_pred, learning_rate):
    # calculate the number of samples in the training data
    m = len(Y_true)
    # update theta_0 using gradient descent
    theta[0] = theta[0] - learning_rate * (1/m) * np.sum(Y_pred - Y_true)
    # update theta_1 using gradient descent
    theta[1] = theta[1] - learning_rate * (1/m) * np.sum((Y_pred - Y_true) * X)
    # return the updated theta values
```

```
    return theta

# Apply gradient descent to the training data
theta = gradient_descent(theta, X_train[best_feature], y_train, univariate_linear_regression(theta, X_train[best_feature]), 0.
theta
```

```
array([1.49184466, 0.01850364])
```

Normalizing the data

```
def normalize(X):
    mean = np.mean(X)
    std = np.std(X)
    X = (X - mean) / std
    return X, mean, std

X_train[best_feature], mean, std = normalize(X_train[best_feature])
```

Training the model

```
def train(X, Y_true, theta, learning_rate, iterations):
    # normalize the features of X
    X, X_mean, X_std = normalize(X)
    # initialize an array to store the cost history for each iteration
    cost_history = np.zeros(iterations)
    for i in range(iterations):
        # get the predicted values for Y using the current theta
        Y_pred = univariate_linear_regression(theta, X)
        # update theta using the gradient descent algorithm
        theta = gradient_descent(theta, X, Y_true, Y_pred, learning_rate)
        # store the cost for the current iteration
        cost_history[i] = compute_cost(Y_pred, Y_true)
    # return the updated theta, the cost history, and the normalization parameter
    return theta, cost_history, X_mean, X_std

def predict(X, theta, X_mean, X_std):
    # normalize the features of X using the normalization parameters
    X = (X - X_mean) / X_std
    # get the predicted values for Y using the updated theta
    Y_pred = univariate_linear_regression(theta, X)
    # return the predictions
    return Y_pred

theta, cost_history, X_mean, X_std = train(X_train[best_feature], y_train, theta, 0.01, 1000)
pred = predict(X_test[best_feature], theta, X_mean, X_std)

print("RMSE: ", np.sqrt(np.mean((pred - y_test) ** 2)))
print("MSE: ", np.mean((pred - y_test) ** 2))
```

```
RMSE:  83.67893323141489
MSE:  7002.163866747592
```

```
compute_cost(pred, y_test)
```

```
15716356.79891497
```

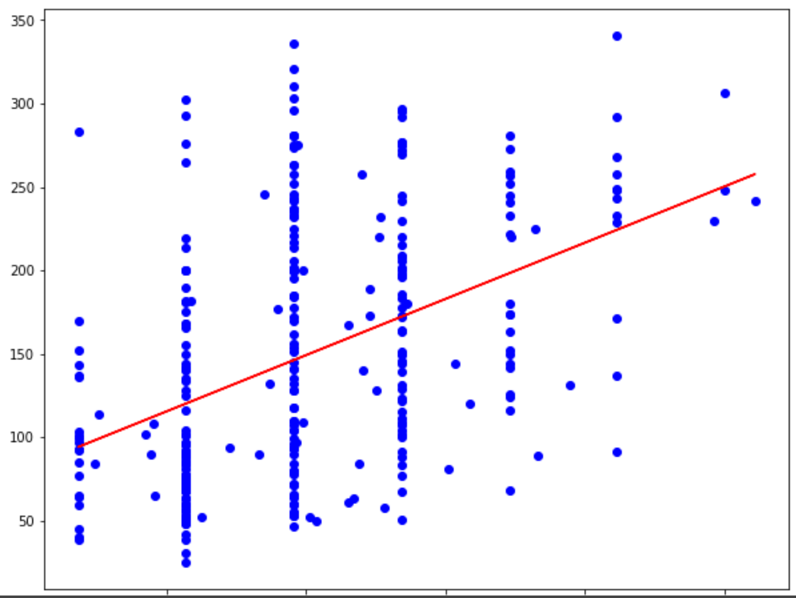
```
# test the model on the dev set
pred = predict(X_dev[best_feature], theta, X_mean, X_std)
print("RMSE: ", np.sqrt(np.mean((pred - y_dev) ** 2)))
print("MSE: ", np.mean((pred - y_dev) ** 2))
```

```
RMSE:  71.39564924684689
MSE:  5097.338731378788
```

```
compute_cost(pred, y_dev)
```

```
11102003.756943
```

```
fig = plt.figure(figsize=(10, 8))
plt.scatter(X_train[best_feature], y_train, color='blue')
plt.plot(X_train[best_feature], univariate_linear_regression(theta, X_train[best_feature]), color='red')
plt.show()
```



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