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(http://cocl.us/pytorch_link_top)



Linear regression 1D: Training Two Parameter

Table of Contents

In this lab, you will train a model with PyTorch by using the data that we created. The model will have the slope and bias. And we will review how to make a prediction in several different ways by using PyTorch.

- [Make Some Data](#)
- [Create the Model and Cost Function \(Total Loss\)](#)
- [Train the Model](#)

Estimated Time Needed: **20 min**

Preparation

We'll need the following libraries:

In [1]:

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

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 = 1, cmap = 'viridis', edgecolor = 'none')
            plt.title('Cost/Total Loss Surface')
            plt.xlabel('w')
            plt.ylabel('b')
            plt.show()
            plt.figure()
            plt.title('Cost/Total 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('Total Loss Surface Contour Iteration' + str(self.n))
    plt.xlabel('w')
    plt.ylabel('b')
    plt.show()

```

Make Some Data

Import PyTorch:

In [3]:

```

# Import PyTorch library

import torch

```

Start with generating 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.

In [4]:

```

# Create f(X) with a slope of 1 and a bias of -1

X = torch.arange(-3, 3, 0.1).view(-1, 1)
f = 1 * X - 1

```

Now, add some noise to the data:

In [5]:

```
# Add noise

Y = f + 0.1 * torch.randn(X.size())
```

Plot the line and y with noise:

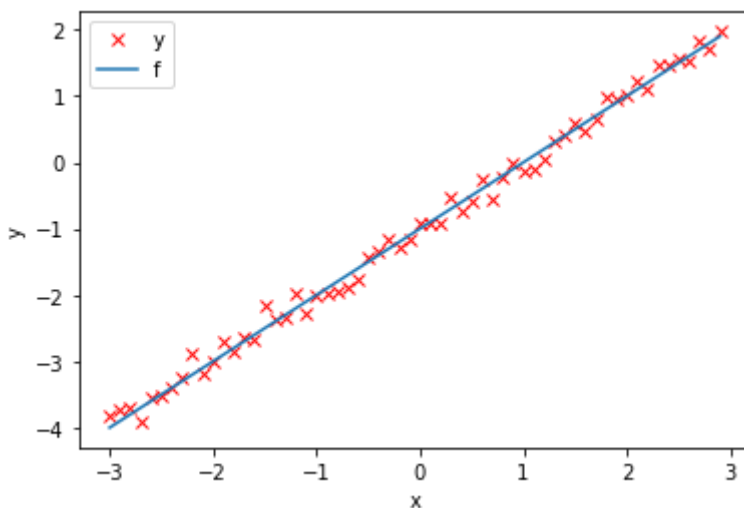
In [6]:

```
# Plot out the line and the points with noise

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()
```

Out[6]:

<matplotlib.legend.Legend at 0x7fa7a82b92e8>



Create the Model and Cost Function (Total Loss)

Define the forward function:

In [7]:

```
# Define the forward function

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

Define the cost or criterion function (MSE):

In [8]:

```
# Define the MSE Loss function

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

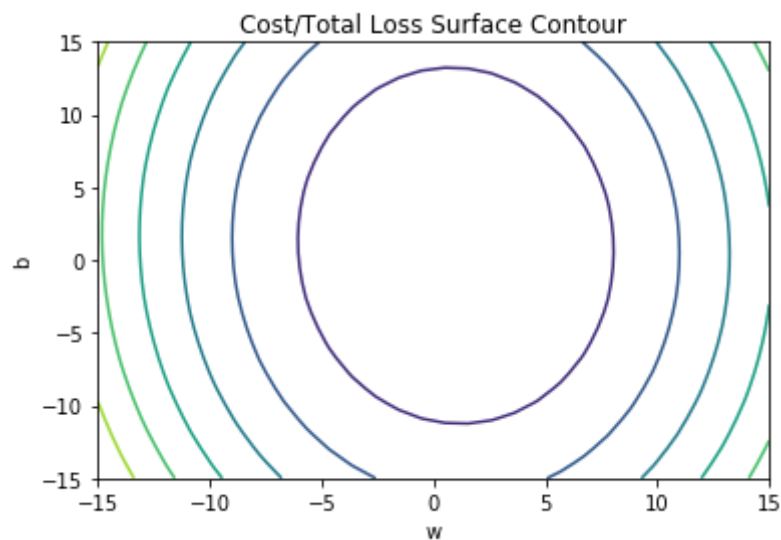
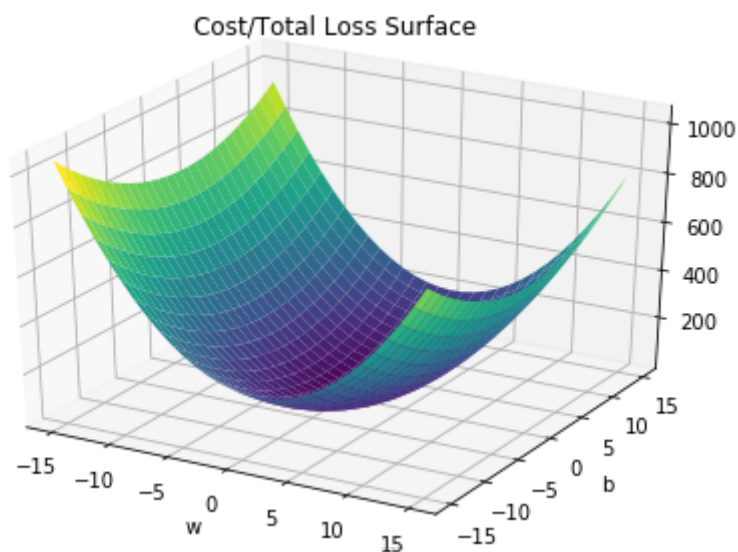
Create a `plot_error_surfaces` object to visualize the data space and the parameter space during training:

In [9]:

```
# Create plot_error_surfaces for viewing the data

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

<Figure size 432x288 with 0 Axes>



Train the Model

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

In [10]:

```
# 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 [11]:

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

lr = 0.1
LOSS = []
```

Define `train_model` function for train the model.

In [12]:

```
# 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())
        if epoch % 3 == 0:
            get_surface.plot_ps()

        # store the loss in the list LOSS
        LOSS.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

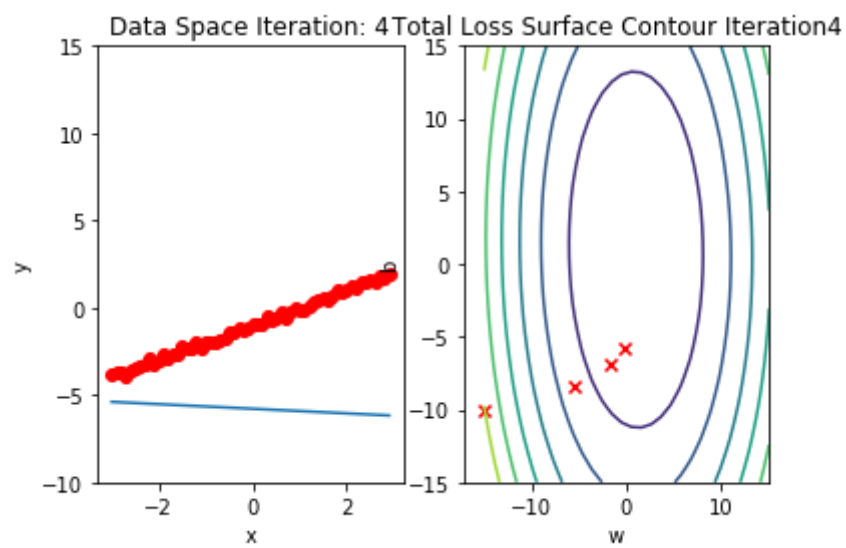
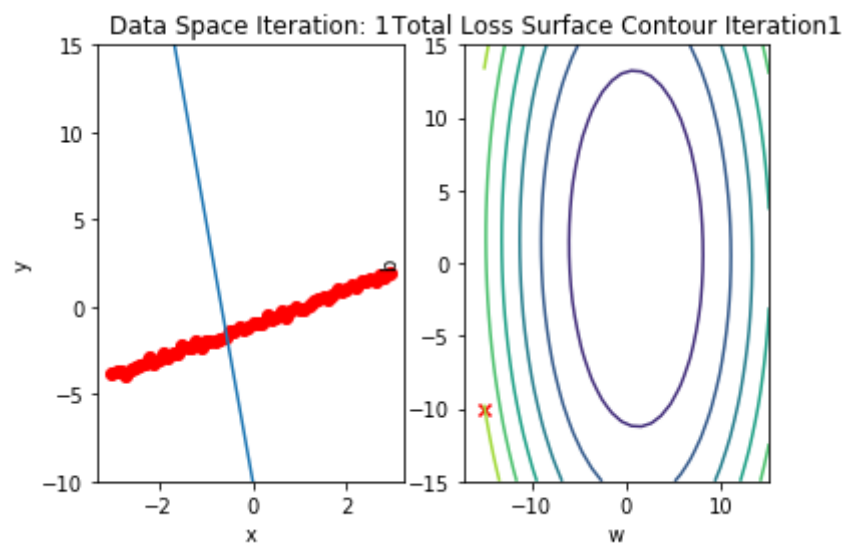
        # zero the gradients before running the backward pass
        w.grad.data.zero_()
        b.grad.data.zero_()
```

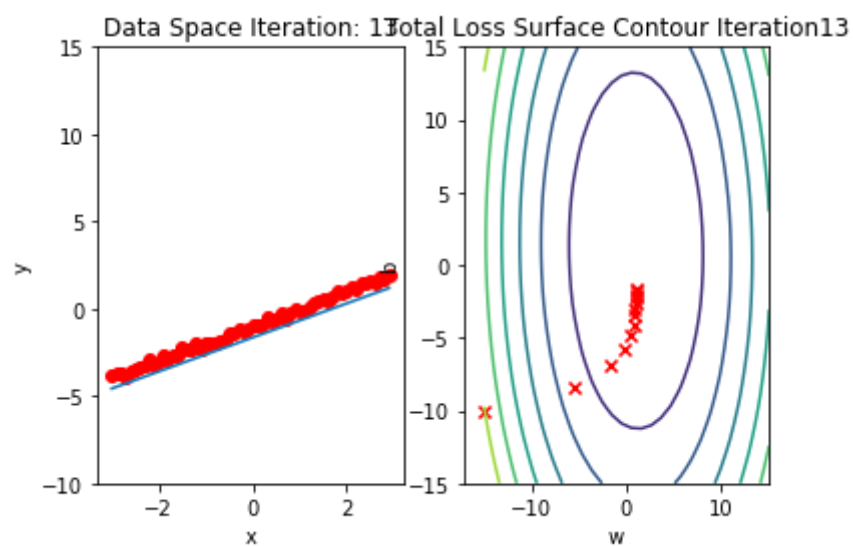
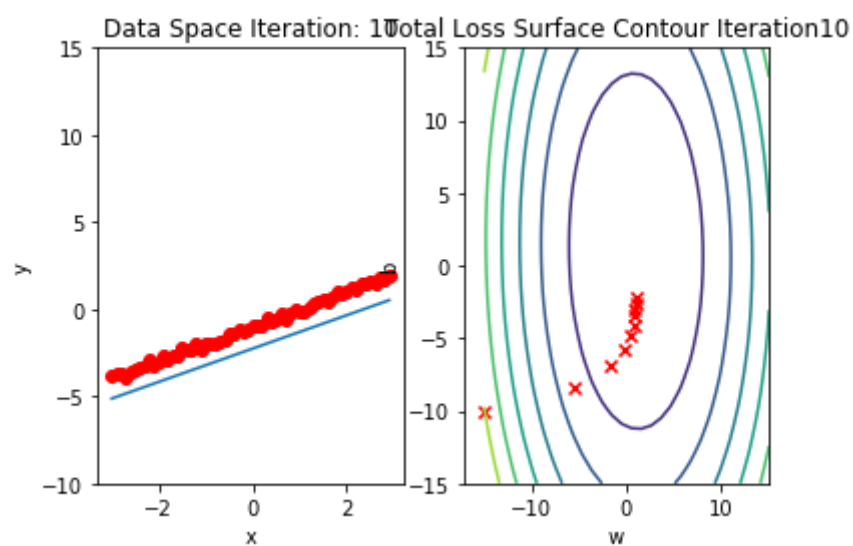
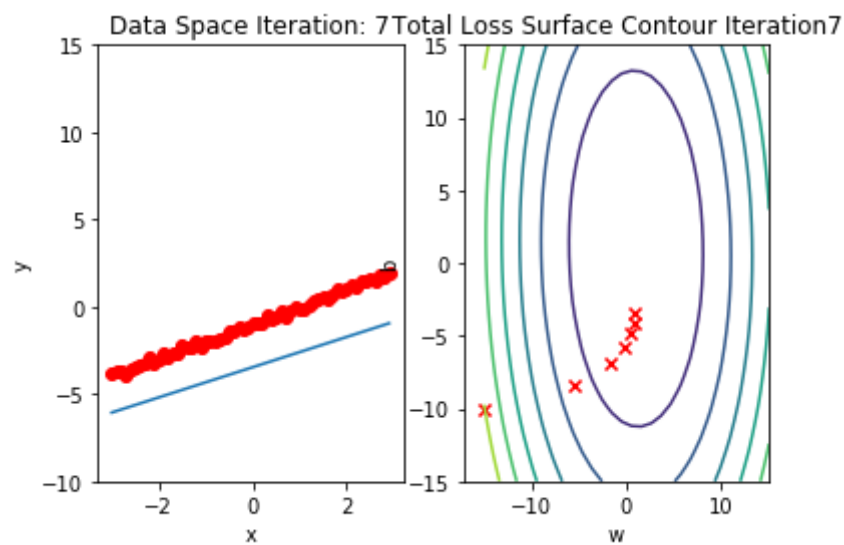
Run 15 iterations of gradient descent: **bug** data space is 1 iteration ahead of parameter space

In [13]:

```
# Train the model with 15 iterations
```

```
train_model(15)
```



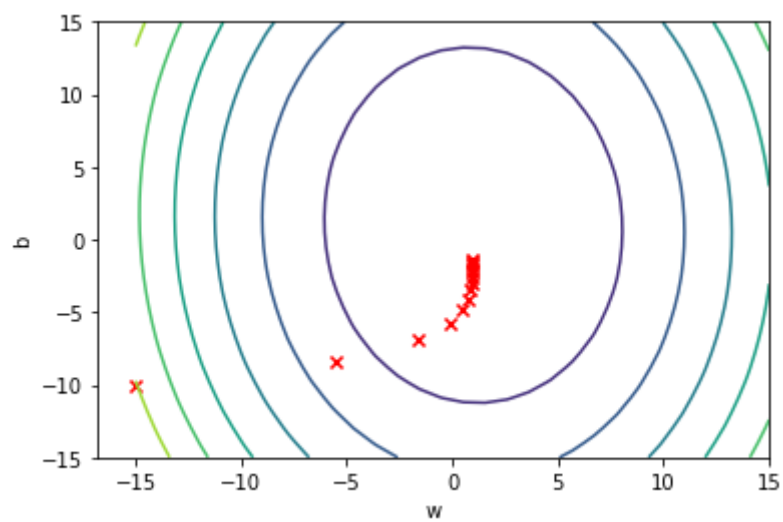
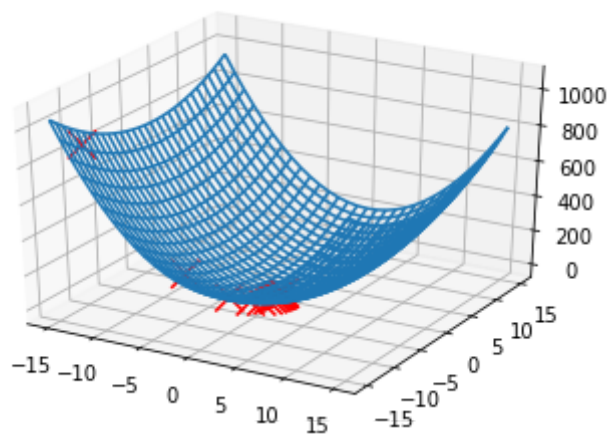


Plot total loss/cost surface with loss values for different parameters in red:

In [14]:

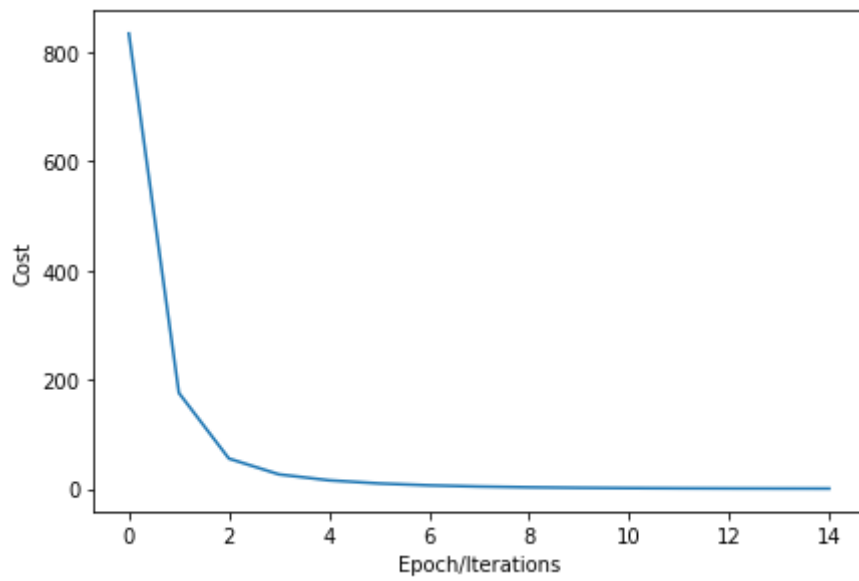
```
# Plot out the Loss Result

get_surface.final_plot()
plt.plot(LOSS)
plt.tight_layout()
plt.xlabel("Epoch/Iterations")
plt.ylabel("Cost")
```



Out[14]:

Text(23.875, 0.5, 'Cost')



Practice

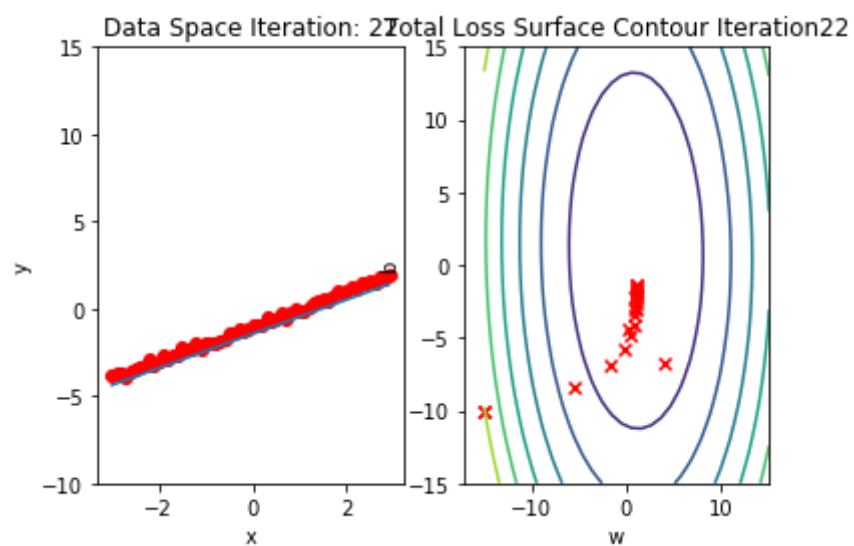
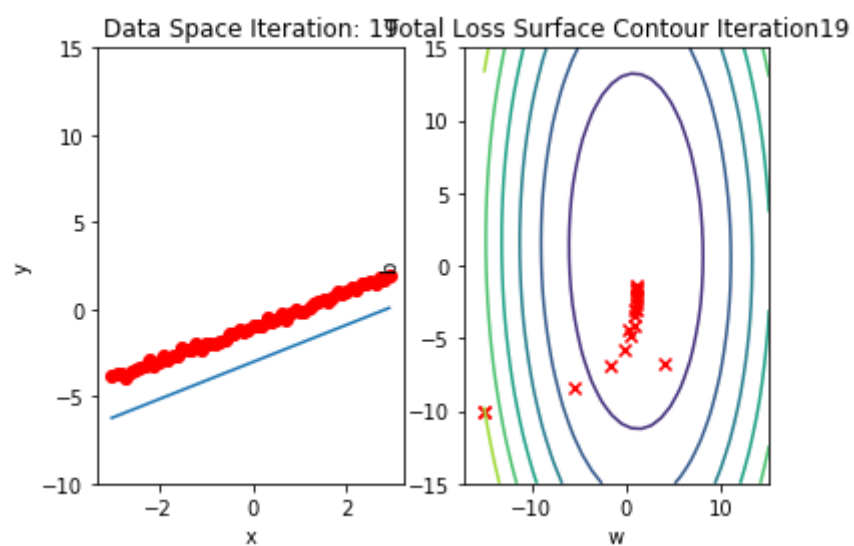
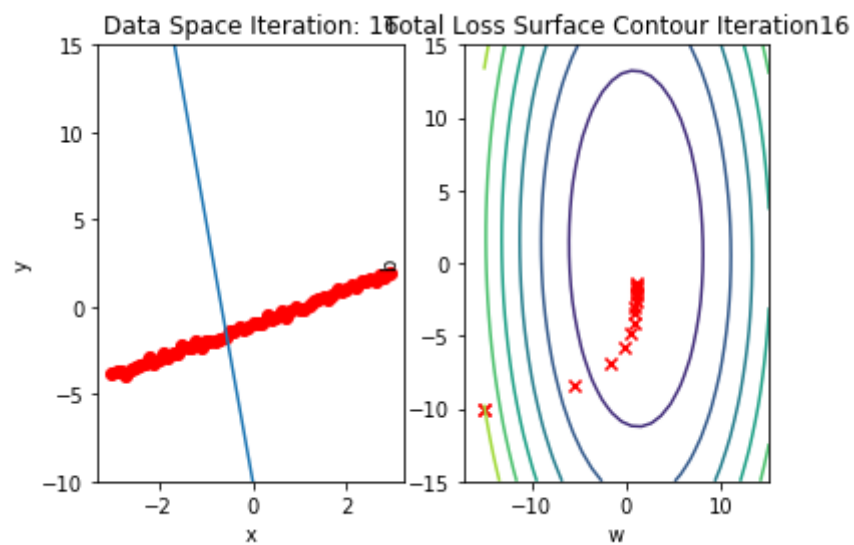
Experiment using a learning rate of 0.2 and with the following parameters. Run 15 iterations.

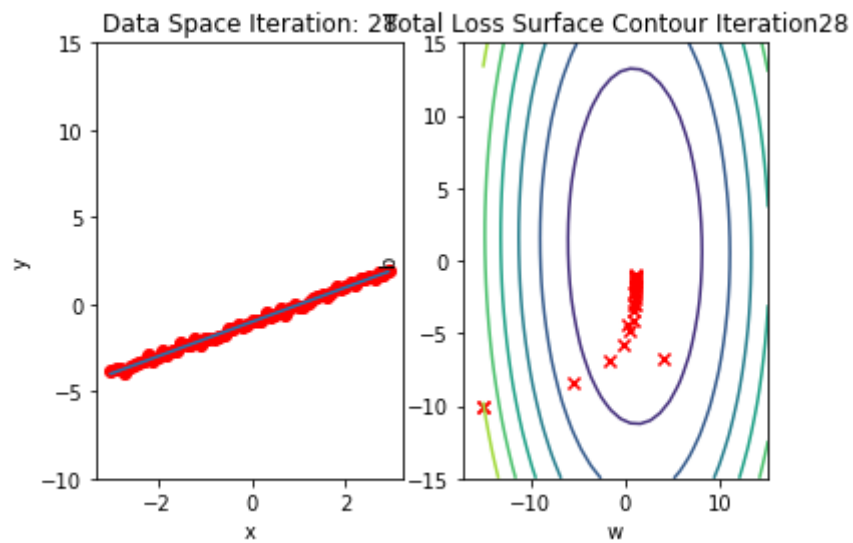
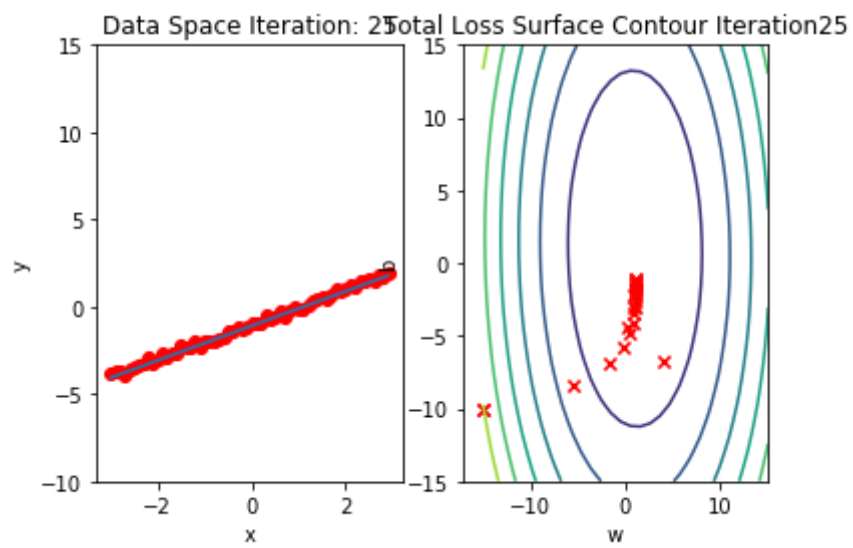
In [16]:

```
# Practice: train and plot the result with lr = 0.2 and the following parameters

w = torch.tensor(-15.0, requires_grad = True)
b = torch.tensor(-10.0, requires_grad = True)
lr = 0.2
LOSS2 = []

def my_train_model(iter):
    for epoch in range(iter):
        Yhat = forward(X)
        loss = criterion(Yhat, Y)
        get_surface.set_para_loss(w.data.tolist(), b.data.tolist(), loss.tolist())
        if epoch % 3 == 0:
            get_surface.plot_ps()
        LOSS2.append(loss)
        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(15)
```



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

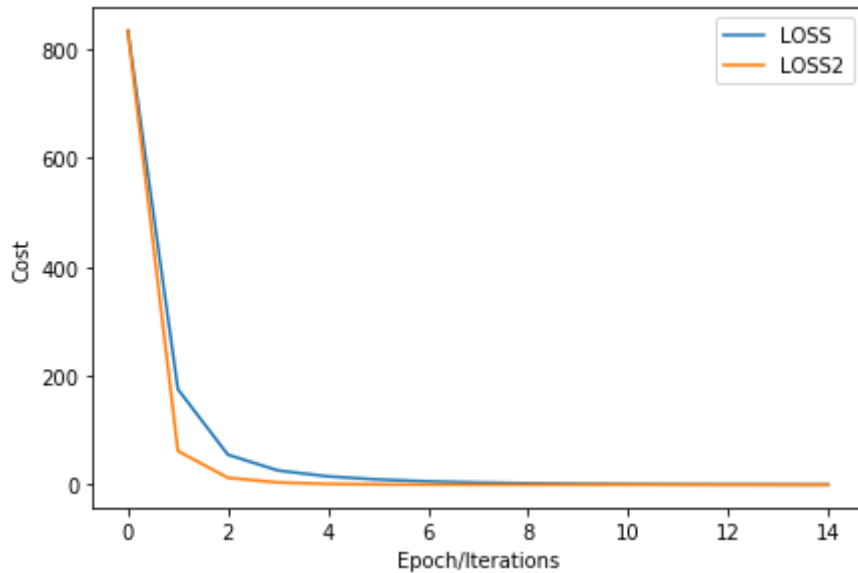
Plot the `LOSS` and `LOSS2`

In [17]:

```
# Practice: Plot the LOSS and LOSS2 in order to compare the Total Loss
plt.plot(LOSS, label = 'LOSS')
plt.plot(LOSS2, label = 'LOSS2')
plt.tight_layout()
plt.xlabel('Epoch/Iterations')
plt.ylabel('Cost')
plt.legend()
```

Out[17]:

<matplotlib.legend.Legend at 0x7fa754392b70>



Double-click [here](#) for the solution.

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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.

Other contributors: [Michelle Carey](https://www.linkedin.com/in/michelleccarey/) (<https://www.linkedin.com/in/michelleccarey/>), [Mavis Zhou](https://www.linkedin.com/in/jiahui-mavis-zhou-a4537814a) (www.linkedin.com/in/jiahui-mavis-zhou-a4537814a).

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