Linear regression 1D: Training Two Parameter Stochastic Gradient Descent (SGD)

Objective

- How to use SGD(Stochastic Gradient Descent) to train the model.

Table of Contents

In this Lab, you will practice training a model by using Stochastic Gradient descent.

Estimated Time Needed: **30 min**

Preparation

We'll need the following libraries:

In [1]:

```
# These are the libraries we are going to use in the lab.

import torch
import matplotlib.pyplot as plt
import numpy as np

from mpl_toolkits import mplot3d
```

The class `plot_error_surfaces` is just to help you visualize the data space and the parameter space during training and has nothing to do with PyTorch.

In [2]:

```
# The class for plot the diagram

class plot_error_surfaces(object):

    # Constructor
    def __init__(self, w_range, b_range, X, Y, n_samples = 30, go = True):
        W = np.linspace(-w_range, w_range, n_samples)
        B = np.linspace(-b_range, b_range, n_samples)
        w, b = np.meshgrid(W, B)
        Z = np.zeros((30, 30))
        count1 = 0
        self.y = Y.numpy()
        self.x = X.numpy()
        for w1, b1 in zip(w, b):
            count2 = 0
            for w2, b2 in zip(w1, b1):
                Z[count1, count2] = np.mean((self.y - w2 * self.x + b2) ** 2)
                count2 += 1
            count1 += 1
        self.Z = Z
        self.w = w
        self.b = b
        self.W = []
        self.B = []
        self.LOSS = []
        self.n = 0
        if go == True:
            plt.figure()
            plt.figure(figsize = (7.5, 5))
            plt.axes(projection = '3d').plot_surface(self.w, self.b, self.Z, rstride = 1, cstride =
            plt.title('Loss Surface')
            plt.xlabel('w')
            plt.ylabel('b')
            plt.show()
            plt.figure()
            plt.title('Loss Surface Contour')
            plt.xlabel('w')
            plt.ylabel('b')
            plt.contour(self.w, self.b, self.Z)
            plt.show()

    # Setter
    def set_para_loss(self, W, B, loss):
        self.n = self.n + 1
        self.W.append(W)
        self.B.append(B)
        self.LOSS.append(loss)

    # Plot diagram
    def final_plot(self):
        ax = plt.axes(projection = '3d')
        ax.plot_wireframe(self.w, self.b, self.Z)
        ax.scatter(self.W, self.B, self.LOSS, c = 'r', marker = 'x', s = 200, alpha = 1)
        plt.figure()
        plt.contour(self.w, self.b, self.Z)
        plt.scatter(self.W, self.B, c = 'r', marker = 'x')
        plt.xlabel('w')
        plt.ylabel('b')
        plt.show()
```

```
    # Plot diagram
    def plot_ps(self):
        plt.subplot(121)
        plt.ylim
        plt.plot(self.x, self.y, 'ro', label = "training points")
        plt.plot(self.x, self.W[-1] * self.x + self.B[-1], label = "estimated line")
        plt.xlabel('x')
        plt.ylabel('y')
        plt.ylim((-10, 15))
        plt.title('Data Space Iteration: ' + str(self.n))
        plt.subplot(122)
        plt.contour(self.w, self.b, self.Z)
        plt.scatter(self.W, self.B, c = 'r', marker = 'x')
        plt.title('Loss Surface Contour Iteration' + str(self.n))
        plt.xlabel('w')
        plt.ylabel('b')
        plt.show()
```

Make Some Data

Set random seed:

In [3]:

```
# Set random seed

torch.manual_seed(1)
```

Out[3]:

```
<torch._C.Generator at 0x1960d3022d0>
```

Generate values from *-3* to *3* that create a line with a slope of *1* and a bias of *-1*. This is the line that you need to estimate. Add some noise to the data:

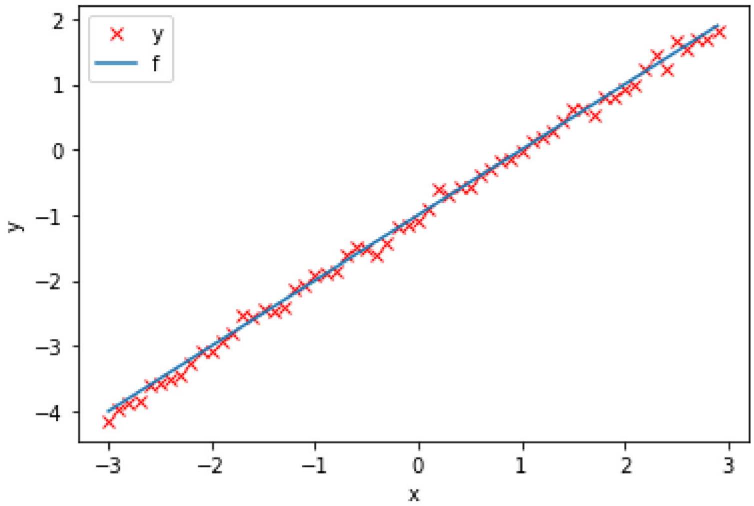
In [4]:

```
# Setup the actual data and simulated data

X = torch.arange(-3, 3, 0.1).view(-1, 1)
f = 1 * X - 1
Y = f + 0.1 * torch.randn(X.size())
```

Plot the results:

In [5]:

```
# Plot out the data dots and line

plt.plot(X.numpy(), Y.numpy(), 'rx', label = 'y')
plt.plot(X.numpy(), f.numpy(), label = 'f')
plt.xlabel('x')
plt.ylabel('y')
plt.legend()
plt.show()
```



Create the Model and Cost Function (Total Loss)

Define the `forward` function:

In [6]:

```
# Define the forward function

def forward(x):
    return w * x + b
```

Define the cost or criterion function (MSE):

In [7]:

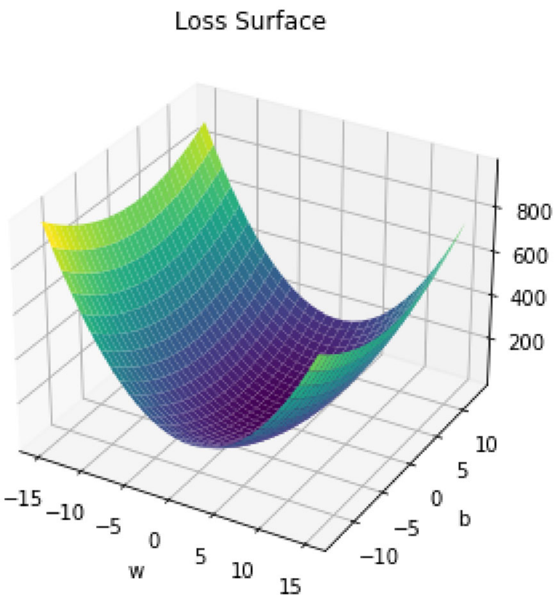
```
# Define the MSE Loss function

def criterion(yhat, y):
    return torch.mean((yhat - y) ** 2)
```

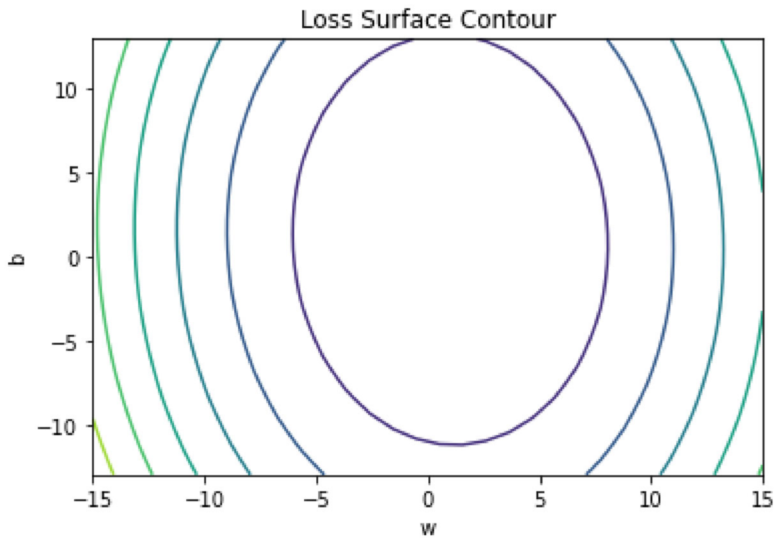
Create a `plot_error_surfaces` object to visualize the data space and the parameter space during training:

In [8]:

```
# Create plot_error_surfaces for viewing the data

get_surface = plot_error_surfaces(15, 13, X, Y, 30)
```

```
<Figure size 432x288 with 0 Axes>
```





Train the Model: Batch Gradient Descent

Create model parameters `w` , `b` by setting the argument `requires_grad` to True because the system must learn it.

In [9]:

```
# Define the parameters w, b for y = wx + b

w = torch.tensor(-15.0, requires_grad = True)
b = torch.tensor(-10.0, requires_grad = True)
```

Set the learning rate to 0.1 and create an empty list `LOSS` for storing the loss for each iteration.

In [10]:

```
# Define learning rate and create an empty list for containing the loss for each iteration.

lr = 0.1
LOSS_BGD = []
```

Define `train_model` function for train the model.

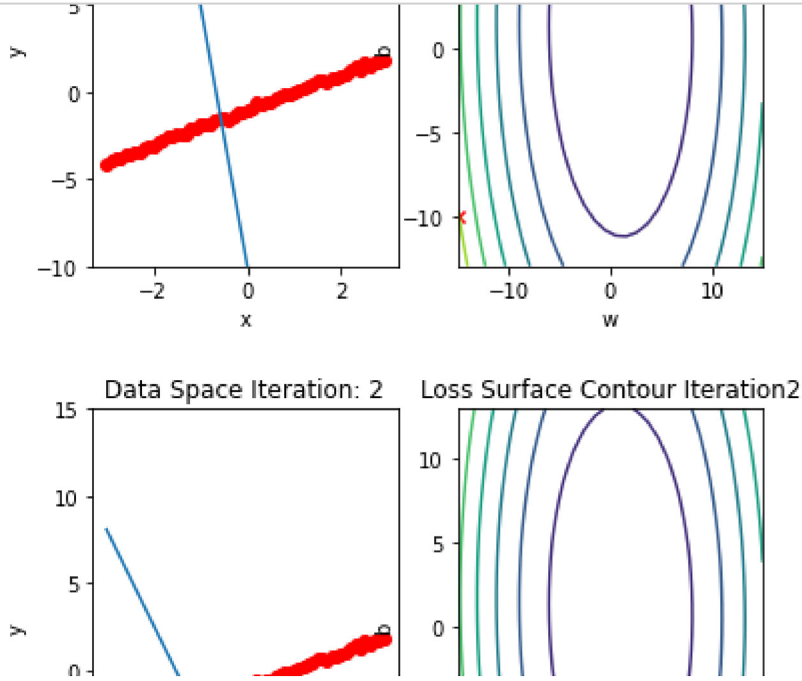
In [11]:

```
# The function for training the model

def train_model(iter):

    # Loop
    for epoch in range(iter):

        # make a prediction
        Yhat = forward(X)

        # calculate the loss
        loss = criterion(Yhat, Y)

        # Section for plotting
        get_surface.set_para_loss(w.data.tolist(), b.data.tolist(), loss.tolist())
        get_surface.plot_ps()

        # store the loss in the list LOSS_BGD
        LOSS_BGD.append(loss)

        # backward pass: compute gradient of the loss with respect to all the learnable parameters
        loss.backward()

        # update parameters slope and bias
        w.data = w.data - lr * w.grad.data
        b.data = b.data - lr * b.grad.data

        # zero the gradients before running the backward pass
        w.grad.data.zero_()
        b.grad.data.zero_()
```

Run 10 epochs of batch gradient descent: **bug** data space is 1 iteration ahead of parameter space.

In [12]:

```
# Train the model with 10 iterations

train_model(10)
```



Train the Model: Stochastic Gradient Descent

Create a `plot_error_surfaces` object to visualize the data space and the parameter space during training:

In [14]:

```
# Create plot_error_surfaces for viewing the data

get_surface = plot_error_surfaces(15, 13, X, Y, 30, go = False)
```

Define `train_model_SGD` function for training the model.

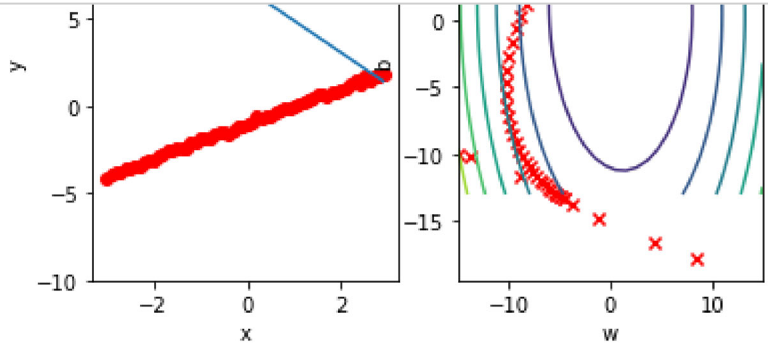
In [15]:

```
# The function for training the model

LOSS_SGD = []
w = torch.tensor(-15.0, requires_grad = True)
b = torch.tensor(-10.0, requires_grad = True)

def train_model_SGD(iter):

    # Loop
    for epoch in range(iter):

        # SGD is an approximation of out true total loss/cost, in this line of code we calculate our
        Yhat = forward(X)

        # store the loss
        LOSS_SGD.append(criterion(Yhat, Y).tolist())

        for x, y in zip(X, Y):

            # make a pridiction
            yhat = forward(x)

            # calculate the loss
            loss = criterion(yhat, y)

            # Section for plotting
            get_surface.set_para_loss(w.data.tolist(), b.data.tolist(), loss.tolist())

            # backward pass: compute gradient of the loss with respect to all the learnable paramete
            loss.backward()

            # update parameters slope and bias
            w.data = w.data - lr * w.grad.data
            b.data = b.data - lr * b.grad.data

            # zero the gradients before running the backward pass
            w.grad.data.zero_()
            b.grad.data.zero_()

        #plot surface and data space after each epoch
        get_surface.plot_ps()
```

Run 10 epochs of stochastic gradient descent: **bug** data space is 1 iteration ahead of parameter space.

In [16]:

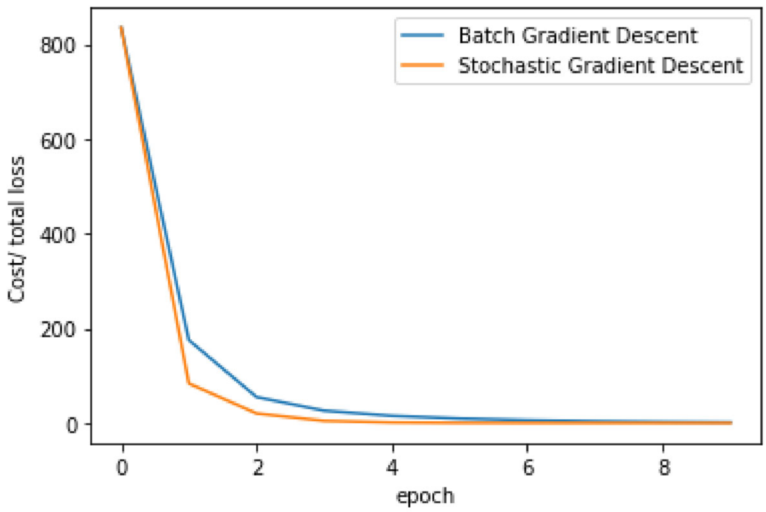
```
# Train the model with 10 iterations

train_model_SGD(10)
```



Compare the loss of both batch gradient descent as SGD.

In [17]:

```
# Plot out the LOSS_BGD and LOSS_SGD

plt.plot(LOSS_BGD,label = "Batch Gradient Descent")
plt.plot(LOSS_SGD,label = "Stochastic Gradient Descent")
plt.xlabel('epoch')
plt.ylabel('Cost/ total loss')
plt.legend()
plt.show()
```



SGD with Dataset DataLoader

Import the module for building a dataset class:

In [18]:

```
# Import the library for DataLoader

from torch.utils.data import Dataset, DataLoader
```

Create a dataset class:

In [19]:

```
# Dataset Class

class Data(Dataset):

    # Constructor
    def __init__(self):
        self.x = torch.arange(-3, 3, 0.1).view(-1, 1)
        self.y = 1 * self.x - 1
        self.len = self.x.shape[0]

    # Getter
    def __getitem__(self,index):
        return self.x[index], self.y[index]

    # Return the length
    def __len__(self):
        return self.len
```

Create a dataset object and check the length of the dataset.

In [20]:

```
# Create the dataset and check the length

dataset = Data()
print("The length of dataset: ", len(dataset))
```

```
The length of dataset:  60
```

Obtain the first training point:

In [21]:

```
# Print the first point

x, y = dataset[0]
print("(", x, ", ", y, ")")
```

```
( tensor([-3.]) ,  tensor([-4.]) )
```

Similarly, obtain the first three training points:

In [22]:

```
# Print the first 3 point

x, y = dataset[0:3]
print("The first 3 x: ", x)
print("The first 3 y: ", y)
```

```
The first 3 x:  tensor([[-3.0000],
        [-2.9000],
        [-2.8000]])
The first 3 y:  tensor([[-4.0000],
        [-3.9000],
        [-3.8000]])
```

Create a `plot_error_surfaces` object to visualize the data space and the parameter space during training:

In [23]:

```
# Create plot_error_surfaces for viewing the data

get_surface = plot_error_surfaces(15, 13, X, Y, 30, go = False)
```

Create a `DataLoader` object by using the constructor:

In [24]:

```
# Create DataLoader

trainloader = DataLoader(dataset = dataset, batch_size = 1)
```

Define `train_model_DataLoader` function for training the model.

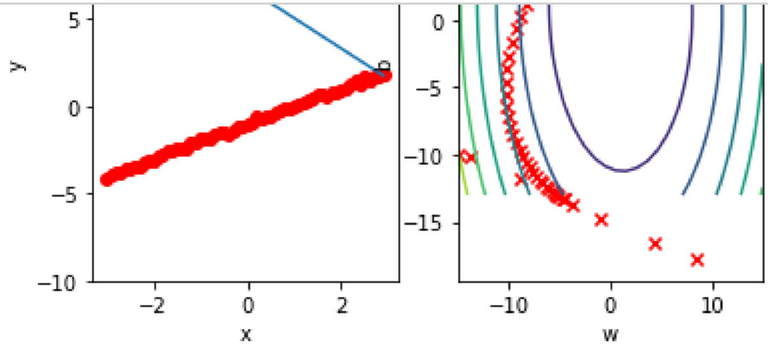
In [25]:

```
# The function for training the model

w = torch.tensor(-15.0,requires_grad=True)
b = torch.tensor(-10.0,requires_grad=True)
LOSS_Loader = []

def train_model_DataLoader(epochs):

    # Loop
    for epoch in range(epochs):

        # SGD is an approximation of out true total loss/cost, in this line of code we calculate our
        Yhat = forward(X)

        # store the loss
        LOSS_Loader.append(criterion(Yhat, Y).tolist())

        for x, y in trainloader:

            # make a prediction
            yhat = forward(x)

            # calculate the loss
            loss = criterion(yhat, y)

            # Section for plotting
            get_surface.set_para_loss(w.data.tolist(), b.data.tolist(), loss.tolist())

            # Backward pass: compute gradient of the loss with respect to all the learnable paramete
            loss.backward()

            # Updata parameters slope
            w.data = w.data - lr * w.grad.data
            b.data = b.data - lr* b.grad.data

            # Clear gradients
            w.grad.data.zero_()
            b.grad.data.zero_()

        #plot surface and data space after each epoch
        get_surface.plot_ps()
```

Run 10 epochs of stochastic gradient descent: **bug** data space is 1 iteration ahead of parameter space.

In [26]:

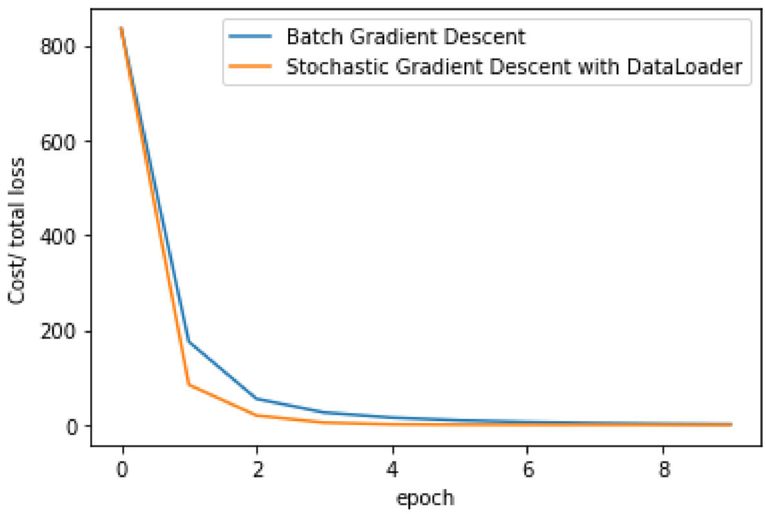
```
# Run 10 iterations

train_model_DataLoader(10)
```



Compare the loss of both batch gradient decent as SGD. Note that SGD converges to a minimum faster, that is, it decreases faster.

In [27]:

```
# Plot the LOSS_BGD and LOSS_Loader

plt.plot(LOSS_BGD,label="Batch Gradient Descent")
plt.plot(LOSS_Loader,label="Stochastic Gradient Descent with DataLoader")
plt.xlabel('epoch')
plt.ylabel('Cost/ total loss')
plt.legend()
plt.show()
```



Practice

For practice, try to use SGD with DataLoader to train model with 10 iterations. Store the total loss in `LOSS` . We are going to use it in the next question.

In [ ]:

```
# Practice: Use SGD with trainloader to train model and store the total loss in LOSS

LOSS = []
w = torch.tensor(-12.0, requires_grad = True)
b = torch.tensor(-10.0, requires_grad = True)
```

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

Plot the total loss

In [ ]:

```
# Practice: Plot the total loss using LOSS

# Type your code here
```

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

About the Authors:

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Change Log

Date (YYYY-MM-DD)	Version	Changed By	Change Description
2020-09-23	2.0	Shubham	Migrated Lab to Markdown and added to course repo in GitLab