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(http://cocl.us/pytorch_link_top)



Linear Regression 1D: Training Two Parameter Mini-Batch Gradient Decent

Table of Contents

In this Lab, you will practice training a model by using Mini-Batch Gradient Descent.

- Make Some Data
- Create the Model and Cost Function (Total Loss)
- Train the Model: Batch Gradient Descent
- Train the Model: Stochastic Gradient Descent with Dataset DataLoader
- Train the Model: Mini Batch Gradient Decent: Batch Size Equals 5
- Train the Model: Mini Batch Gradient Decent: Batch Size Equals 10

Estimated Time Needed: 30 min

</div>

Preparation

We'll need the following libraries:

In [1]:

```
# Import the libraries we need for this lab
import numpy as np
import matplotlib.pyplot as plt
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.

```
# The class for plotting the diagrams
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, rstrid
e = 1, cstride = 1, cmap = 'viridis', edgecolor = 'none')
            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.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')
        plt.xlabel('w')
        plt.ylabel('b')
        plt.show()
```

Make Some Data

Import PyTorch and set random seed:

```
In [3]:
```

```
# Import PyTorch library
import torch
torch.manual_seed(1)
```

```
Out[3]:
```

```
<torch. C.Generator at 0x7f23772dc050>
```

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]:
```

```
# Generate the data with noise and the line

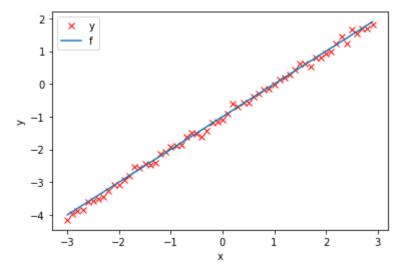
X = torch.arange(-3, 3, 0.1).view(-1, 1)
f = 1 * X - 1
Y = f + 0.1 * torch.randn(X.size())
```

Plot the results:

```
In [5]:
```

```
# Plot the line and the data

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 prediction function

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

Define the cost or criterion function:

```
In [7]:
```

```
# Define the cost function

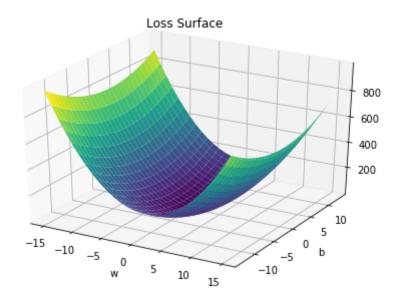
def criterion(yhat, y):
    return torch.mean((yhat - y) ** 2)
```

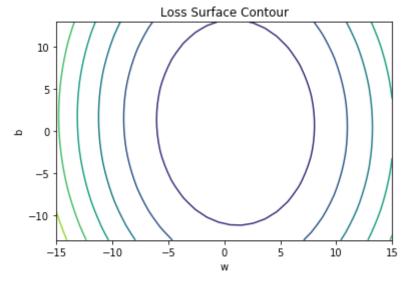
Create a plot_error_surfaces object to visualize the data space and the parameter space during training:

In [8]:

```
# Create a plot_error_surfaces object.
get_surface = plot_error_surfaces(15, 13, X, Y, 30)
```

<Figure size 432x288 with 0 Axes>





Train the Model: Batch Gradient Descent (BGD)

Define train_model_BGD function.

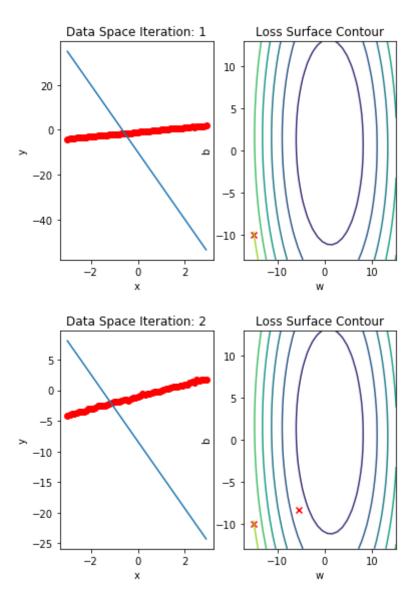
In [9]:

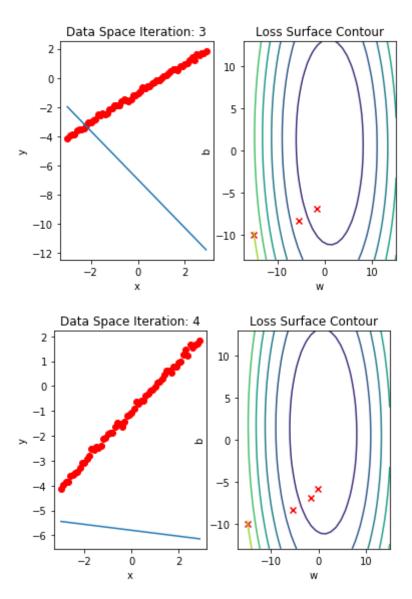
```
# Define the function for training model
w = torch.tensor(-15.0, requires_grad = True)
b = torch.tensor(-10.0, requires_grad = True)
lr = 0.1
LOSS_BGD = []
def train model BGD(epochs):
    for epoch in range(epochs):
        Yhat = forward(X)
        loss = criterion(Yhat, Y)
        LOSS_BGD.append(loss)
        get_surface.set_para_loss(w.data.tolist(), b.data.tolist(), loss.tolist())
        get_surface.plot_ps()
        loss.backward()
        w.data = w.data - lr * w.grad.data
        b.data = b.data - lr * b.grad.data
        w.grad.data.zero_()
        b.grad.data.zero_()
```

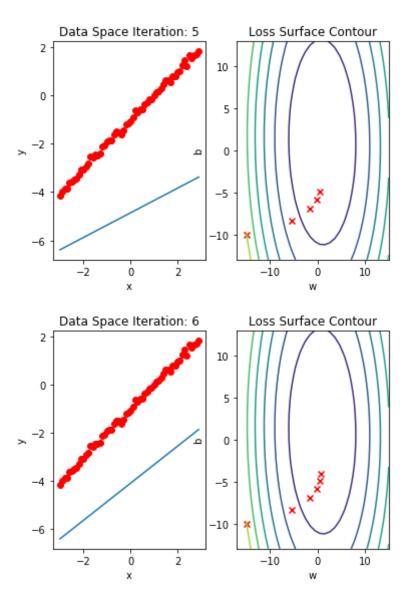
Run 10 epochs of batch gradient descent: **bug** data space is 1 iteration ahead of parameter space.

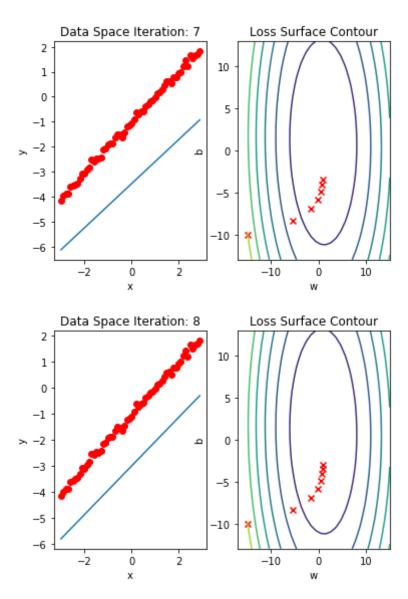
```
In [10]:
```

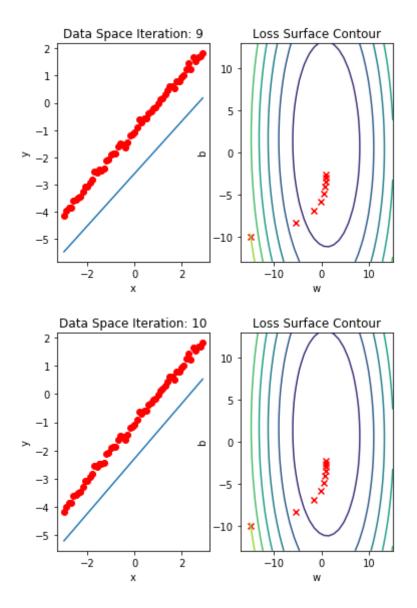
```
# Run train_model_BGD with 10 iterations
train_model_BGD(10)
```











Stochastic Gradient Descent (SGD) with Dataset DataLoader

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

In [11]:

```
# Create a plot_error_surfaces object.
get_surface = plot_error_surfaces(15, 13, X, Y, 30, go = False)
```

Import Dataset and DataLoader libraries

```
In [12]:
```

```
# Import libraries
from torch.utils.data import Dataset, DataLoader
```

Create Data class

```
In [13]:
```

```
# Create class Data

class Data(Dataset):

# Constructor

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

# Getter

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

# Get length

def __len__(self):
    return self.len
```

Create a dataset object and a dataloader object:

In [14]:

```
# Create Data object and DataLoader object

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

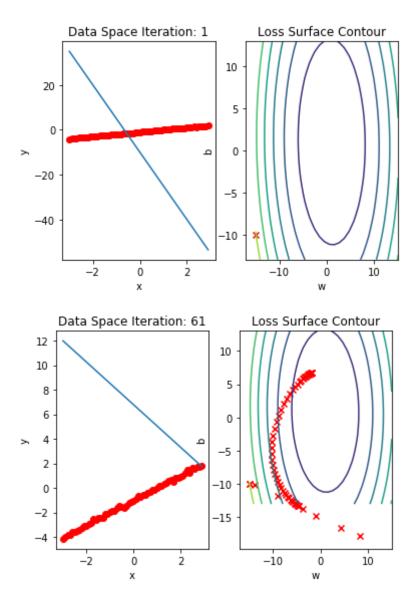
Define train model SGD function for training the model.

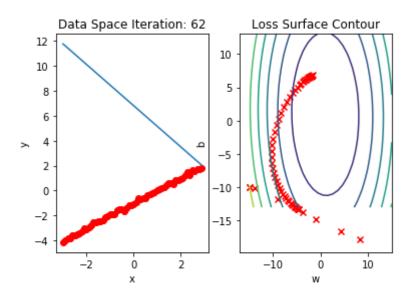
```
# Define train model SGD function
w = torch.tensor(-15.0, requires grad = True)
b = torch.tensor(-10.0, requires_grad = True)
LOSS SGD = []
lr = 0.1
def train_model_SGD(epochs):
    for epoch in range(epochs):
        Yhat = forward(X)
        get_surface.set_para_loss(w.data.tolist(), b.data.tolist(), criterion(Yhat,
Y).tolist())
        get_surface.plot_ps()
        LOSS_SGD.append(criterion(forward(X), Y).tolist())
        for x, y in trainloader:
            yhat = forward(x)
            loss = criterion(yhat, y)
            get_surface.set_para_loss(w.data.tolist(), b.data.tolist(), loss.tolist
())
            loss.backward()
            w.data = w.data - lr * w.grad.data
            b.data = b.data - lr * b.grad.data
            w.grad.data.zero_()
            b.grad.data.zero_()
        get_surface.plot_ps()
```

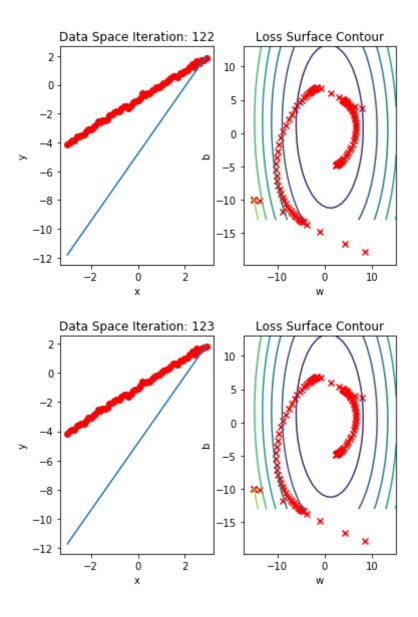
Run 10 epochs of stochastic gradient descent: **bug** data space is 1 iteration ahead of parameter space.

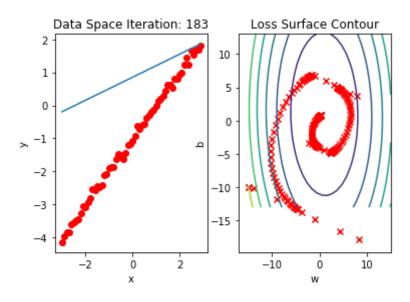
```
In [16]:
```

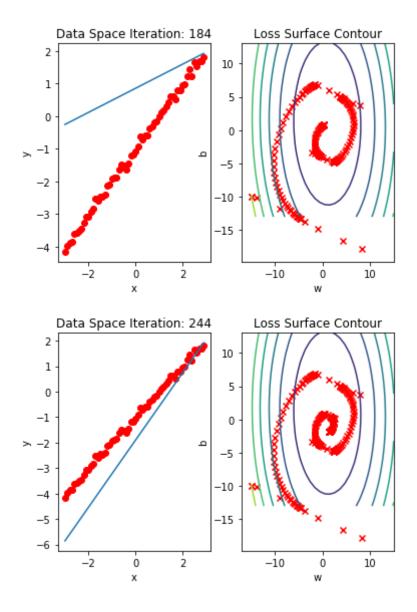
```
# Run train_model_SGD(iter) with 10 iterations
train_model_SGD(10)
```

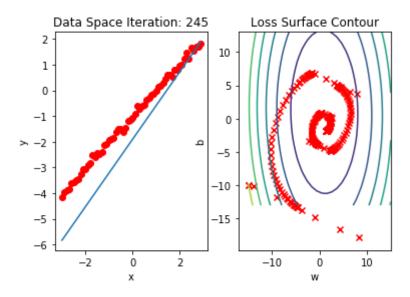


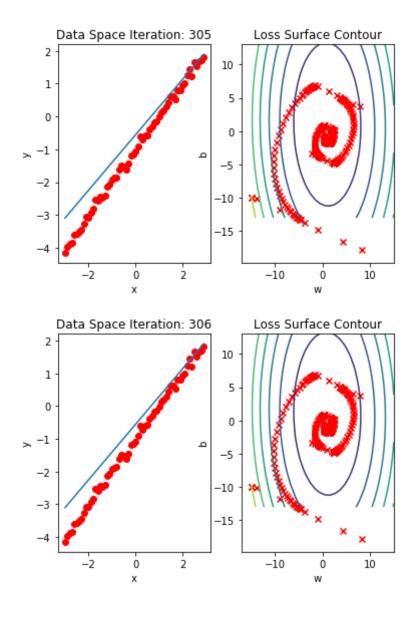


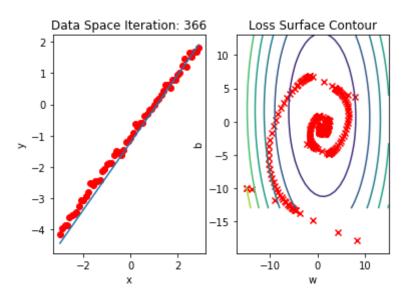


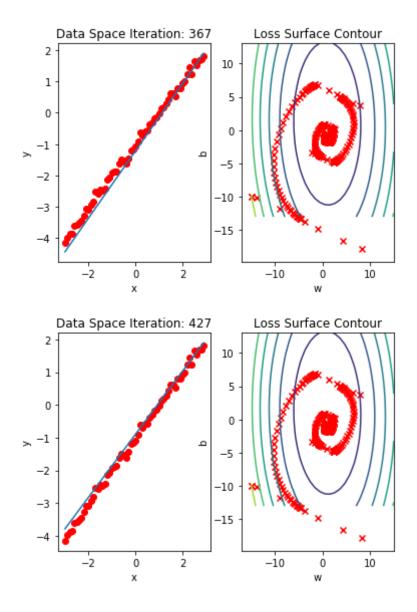


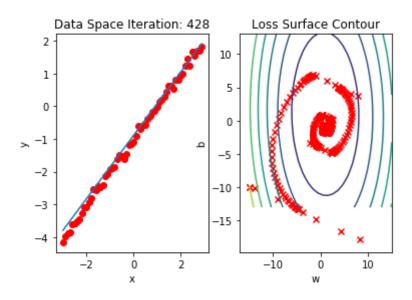


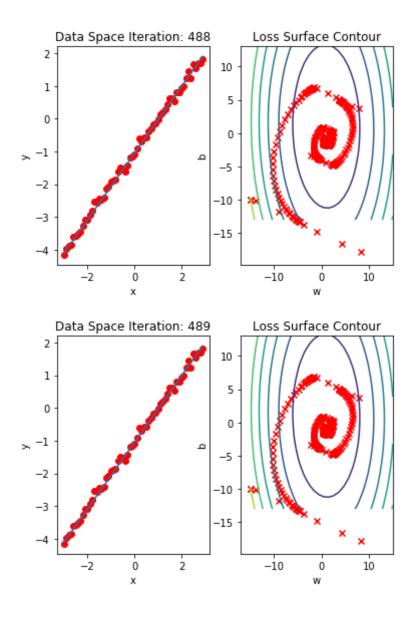


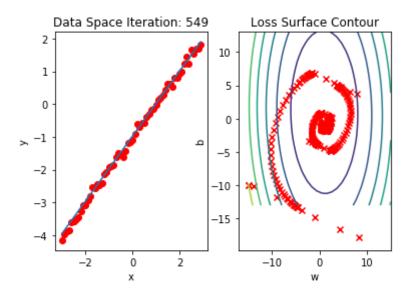


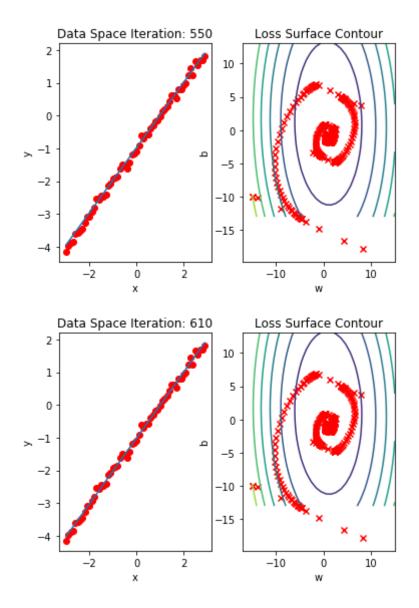












Mini Batch Gradient Descent: Batch Size Equals 5

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

```
In [17]:
```

```
# Create a plot_error_surfaces object.
get_surface = plot_error_surfaces(15, 13, X, Y, 30, go = False)
```

Create Data object and create a Dataloader object where the batch size equals 5:

```
In [18]:
```

```
# Create DataLoader object and Data object

dataset = Data()
trainloader = DataLoader(dataset = dataset, batch_size = 5)
```

Define train_model_Mini5 function to train the model.

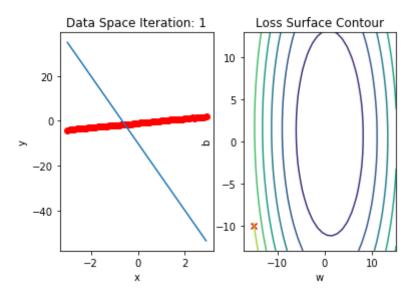
In [19]:

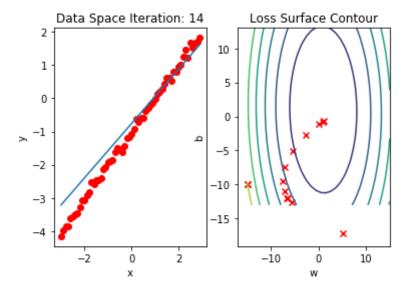
```
# Define train model Mini5 function
w = torch.tensor(-15.0, requires_grad = True)
b = torch.tensor(-10.0, requires_grad = True)
LOSS_MINI5 = []
lr = 0.1
def train model Mini5(epochs):
    for epoch in range(epochs):
        Yhat = forward(X)
        get_surface.set_para_loss(w.data.tolist(), b.data.tolist(), criterion(Yhat,
Y).tolist())
        get surface.plot ps()
        LOSS_MINI5.append(criterion(forward(X), Y).tolist())
        for x, y in trainloader:
            yhat = forward(x)
            loss = criterion(yhat, y)
            get_surface.set_para_loss(w.data.tolist(), b.data.tolist(), loss.tolist
())
            loss.backward()
            w.data = w.data - lr * w.grad.data
            b.data = b.data - lr * b.grad.data
            w.grad.data.zero_()
            b.grad.data.zero ()
```

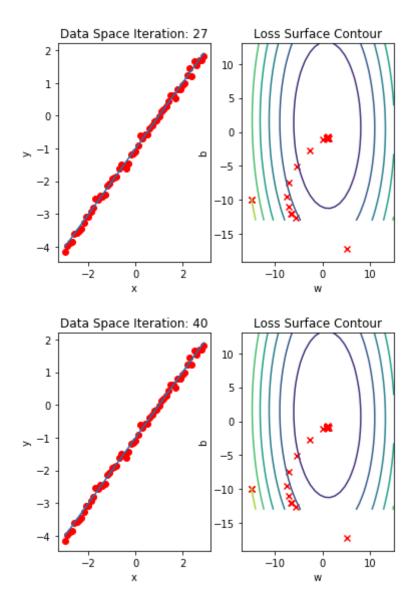
Run 10 epochs of mini-batch gradient descent: bug data space is 1 iteration ahead of parameter space.

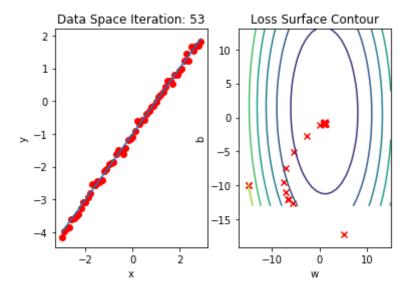
```
In [20]:
```

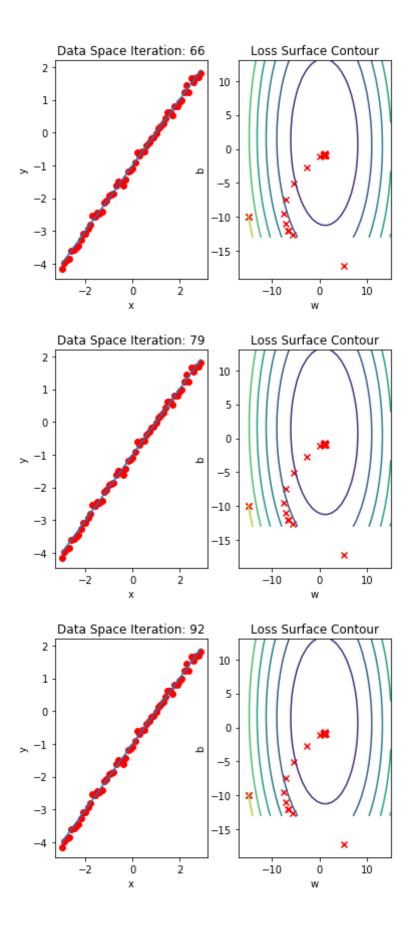
```
# Run train_model_Mini5 with 10 iterations.
train_model_Mini5(10)
```

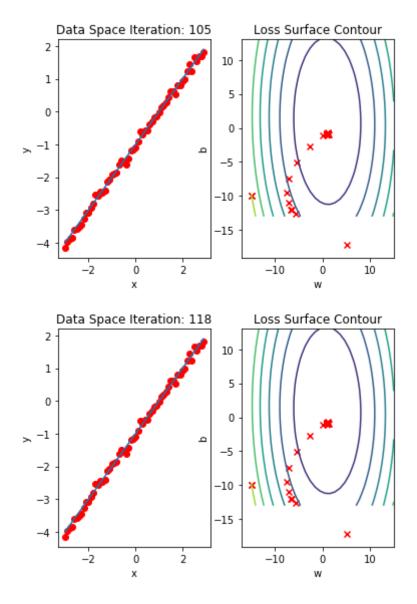












Mini Batch Gradient Descent: Batch Size Equals 10

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

```
In [21]:
```

```
# Create a plot_error_surfaces object.
get_surface = plot_error_surfaces(15, 13, X, Y, 30, go = False)
```

In [22]:

```
# Create DataLoader object

dataset = Data()
trainloader = DataLoader(dataset = dataset, batch_size = 10)
```

Define train model Mini10 function for training the model.

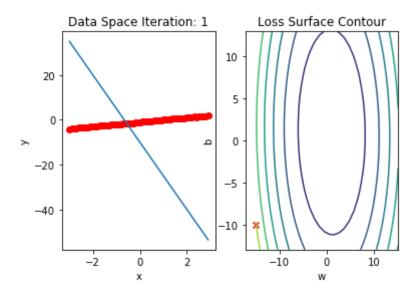
In [23]:

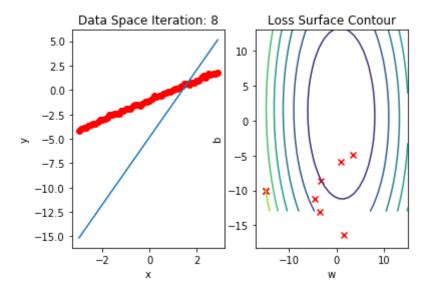
```
# Define train model Mini5 function
w = torch.tensor(-15.0, requires grad = True)
b = torch.tensor(-10.0, requires_grad = True)
LOSS_MINI10 = []
lr = 0.1
def train_model_Mini10(epochs):
    for epoch in range(epochs):
        Yhat = forward(X)
        get_surface.set_para_loss(w.data.tolist(), b.data.tolist(), criterion(Yhat,
Y).tolist())
        get surface.plot ps()
        LOSS MINI10.append(criterion(forward(X),Y).tolist())
        for x, y in trainloader:
            yhat = forward(x)
            loss = criterion(yhat, y)
            get surface.set para loss(w.data.tolist(), b.data.tolist(), loss.tolist
())
            loss.backward()
            w.data = w.data - lr * w.grad.data
            b.data = b.data - lr * b.grad.data
            w.grad.data.zero ()
            b.grad.data.zero ()
```

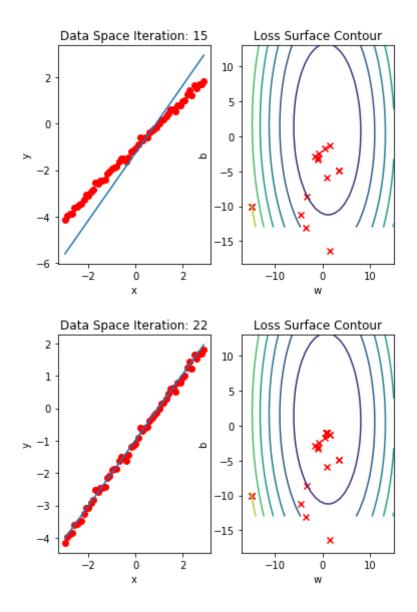
Run 10 epochs of mini-batch gradient descent: **bug** data space is 1 iteration ahead of parameter space.

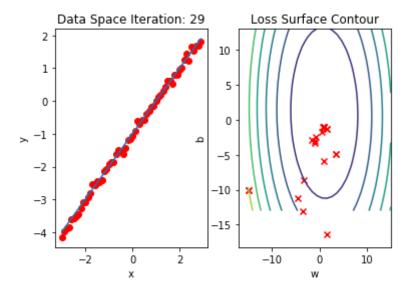
In [24]:

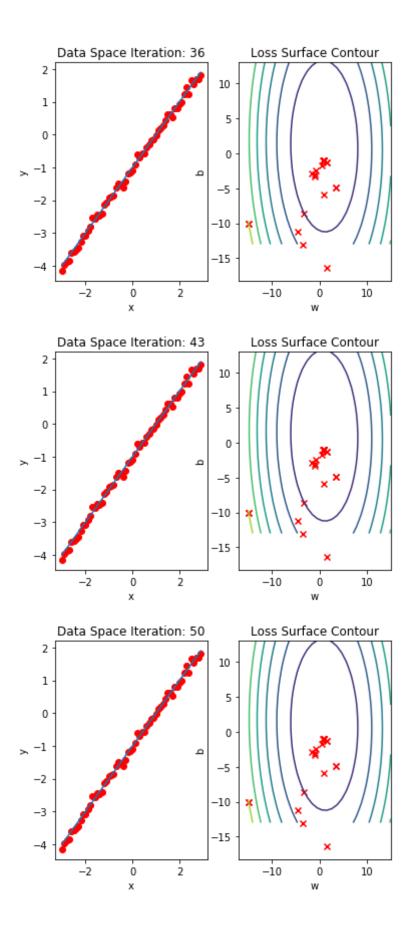
```
# Run train_model_Mini5 with 10 iterations.
train_model_Mini10(10)
```

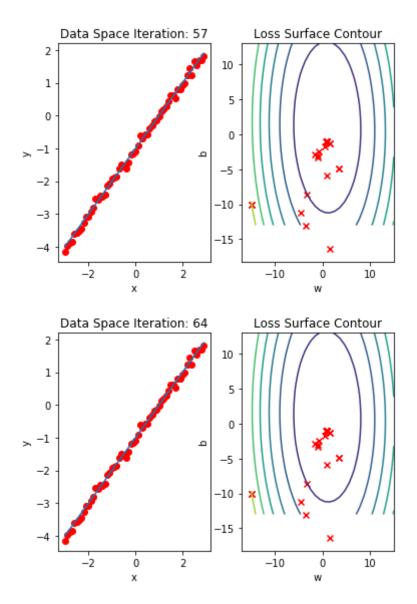












Plot the loss for each epoch:

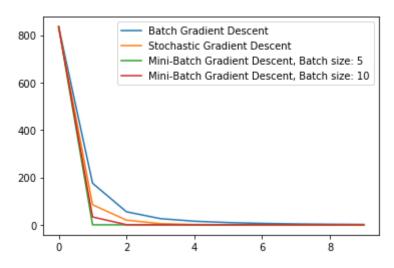
In [25]:

```
# Plot out the LOSS for each method

plt.plot(LOSS_BGD, label = "Batch Gradient Descent")
plt.plot(LOSS_SGD, label = "Stochastic Gradient Descent")
plt.plot(LOSS_MINI5, label = "Mini-Batch Gradient Descent, Batch size: 5")
plt.plot(LOSS_MINI10, label = "Mini-Batch Gradient Descent, Batch size: 10")
plt.legend()
```

Out[25]:

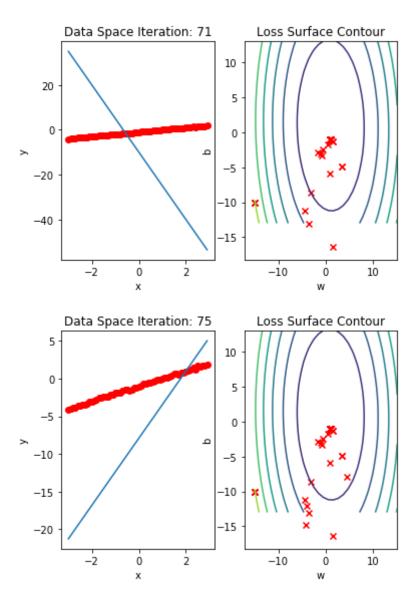
<matplotlib.legend.Legend at 0x7f23703b8b38>

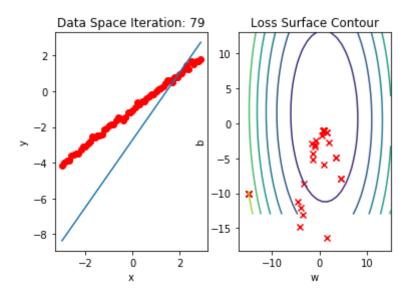


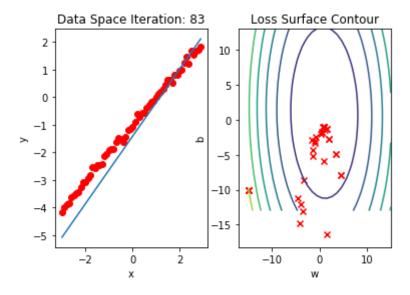
Practice

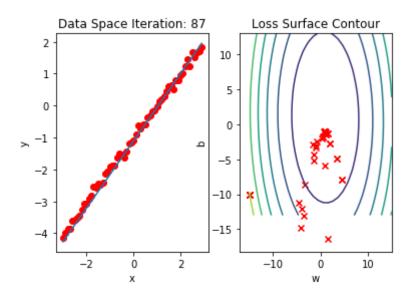
Perform mini batch gradient descent with a batch size of 20. Store the total loss for each epoch in the list LOSS20.

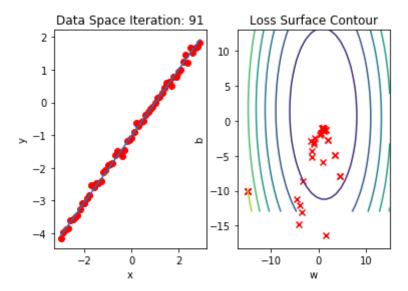
```
# Practice: Perform mini batch gradient descent with a batch size of 20.
dataset = Data()
trainloader = DataLoader(dataset = dataset, batch_size = 20)
w = torch.tensor(-15.0, requires_grad = True)
b = torch.tensor(-10.0, requires_grad = True)
LOSS MINI20 = []
lr = 0.1
def my train model(epochs):
    for epoch in range(epochs):
        Yhat = forward(X)
        get_surface.set_para_loss(w.data.tolist(), b.data.tolist(), criterion(Yhat,
Y).tolist())
        get_surface.plot_ps()
        LOSS_MINI20.append(criterion(forward(X), Y).tolist())
        for x, y in trainloader:
            yhat = forward(x)
            loss =criterion(yhat, y)
            get surface.set para loss(w.data.tolist(), b.data.tolist(), loss.tolist
())
            loss.backward()
            w.data = w.data - lr * w.grad.data
            b.data = b.data - lr * b.grad.data
            w.grad.data.zero ()
            b.grad.data.zero ()
my train model(10)
```

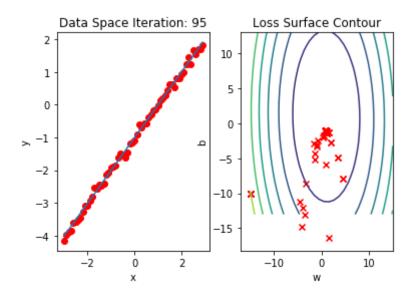


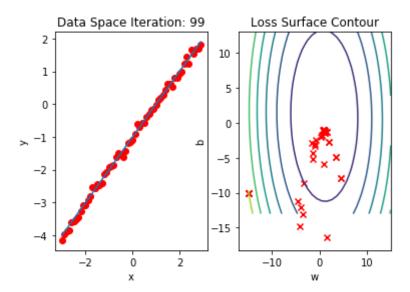


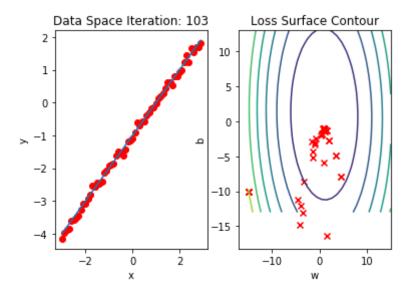


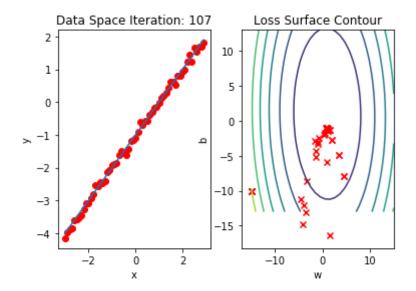












Double-click here for the solution.

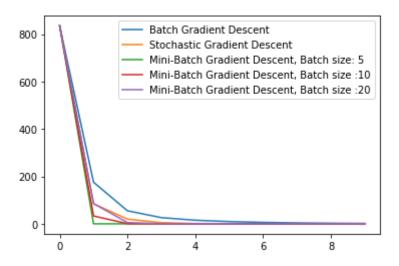
Plot a graph that shows the LOSS results for all the methods.

In [27]:

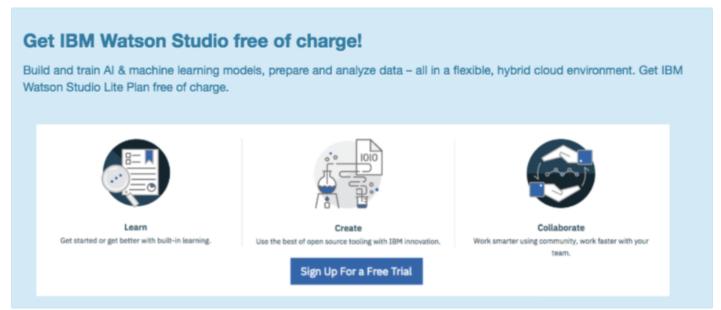
```
# Practice: Plot a graph to show all the LOSS functions
plt.plot(LOSS_BGD, label = 'Batch Gradient Descent')
plt.plot(LOSS_SGD, label = 'Stochastic Gradient Descent')
plt.plot(LOSS_MINI5, label = 'Mini-Batch Gradient Descent, Batch size: 5')
plt.plot(LOSS_MINI10, label = 'Mini-Batch Gradient Descent, Batch size :10')
plt.plot(LOSS_MINI20, label = 'Mini-Batch Gradient Descent, Batch size :20')
plt.legend()
```

Out[27]:

<matplotlib.legend.Legend at 0x7f237007e4a8>



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



(http://cocl.us/pytorch_link_bottom)

About the Authors:

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