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(http://cocl.us/pytorch_link_top)

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

Table of Contents

In this Lab, you will practice training a model by using Stochastic 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
- Train the Model:Stochastic gradient descent with Data Loader

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, 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.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 0x7fa389e482f0>
```

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:

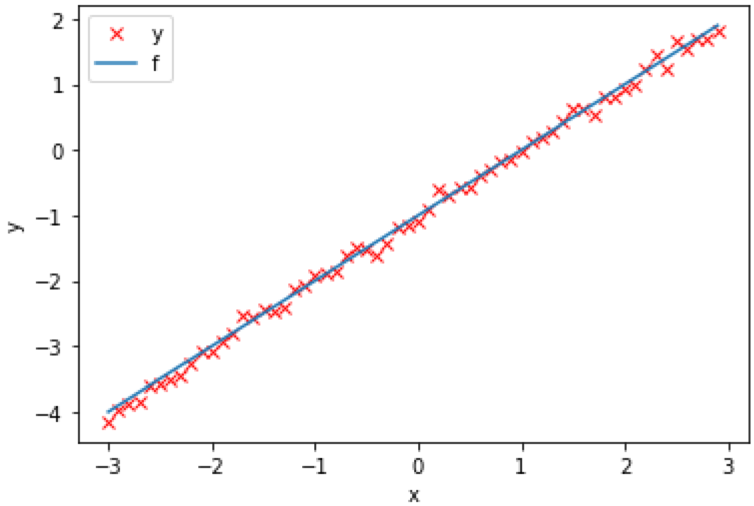
In [4]:

```
# 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]:

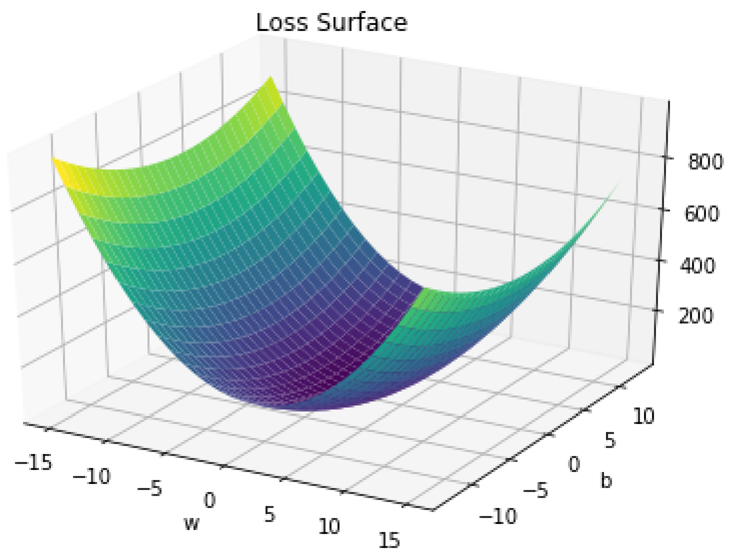
```
# Define the MSE Loss function

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

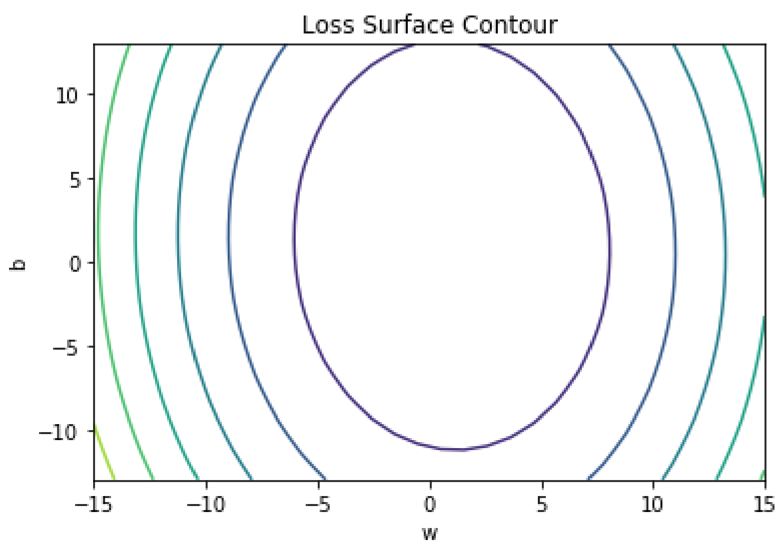
Create a `plot_error_surfaces` object to visualize the data space and the parameter space during training:

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 it
eration.

lr = 0.1
LOSS_BGD = []
```

Define `train_model` function for train the model.

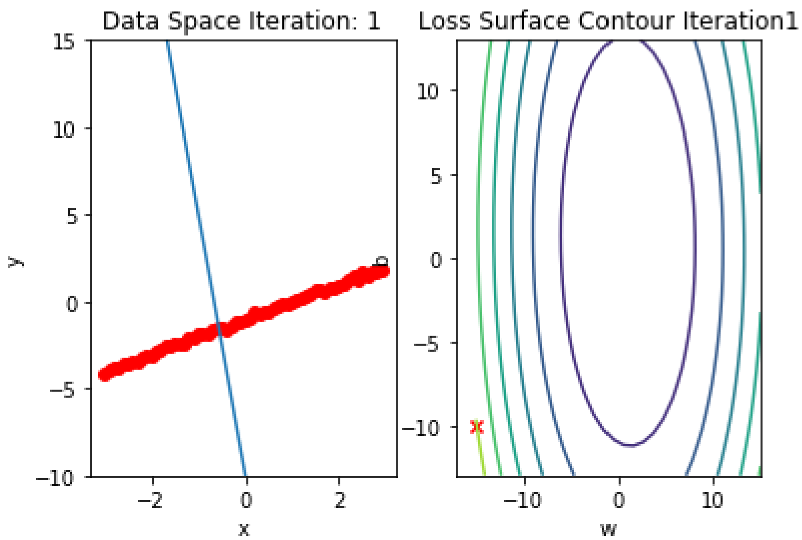
In [11]:

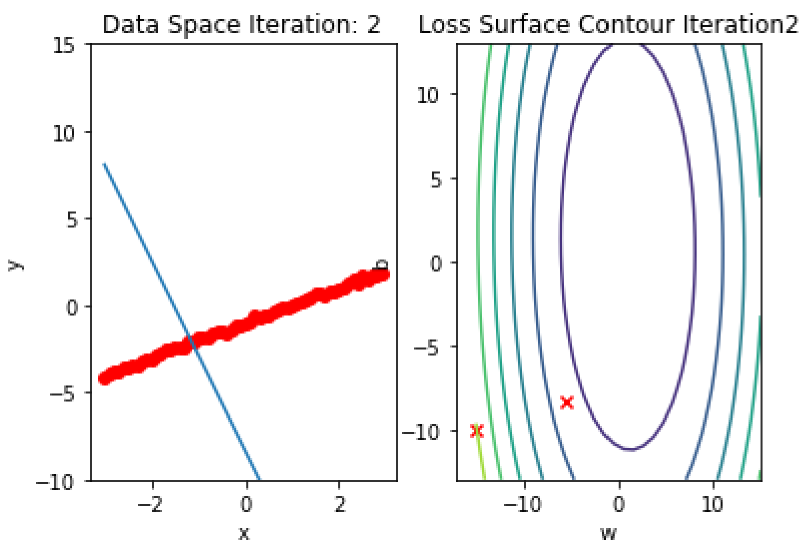
```
# The function for training the model

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 learn
able 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_()
```

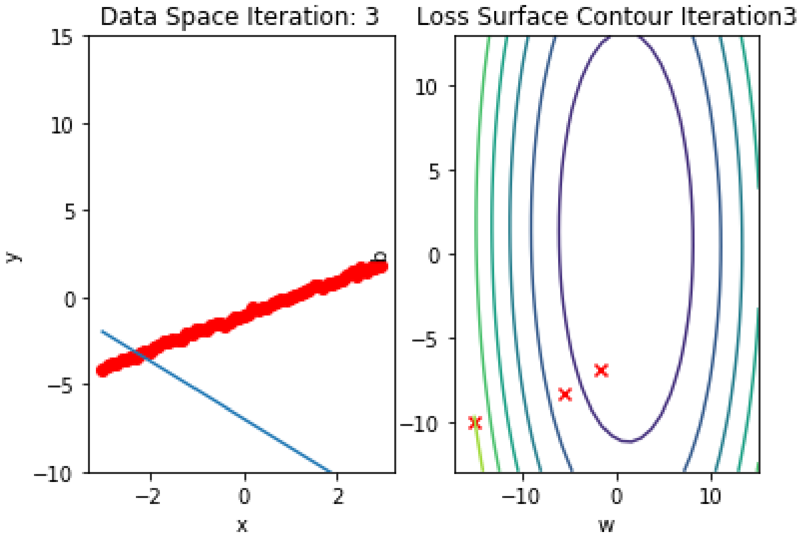
Run 10 epochs of batch gradient descent: **bug** data space is 1 iteration ahead of parameter space.

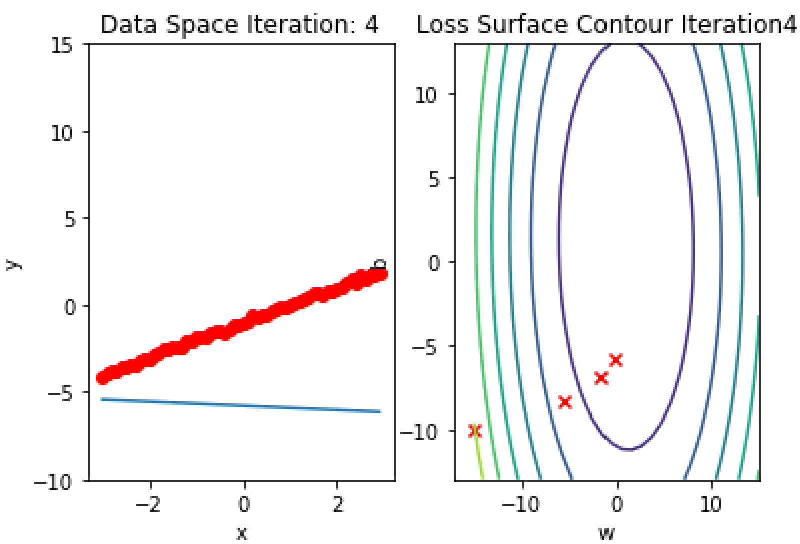
In [12]:

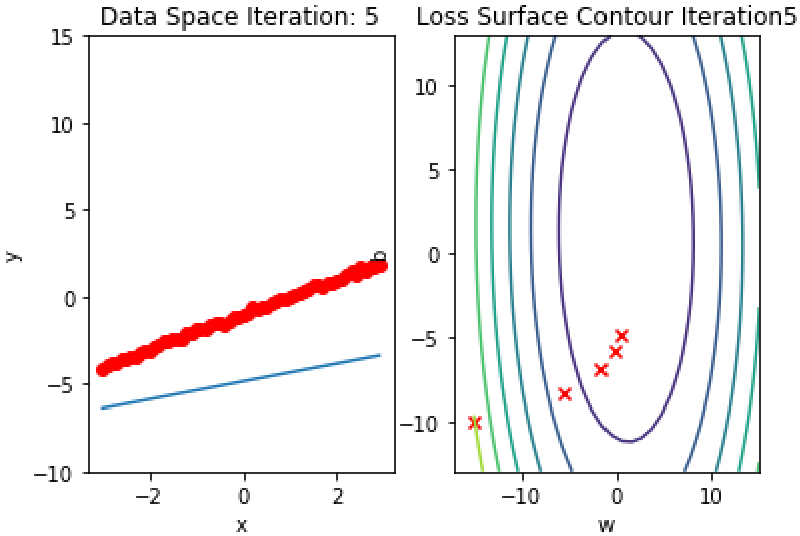
```
# Train the model with 10 iterations

train_model(10)
```

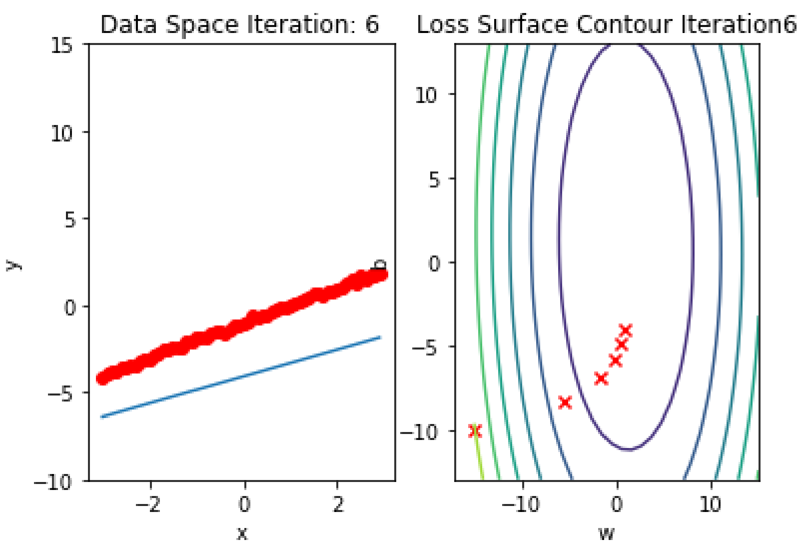

Data Space Iteration: 1
Loss Surface Contour Iteration1
x
y
w
b

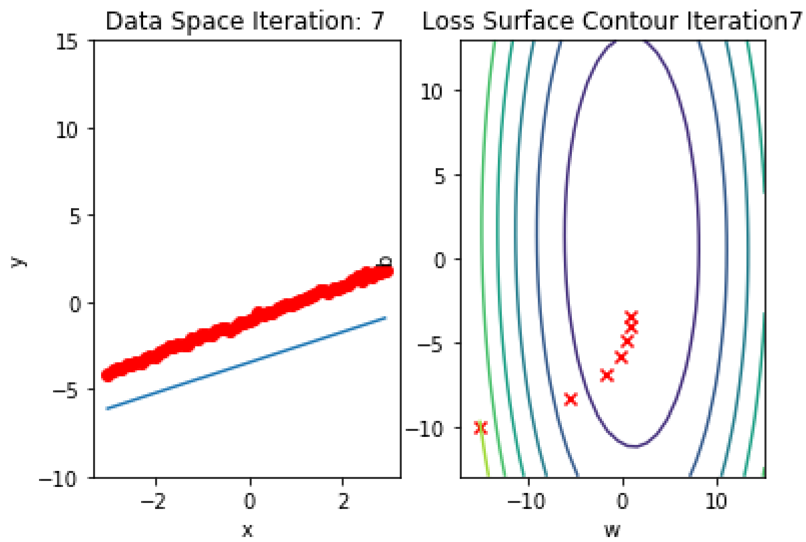

Data Space Iteration: 2
Loss Surface Contour Iteration2
x
y
w
b


Data Space Iteration: 3
Loss Surface Contour Iteration3
y
x
b
w

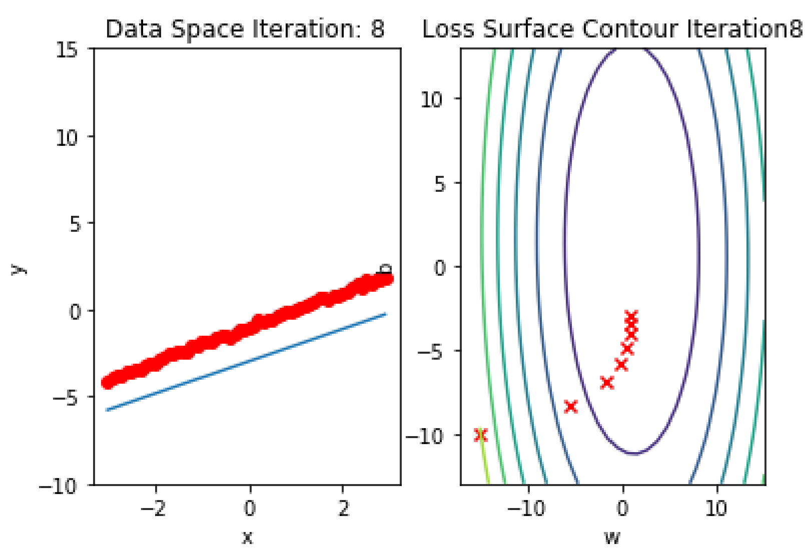

Data Space Iteration: 4
Loss Surface Contour Iteration4
y
x
b
w


Data Space Iteration: 5
Loss Surface Contour Iteration5
y
x
b
w

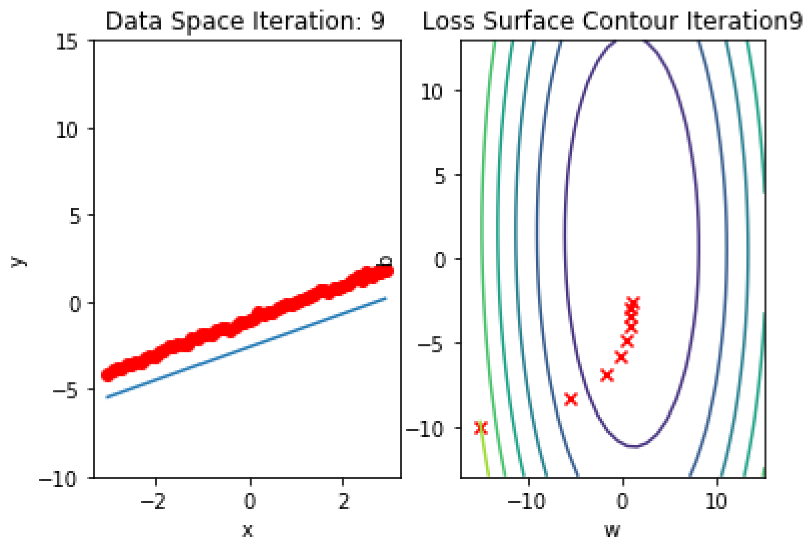

Data Space Iteration: 6
Loss Surface Contour Iteration6
y
x
b
w

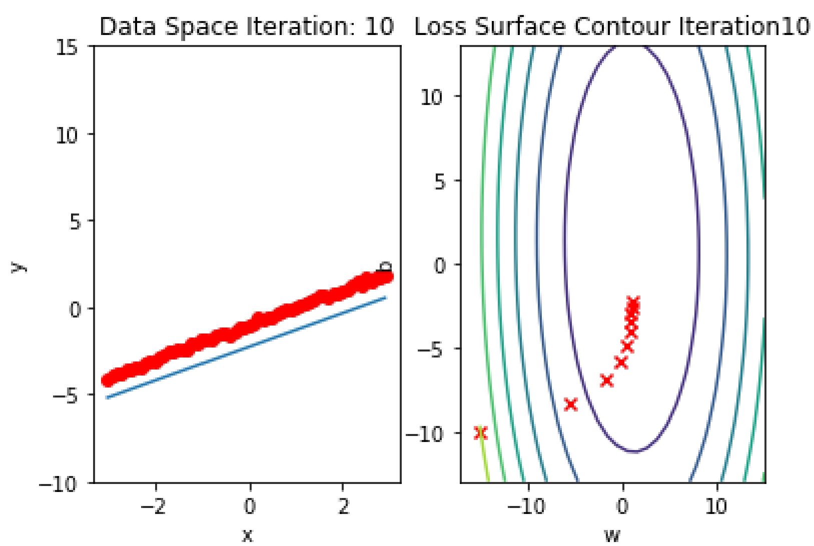


Data Space Iteration: 7
Loss Surface Contour Iteration7
y
x
b
w



Data Space Iteration: 8
Loss Surface Contour Iteration8
y
x
b
w





Train the Model: Stochastic Gradient Descent

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

In [13]:

```
# 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.

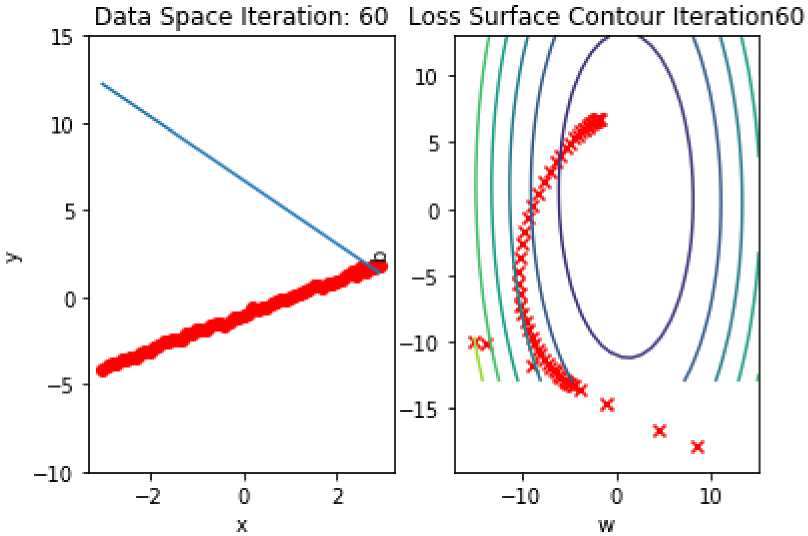
In [14]:

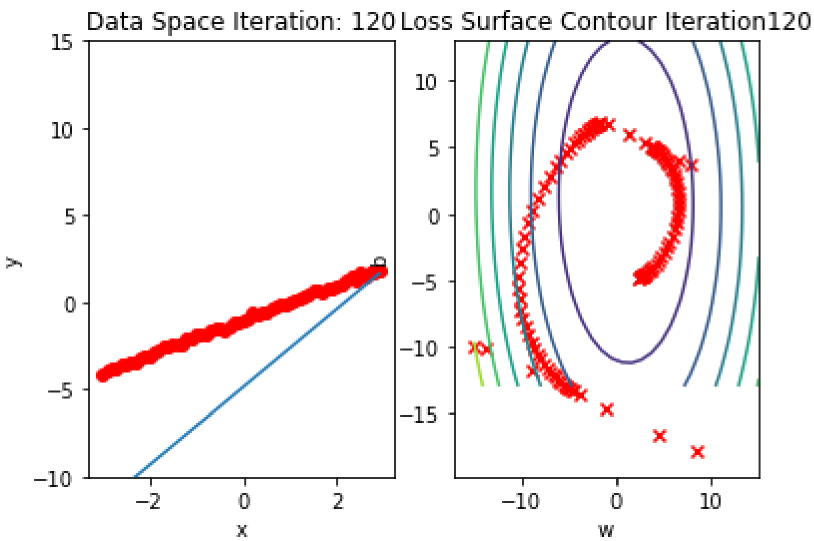
```
# The function for training the model

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 true loss/cost and store it
        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 l
earnable 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_()

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

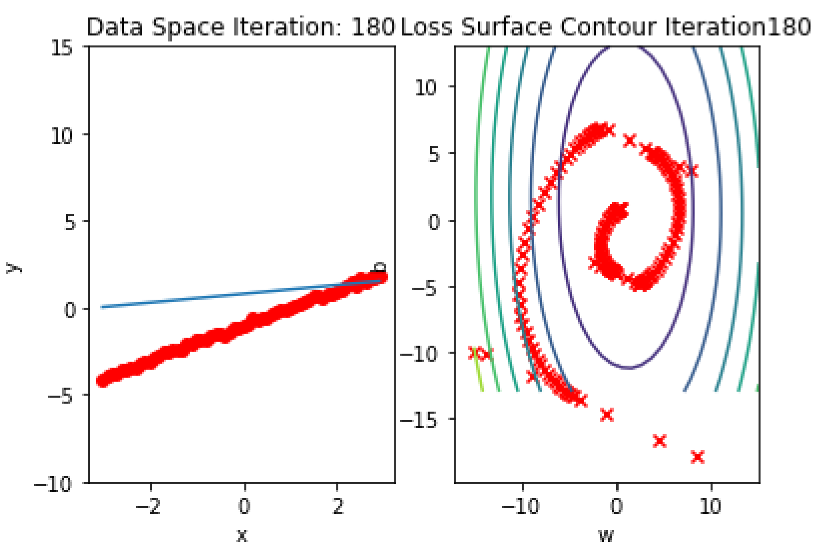
Run 10 epochs of stochastic gradient descent: **bug** data space is 1 iteration ahead of parameter space.

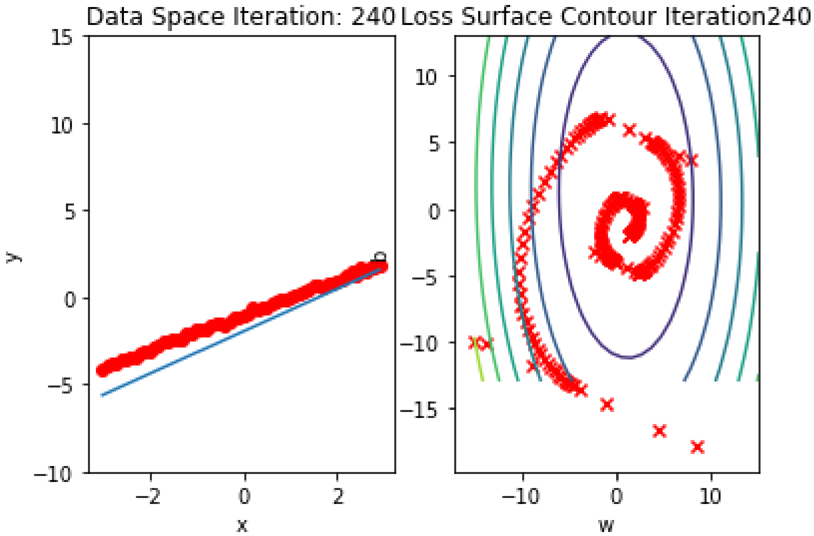
In [15]:

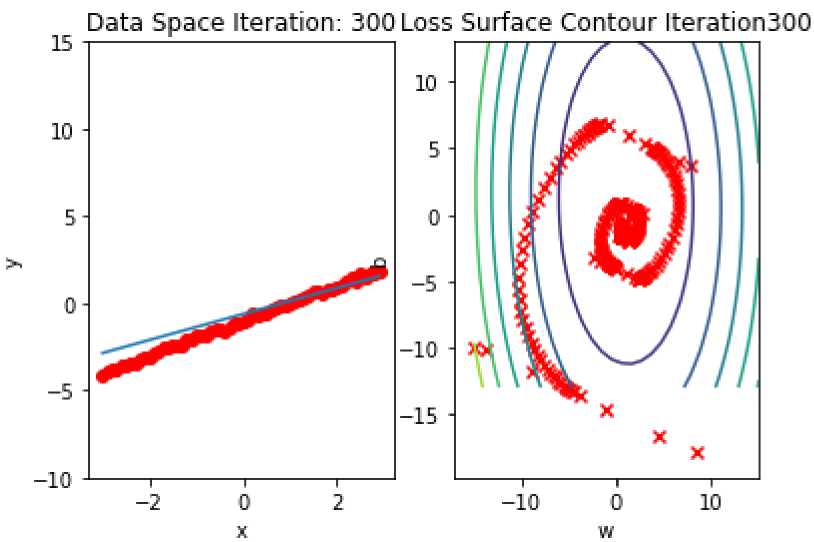
```
# Train the model with 10 iterations

train_model_SGD(10)
```

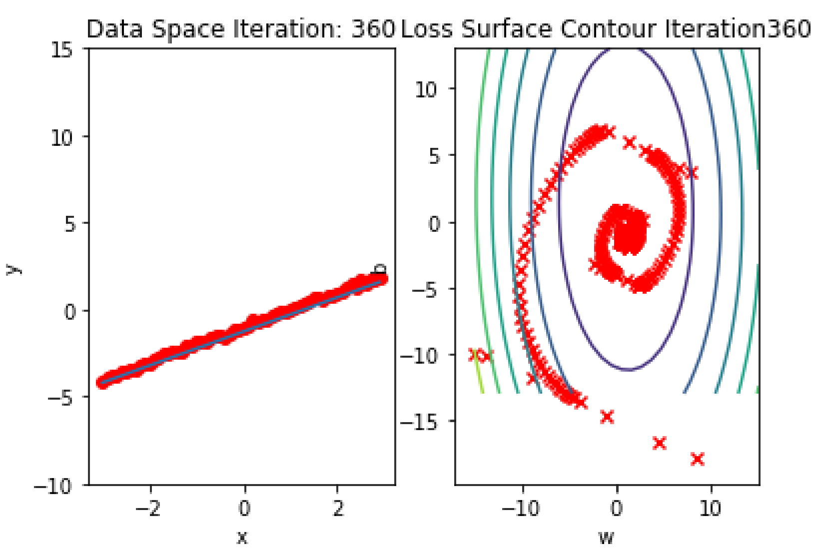

Data Space Iteration: 60
Loss Surface Contour Iteration60
y
x
w
b

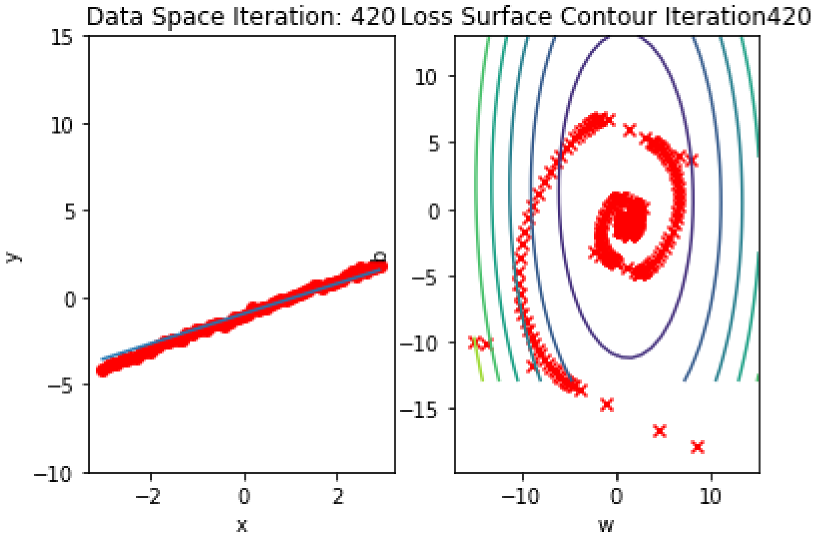

Data Space Iteration: 120
Loss Surface Contour Iteration120
y
x
w
b

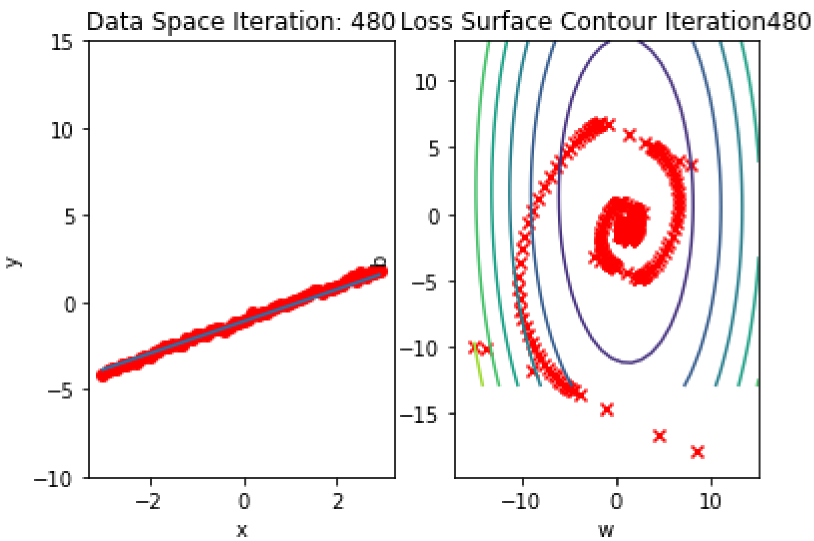

Data Space Iteration: 180
Loss Surface Contour Iteration180
y
x
w
b

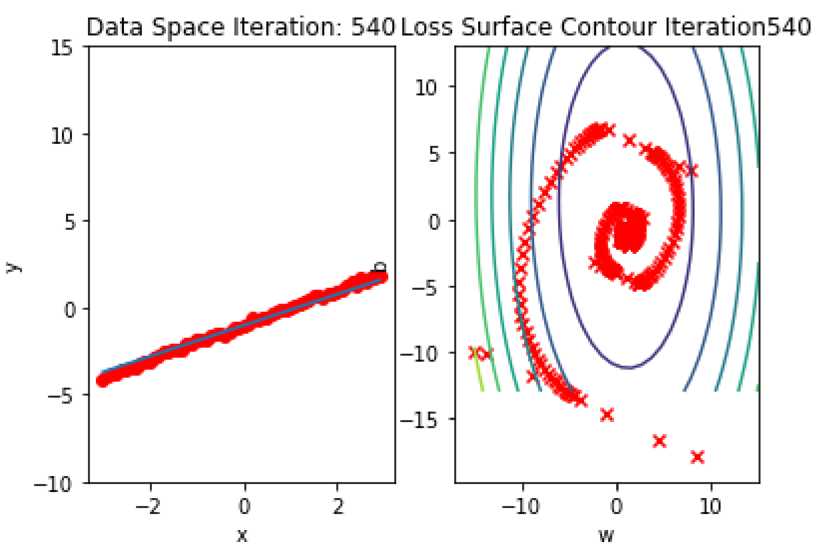

Data Space Iteration: 240
Loss Surface Contour Iteration240
y
x
w
b

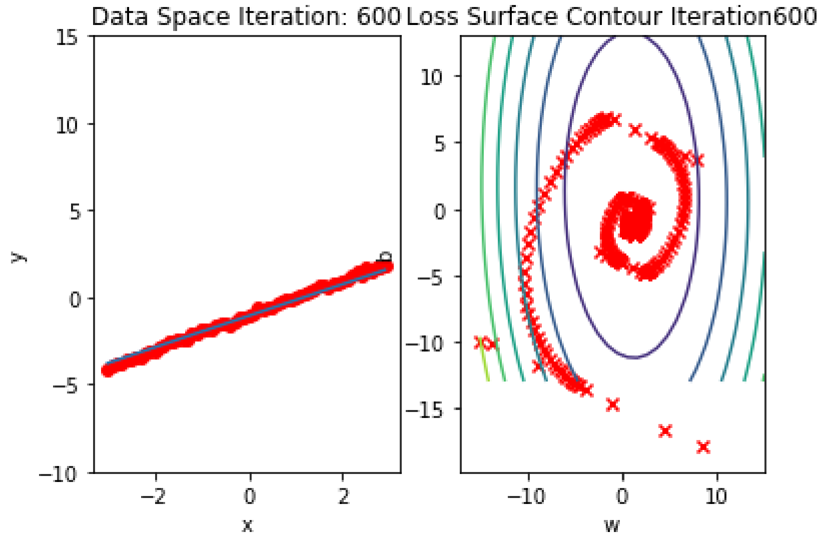

Data Space Iteration: 300
Loss Surface Contour Iteration300
y
x
w
b


Data Space Iteration: 360
Loss Surface Contour Iteration360
y
x
w
b


Data Space Iteration: 420
Loss Surface Contour Iteration420
y
x
b
w


Data Space Iteration: 480
Loss Surface Contour Iteration480
y
x
b
w

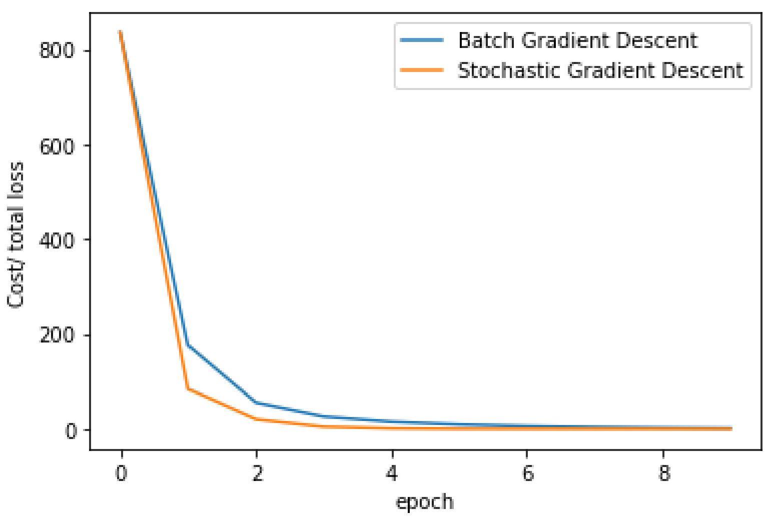

Data Space Iteration: 540
Loss Surface Contour Iteration540
y
x
b
w



Compare the loss of both batch gradient descent as SGD.

In [16]:

```
# 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 [17]:

```
# Import the library for DataLoader

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

Create a dataset class:

In [18]:

```
# 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 [19]:

```
# 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 [20]:

```
# Print the first point

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

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

Similarly, obtain the first three training points:

In [21]:

```
# 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 [22]:

```
# 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 [23]:

```
# Create DataLoader

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

Define `train_model_DataLoader` function for training the model.

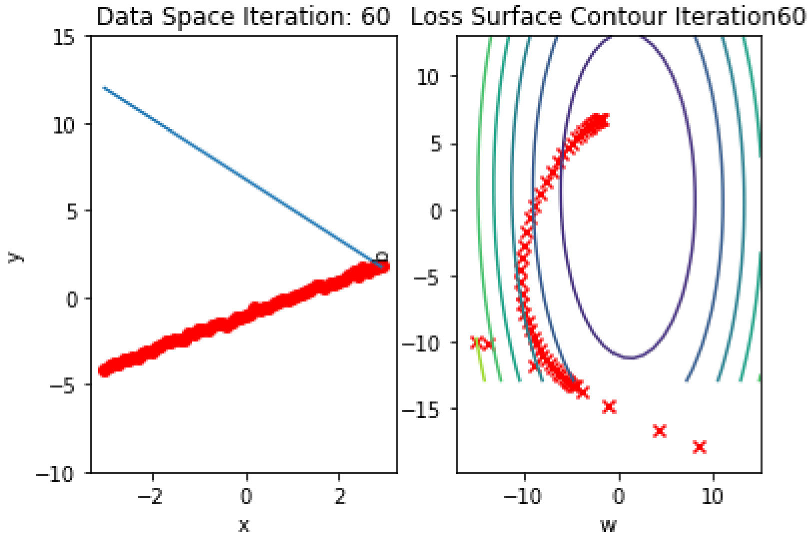
In [24]:

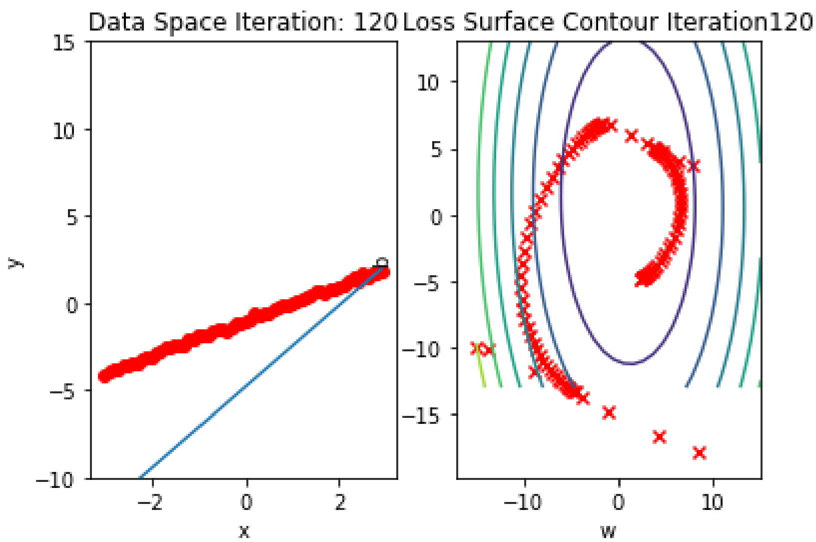
```
# The function for training the model

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 true loss/cost and store it
        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 l
earnable parameters
            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()
```

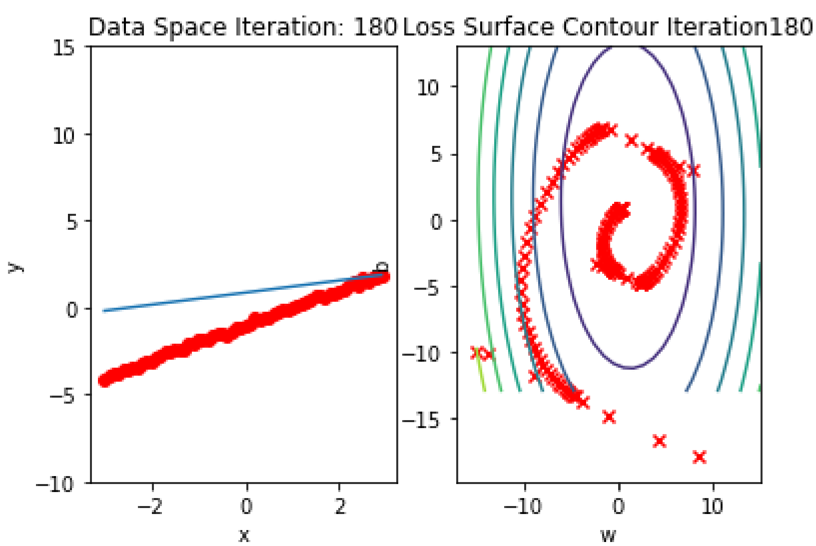
Run 10 epochs of stochastic gradient descent: **bug** data space is 1 iteration ahead of parameter space.

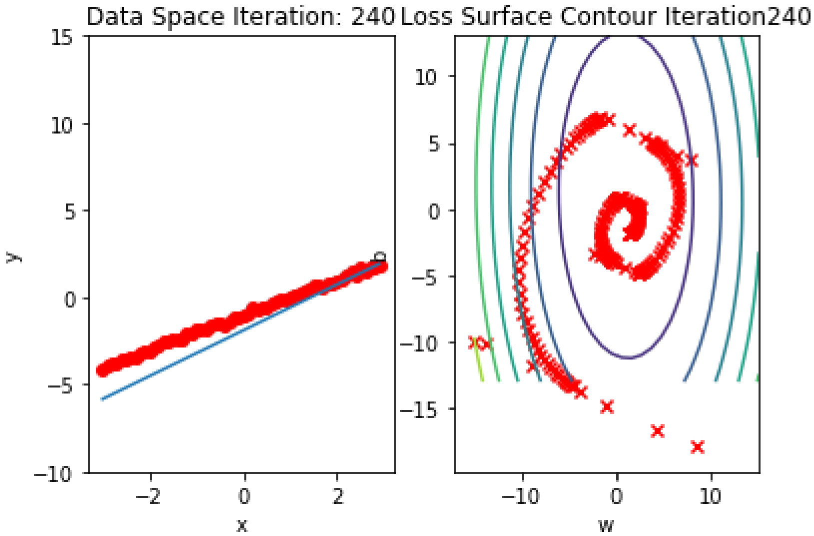
In [25]:

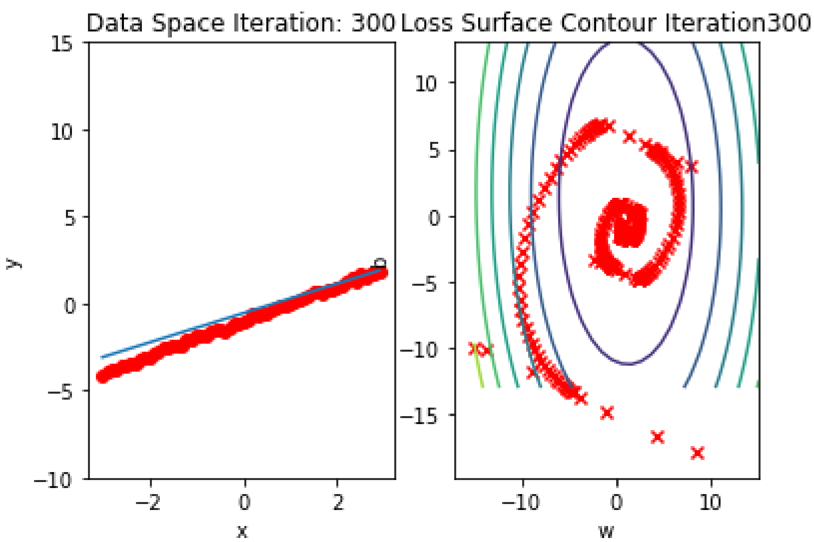
```
# Run 10 iterations

train_model_DataLoader(10)
```

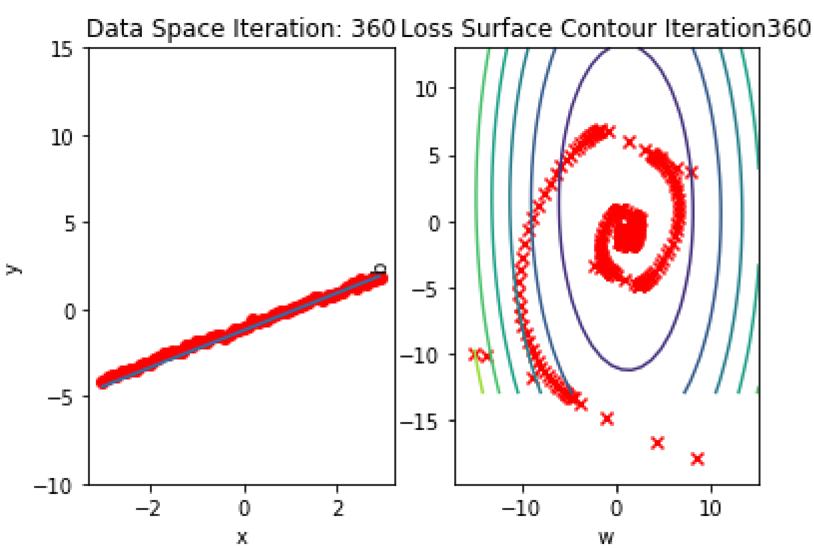

Data Space Iteration: 60
Loss Surface Contour Iteration60
x
y
w
b

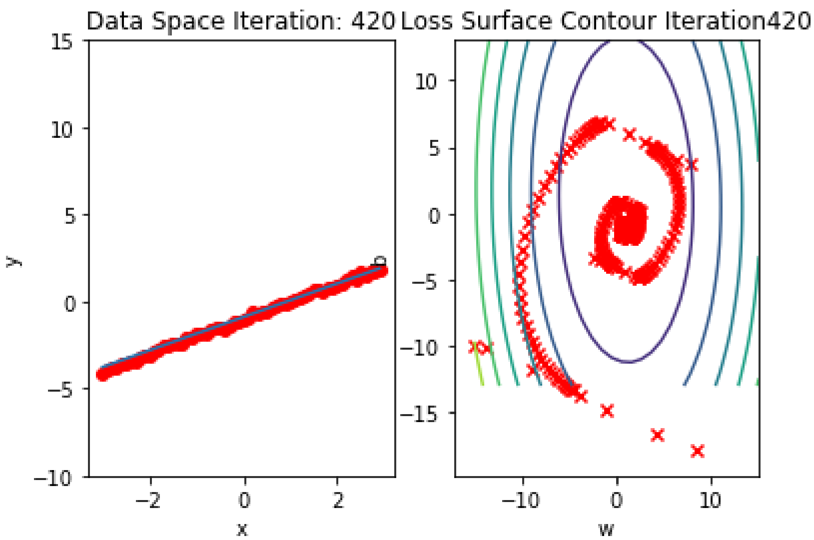

Data Space Iteration: 120
Loss Surface Contour Iteration120
x
y
w
b

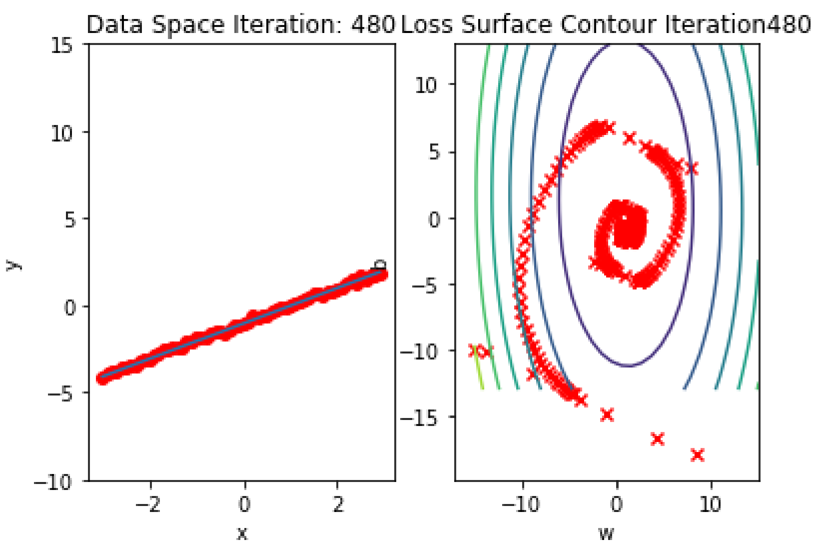

Data Space Iteration: 180
Loss Surface Contour Iteration180
x
y
w
b

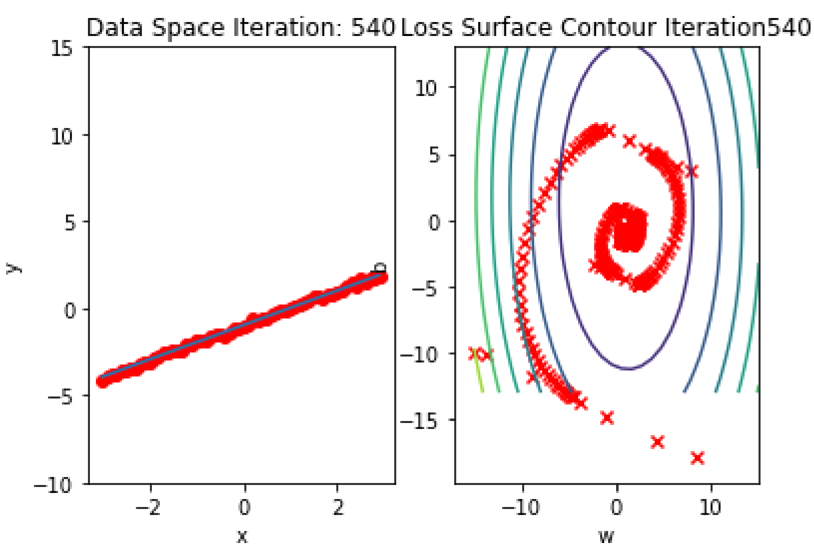

Data Space Iteration: 240
Loss Surface Contour Iteration240
x
y
w
b

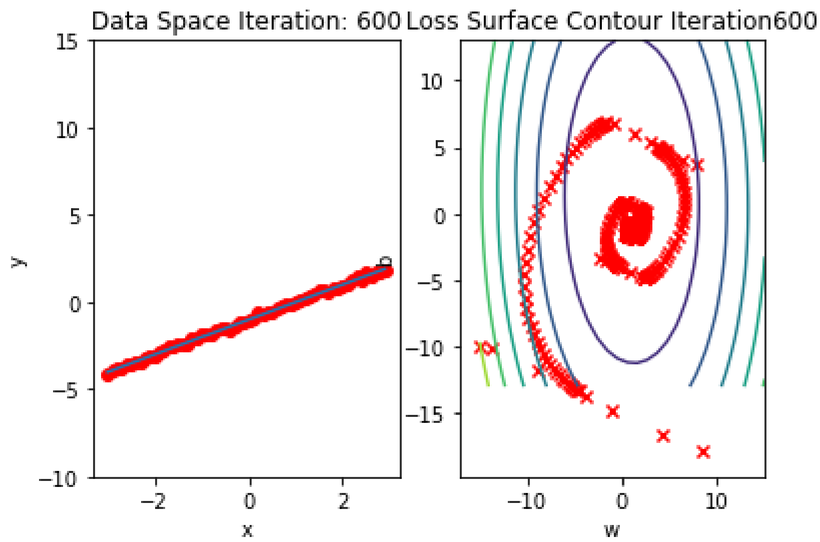

Data Space Iteration: 300
Loss Surface Contour Iteration300
x
y
w
b


Data Space Iteration: 360
Loss Surface Contour Iteration360
x
y
w
b


Data Space Iteration: 420
Loss Surface Contour Iteration420
x
y
w
b


Data Space Iteration: 480
Loss Surface Contour Iteration480
x
y
w
b

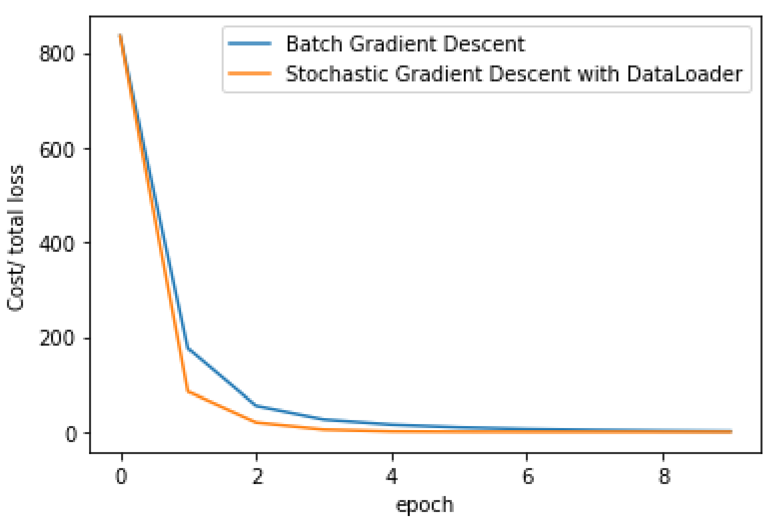

Data Space Iteration: 540
Loss Surface Contour Iteration540
x
y
w
b



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

In [26]:

```
# 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()
```

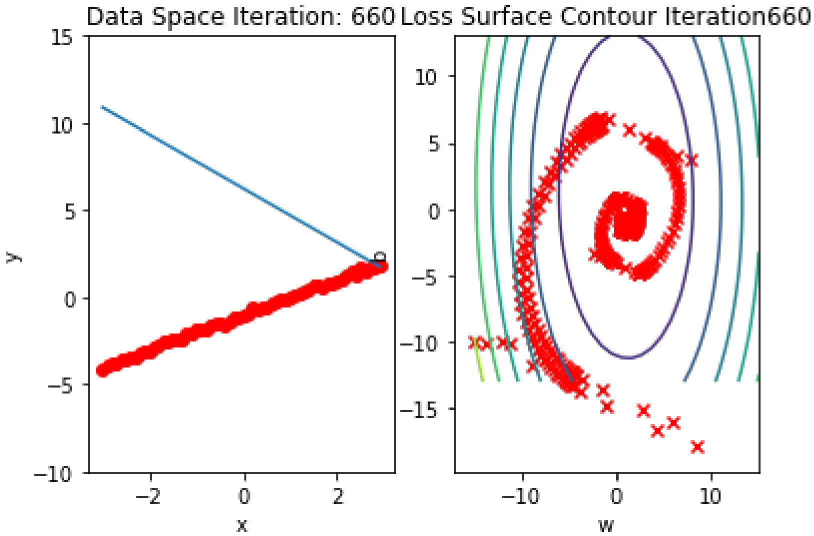


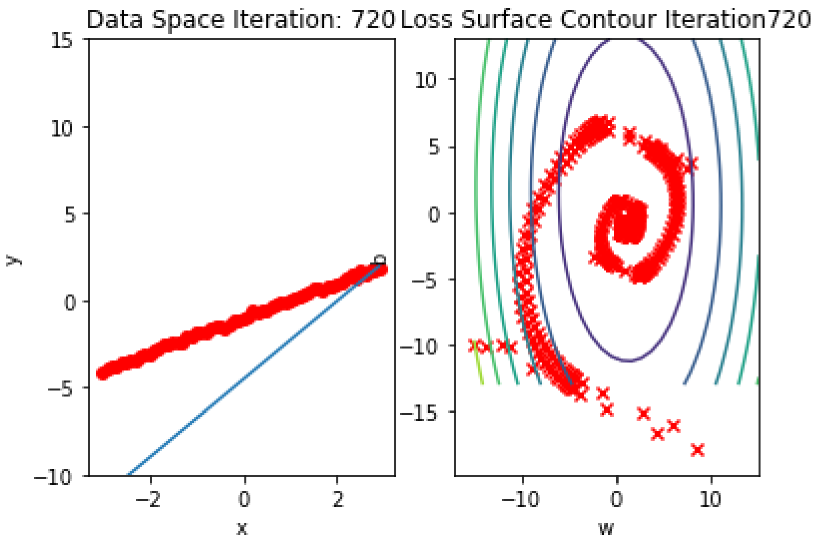
Practice

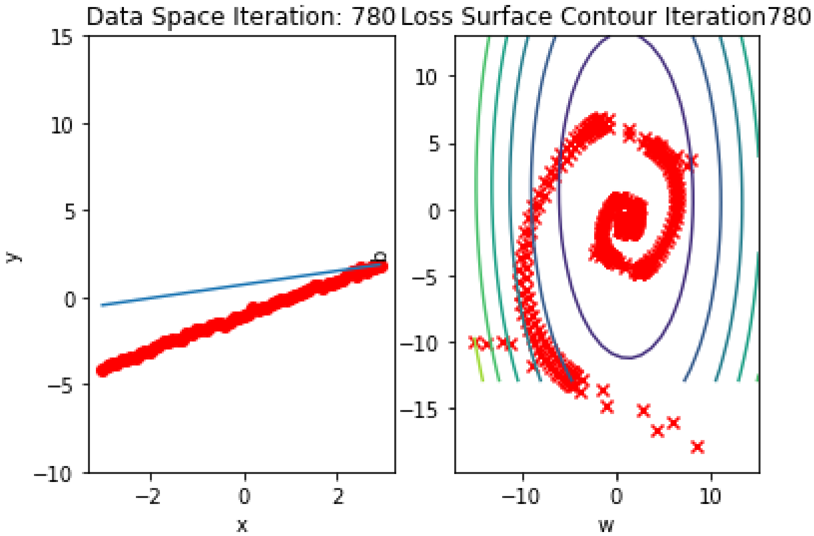
For practice, try to use SGD with DataLoader to train model with 10 iterations. Store the total loss in `LOSS` . We are going to use it in the next question.

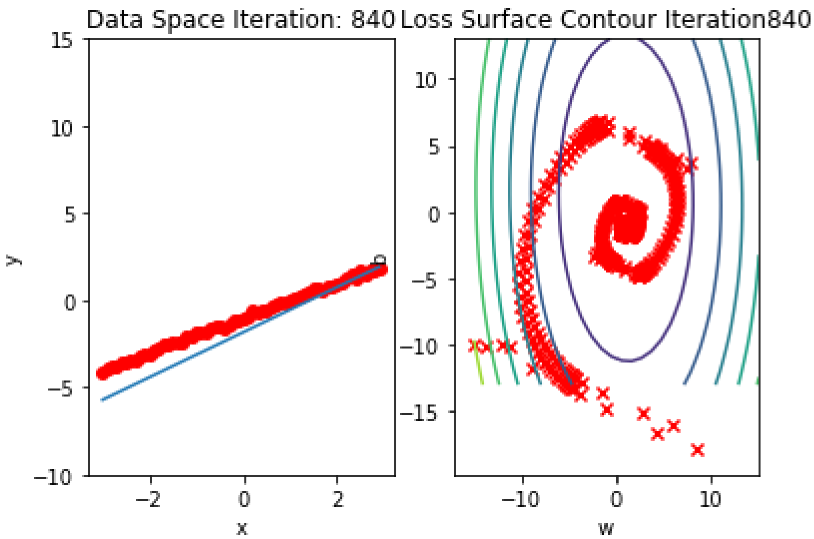
In [27]:

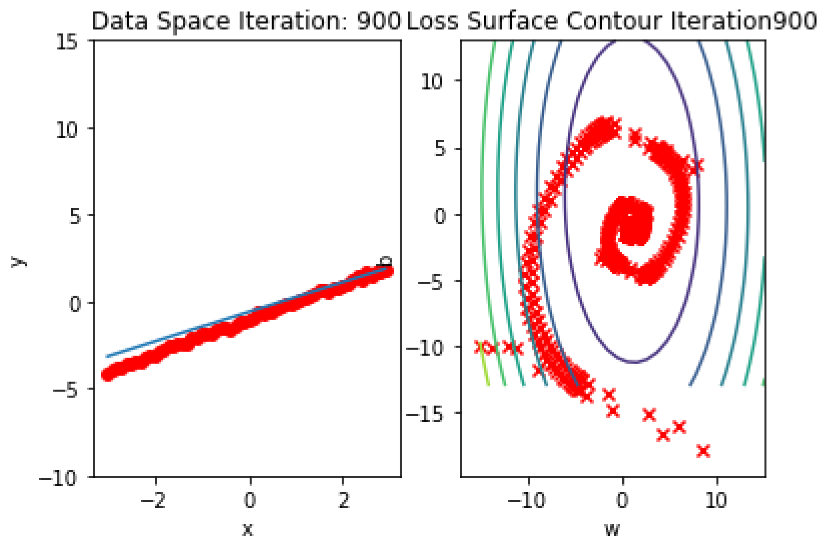
```
# Practice: Use SGD with trainloader to train model and store the total loss in LOS
S

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

def my_train_model(epochs):
    for epoch in range(epochs):
        Yhat = forward(X)
        LOSS.append(criterion(Yhat, X))
        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()
my_train_model(10)
```

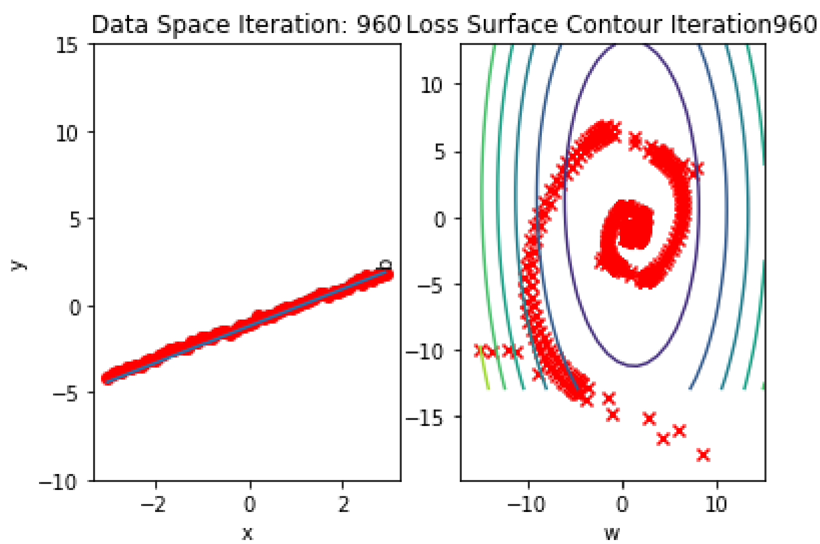

Data Space Iteration: 660
Loss Surface Contour Iteration660
y
x
w
b
15
10
5
0
−5
−10
−2
0
2
10
5
0
−5
−10
−15
−10
0
10

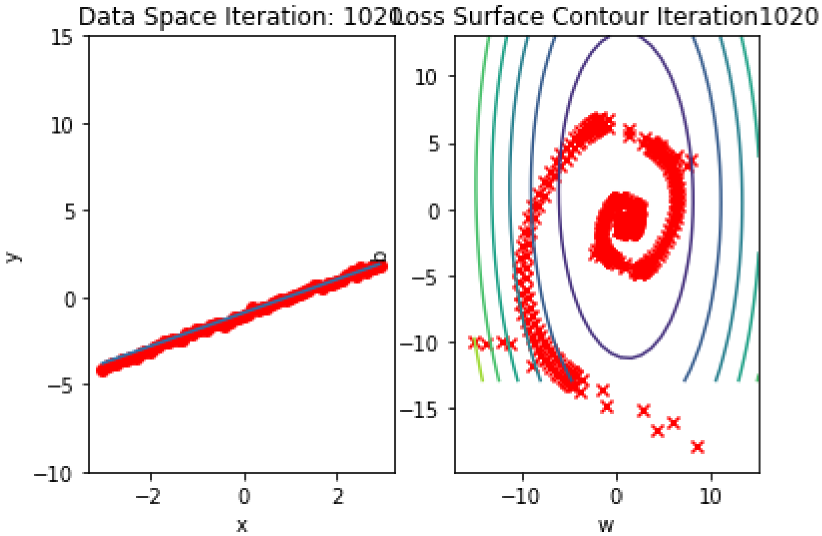

Data Space Iteration: 720
Loss Surface Contour Iteration720
y
x
w
b
15
10
5
0
−5
−10
−2
0
2
10
5
0
−5
−10
−15
−10
0
10

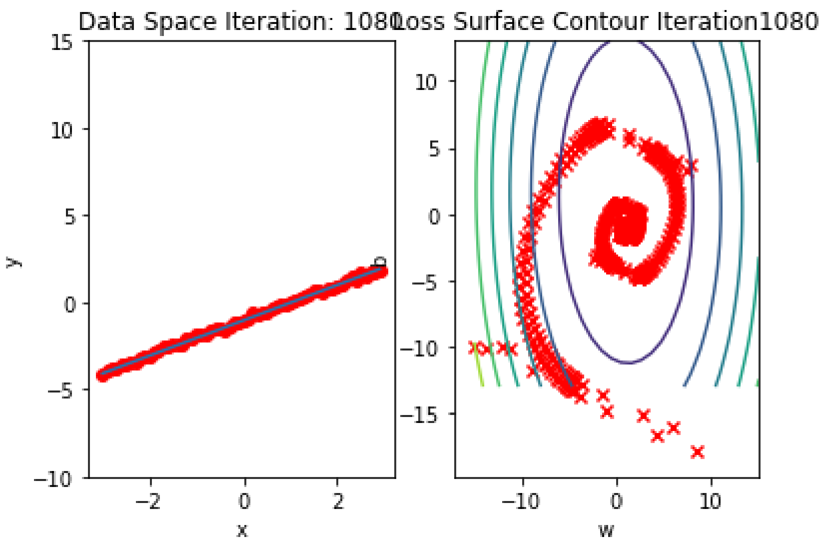

Data Space Iteration: 780
Loss Surface Contour Iteration780
y
x
w

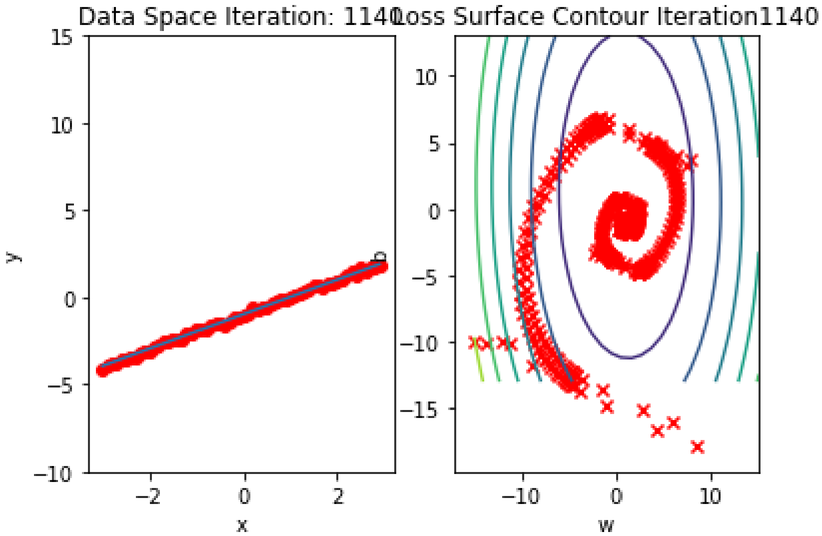

Data Space Iteration: 840
Loss Surface Contour Iteration840
y
x
w

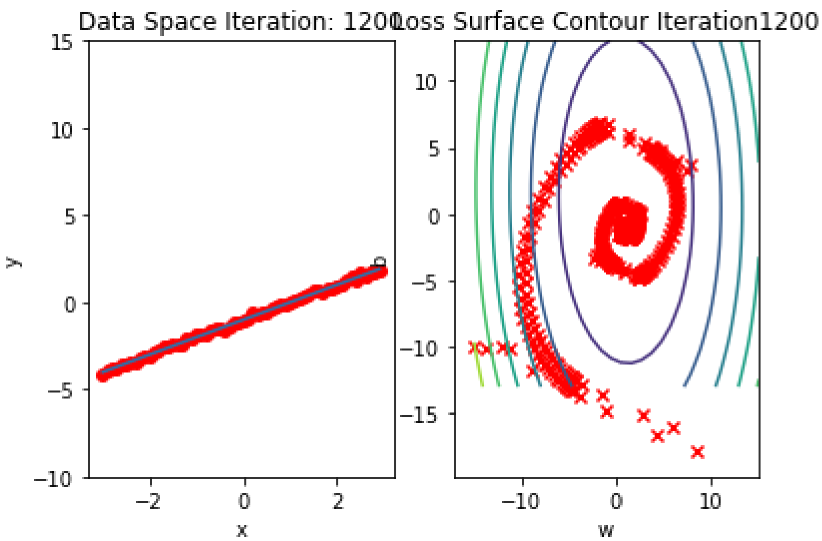

Data Space Iteration: 900
Loss Surface Contour Iteration900
y
x
w
b


Data Space Iteration: 960
Loss Surface Contour Iteration960
y
x
w
b


Data Space Iteration: 1020
Loss Surface Contour Iteration1020
y
x
w
b


Data Space Iteration: 1080
Loss Surface Contour Iteration1080
y
x
w
b



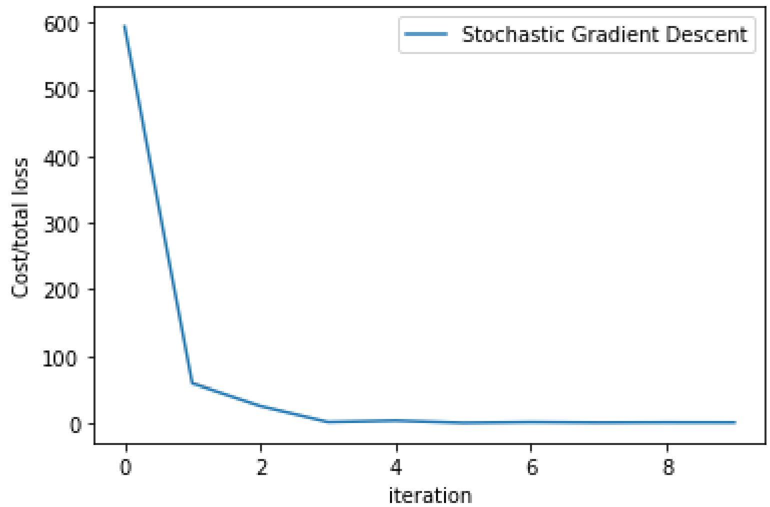


Double-click **here** for the solution.

Plot the total loss

In [28]:

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

plt.plot(LOSS, label = 'Stochastic Gradient Descent')
plt.xlabel('iteration')
plt.ylabel('Cost/total loss')
plt.legend()
plt.show()
```



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

About the Authors:

[Joseph Santarcangelo (https://www.linkedin.com/in/joseph-s-50398b136/)](https://www.linkedin.com/in/joseph-s-50398b136/) has a PhD in Electrical Engineering, his research focused on using machine learning, signal processing, and computer vision to determine how videos impact human cognition. Joseph has been working for IBM since he completed his PhD.

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Thanks to: Andrew Kin ,Alessandro Barboza

In [ ]:

```

```