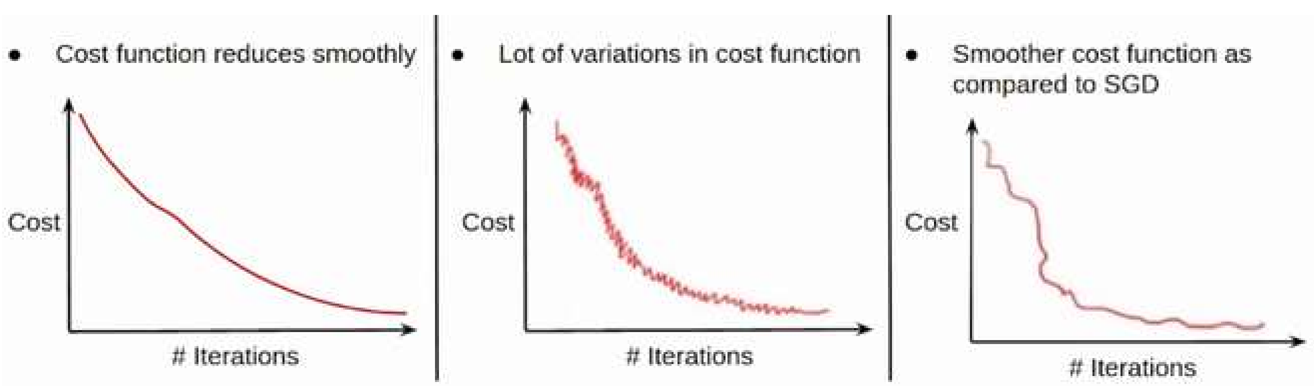
ML | Mini-Batch Gradient Descent with Python

In machine learning, gradient descent is an optimization technique used for computing the model parameters (coefficients and bias) for algorithms like linear regression, logistic regression, neural networks, etc. In this technique, we repeatedly iterate through the training set and update the model parameters in accordance with the gradient of the error with respect to the training set. Depending on the number of training examples considered in updating the model parameters, we have 3-types of gradient descents:

1. **Batch Gradient Descent:** Parameters are updated after computing the gradient of the error with respect to the entire training set
2. **Stochastic Gradient Descent:** Parameters are updated after computing the gradient of the error with respect to a single training example
3. **Mini-Batch Gradient Descent:** Parameters are updated after computing the gradient of the error with respect to a subset of the training set

- Batch Gradient Descent: Since the entire training data is considered before taking a step in the direction of gradient, therefore it takes a lot of time for making a single update.
  - Stochastic Gradient Descent: Since only a single training example is considered before taking a step in the direction of gradient, we are forced to loop over the training set and thus cannot exploit the speed associated with vectorizing the code.
  - Mini-Batch Gradient Descent: Since a subset of training examples is considered, it can make quick updates in the model parameters and can also exploit the speed associated with vectorizing the code.
- Batch Gradient Descent: It makes smooth updates in the model parameters
  - Stochastic Gradient Descent: It makes very noisy updates in the parameters
  - Mini-Batch Gradient Descent: Depending upon the batch size, the updates can be made less noisy – greater the batch size less noisy is the update

Thus, mini-batch gradient descent makes a compromise between the speedy convergence and the noise associated with gradient update which makes it a more flexible and robust algorithm.



Convergence in BGD, SGD & MBGD

Mini-Batch Gradient Descent: Algorithm-

> Let theta = model parameters and max_iters = number of epochs. for itr = 1, 2, 3, …, max_iters:
> for mini_batch (X_mini, y_mini):
>
> - Forward Pass on the batch X_mini:
>   - Make predictions on the mini-batch
>   - Compute error in predictions (J(theta)) with the current values of the parameters
> - Backward Pass:
>   - Compute gradient(theta) = partial derivative of J(theta) w.r.t. theta
> - Update parameters:
>   - theta = theta – learning_rate*gradient(theta)

Below is the Python Implementation:

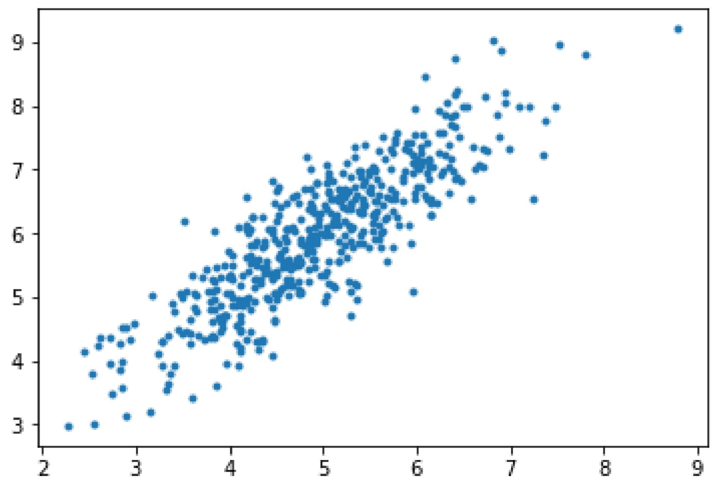
Step #1: First step is to import dependencies, generate data for linear regression, and visualize the generated data. We have generated 8000 data examples, each having 2 attributes/features. These data examples are further divided into training sets (X_train, y_train) and testing set (X_test, y_test) having 7200 and 800 examples respectively.

Python3

```
import  numpy as np

import  matplotlib.pyplot as plt

mean  =  np.array([``5.0``,  6.0``])

cov  =  np.array([[``1.0``,  0.95``], [``0.95``,  1.2``]])

data  =  np.random.multivariate_normal(mean, cov,  8000``)

plt.scatter(data[:``500``,  0``], data[:``500``,  1``], marker``=``'.'``)

plt.show()

data  =  np.hstack((np.ones((data.shape[``0``],  1``)), data))

split_factor  =  0.90

split  =  int``(split_factor  *  data.shape[``0``])

X_train  =  data[:split, :``-``1``]
```

```
y_train = data[:split, -``1``].reshape((``-``1``, 1``))

X_test = data[split:, :``-``1``]

y_test = data[split:, -``1``].reshape((``-``1``, 1``))

print``(& quot

    Number of examples in training set``= % d & quot

    % (X_train.shape[``0``]))

print``(& quot

    Number of examples in testing set``= % d & quot

    % (X_test.shape[``0``]))
```

Output:



Number of examples in training set = 7200 Number of examples in testing set = 800

Step #2: Next, we write the code for implementing linear regression using mini-batch gradient descent. gradientDescent() is the main driver function and other functions are helper functions used for making predictions – hypothesis(), computing gradients – gradient(), computing error – cost() and creating mini-batches – create_mini_batches(). The driver function initializes the parameters, computes the best set of parameters for the model, and returns these parameters along with a list containing a history of errors as the parameters get updated.

Example

Python3

```
def  hypothesis(X, theta):

  return  np.dot(X, theta)

def  gradient(X, y, theta):

  h  =  hypothesis(X, theta)

  grad  =  np.dot(X.transpose(), (h  -  y))

  return  grad

def  cost(X, y, theta):

  h  =  hypothesis(X, theta)

  J  =  np.dot((h  -  y).transpose(), (h  -  y))

  J  /``=  2

  return  J[``0``]

def  create_mini_batches(X, y, batch_size):

  mini_batches  =  []

  data  =  np.hstack((X, y))

  np.random.shuffle(data)

  n_minibatches  =  data.shape[``0``]  /``/  batch_size

  i  =  0

  for  i  in  range``(n_minibatches  +  1``):

    mini_batch  =  data[i  *  batch_size:(i  +  1``)``*``batch_size, :]

    X_mini  =  mini_batch[:, :``-``1``]

    Y_mini  =  mini_batch[:,  -``1``].reshape((``-``1``,  1``))

    mini_batches.append((X_mini, Y_mini))

  if  data.shape[``0``]  %  batch_size !``=  0``:

    mini_batch  =  data[i  *  batch_size:data.shape[``0``]]
```

```
      X_mini  =  mini_batch[:, :``-``1``]

      Y_mini  =  mini_batch[:,  -``1``].reshape((``-``1``,  1``))

      mini_batches.append((X_mini, Y_mini))

    return  mini_batches

def  gradientDescent(X, y, learning_rate``=``0.001``, batch_size``=``32``):

    theta  =  np.zeros((X.shape[``1``],  1``))

    error_list  =  []

    max_iters  =  3

    for  itr  in  range``(max_iters):

      mini_batches  =  create_mini_batches(X, y, batch_size)

      for  mini_batch  in  mini_batches:

        X_mini, y_mini  =  mini_batch

        theta  =  theta  -  learning_rate  *  gradient(X_mini, y_mini, theta)

        error_list.append(cost(X_mini, y_mini, theta))

    return  theta, error_list
```

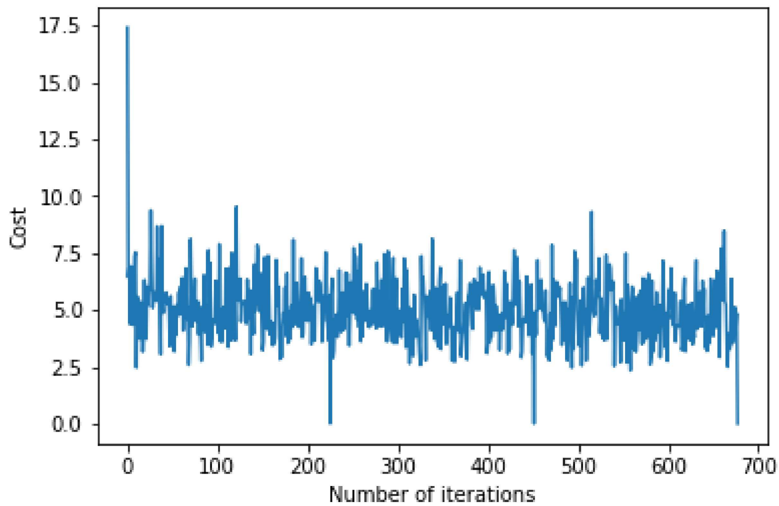
Calling the gradientDescent() function to compute the model parameters (theta) and visualize the change in the error function.

Python3

```
theta, error_list  =  gradientDescent(X_train, y_train)

print``("Bias  =  ", theta[``0``])

print``("Coefficients  =  ", theta[``1``:])

plt.plot(error_list)

plt.xlabel("Number of iterations")

plt.ylabel("Cost")
```

```
plt.show()
```

Output: Bias = [0.81830471] Coefficients = [[1.04586595]]

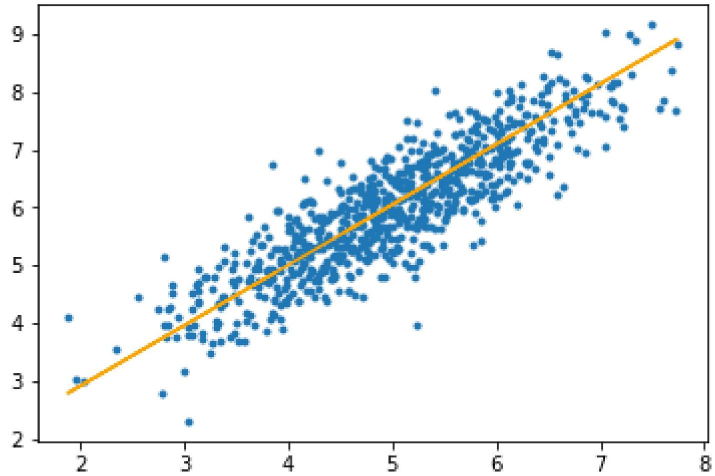


Step #3: Finally, we make predictions on the testing set and compute the mean absolute error in predictions.

Python3

```
y_pred  =  hypothesis(X_test, theta)

plt.scatter(X_test[:,  1``], y_test[:, ], marker``=``'.'``)

plt.plot(X_test[:,  1``], y_pred, color``=``'orange'``)

plt.show()

error  =  np.``sum``(np.``abs``(y_test  -  y_pred)  /  y_test.shape[``0``])

print``(& quot

    Mean absolute error  =  & quot

    , error)
```

Output:



> Mean absolute error = 0.4366644295854125

The orange line represents the final hypothesis function: **theta[0] + theta[1]*X_test[:, 1] + theta[2]*X_test[:, 2] = 0**