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(http://cocl.us/pytorch_link_top)

Logistic Regression and Bad Initialization Value

Table of Contents

In this lab, you will see what happens when you use the root mean square error cost or total loss function and select a bad initialization value for the parameter values.

Estimated Time Needed: **30 min**

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

Helper functions

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]:

```
# Create class for plotting and the function for plotting

class plot_error_surfaces(object):

    # Construstor
    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 - (1 / (1 + np.exp(-1*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('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, model, loss):
        self.n = self.n + 1
        self.W.append(list(model.parameters())[0].item())
        self.B.append(list(model.parameters())[1].item())
        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.plot(self.x, 1 / (1 + np.exp(-1 * (self.W[-1] * self.x + self.B[-1]))),
label='sigmoid')
        plt.xlabel('x')
        plt.ylabel('y')
        plt.ylim((-0.1, 2))
        plt.title('Data Space Iteration: ' + str(self.n))
        plt.show()
        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')

# Plot the diagram

def PlotStuff(X, Y, model, epoch, leg=True):
    plt.plot(X.numpy(), model(X).detach().numpy(), label=('epoch ' + str(epoch)))
    plt.plot(X.numpy(), Y.numpy(), 'r')
    if leg == True:
        plt.legend()
    else:
        pass
```

Set the random seed:

In [3]:

```
# Set random seed

torch.manual_seed(0)
```

Out[3]:

```
<torch._C.Generator at 0x7f4d52436090>
```

Get Some Data

Create the `Data` class

In [4]:

```
# Create the data class

class Data(Dataset):

    # Constructor
    def __init__(self):
        self.x = torch.arange(-1, 1, 0.1).view(-1, 1)
        self.y = torch.zeros(self.x.shape[0], 1)
        self.y[self.x[:, 0] > 0.2] = 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
```

Make `Data` object

In [5]:

```
# Create Data object

data_set = Data()
```

Create the Model and Total Loss Function (Cost)

Create a custom module for logistic regression:

In [6]:

```
# Create logistic_regression class

class logistic_regression(nn.Module):

    # Constructor
    def __init__(self, n_inputs):
        super(logistic_regression, self).__init__()
        self.linear = nn.Linear(n_inputs, 1)

    # Prediction
    def forward(self, x):
        yhat = torch.sigmoid(self.linear(x))
        return yhat
```

Create a logistic regression object or model:

In [7]:

```
# Create the logistic_regression result

model = logistic_regression(1)
```

Replace the random initialized variable values with some predetermined values that will not converge:

In [8]:

```
# Set the weight and bias

model.state_dict() ['linear.weight'].data[0] = torch.tensor([[-5]])
model.state_dict() ['linear.bias'].data[0] = torch.tensor([[-10]])
print("The parameters: ", model.state_dict())
```

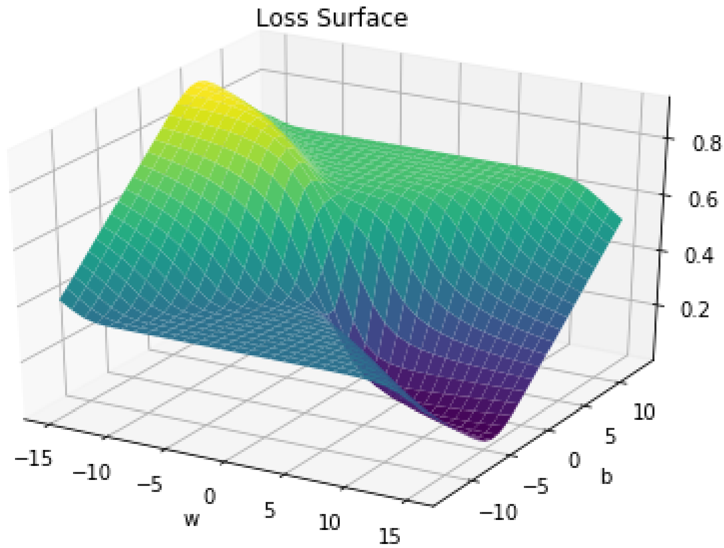
```
The parameters:  OrderedDict([('linear.weight', tensor([[-5.]])), ('lin
ear.bias', tensor([-10.]))])
```

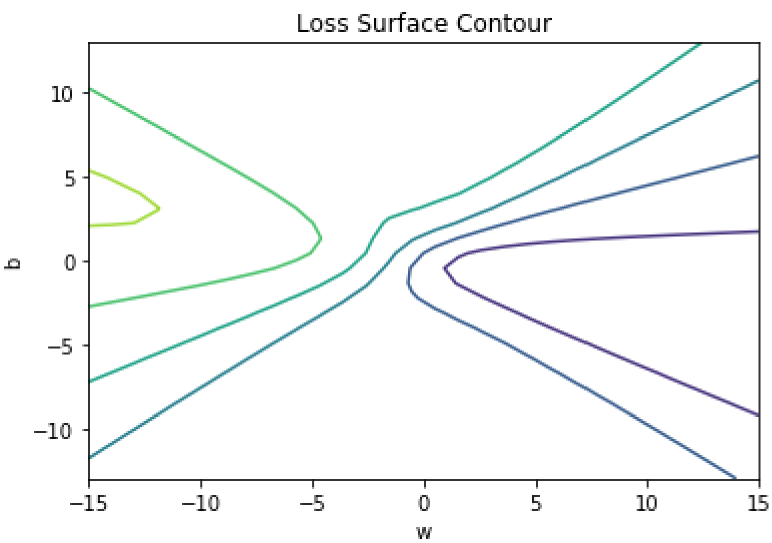
Create a `plot_error_surfaces` object to visualize the data space and the parameter space during training:

In [9]:

```
# Create the plot_error_surfaces object

get_surface = plot_error_surfaces(15, 13, data_set[:][0], data_set[:][1], 30)
```

<Figure size 432x288 with 0 Axes>





Define the dataloader, the cost or criterion function, the optimizer:

In [10]:

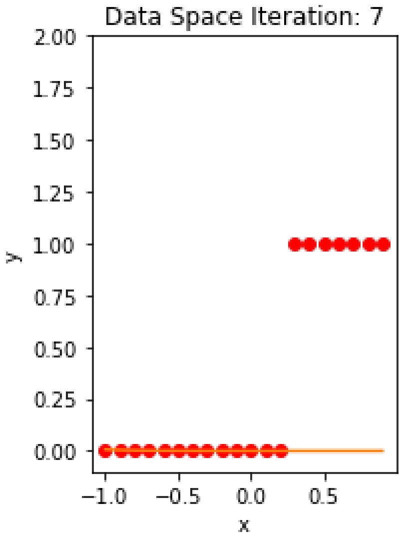
```
# Create dataloader object, crierion function and optimizer.

trainloader = DataLoader(dataset=data_set, batch_size=3)
criterion_rms = nn.MSELoss()
learning_rate = 2
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
```

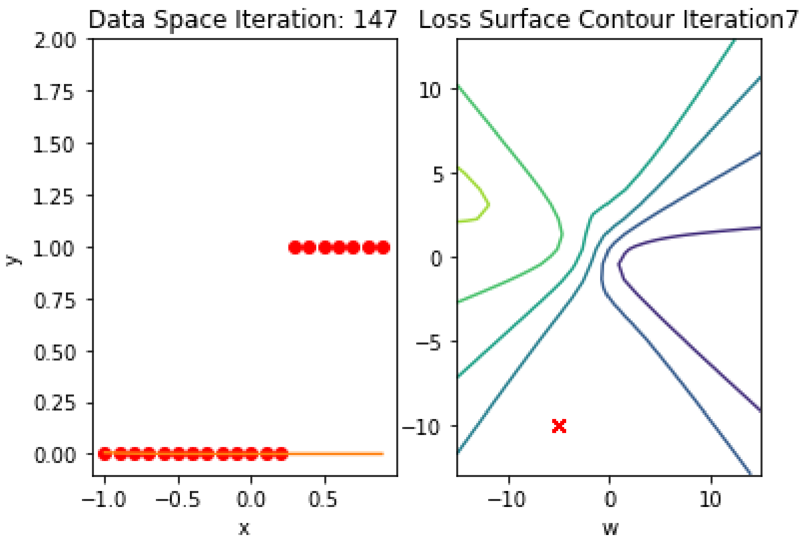
Train the Model via Batch Gradient Descent

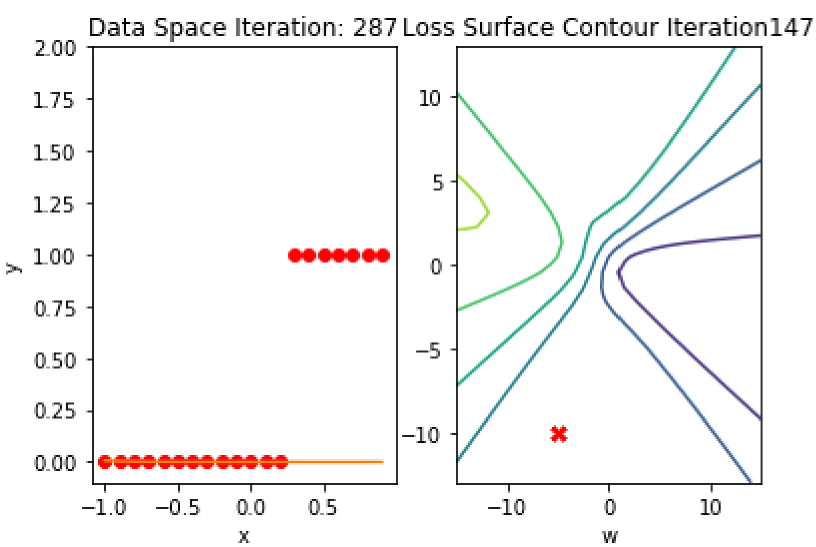
Train the model

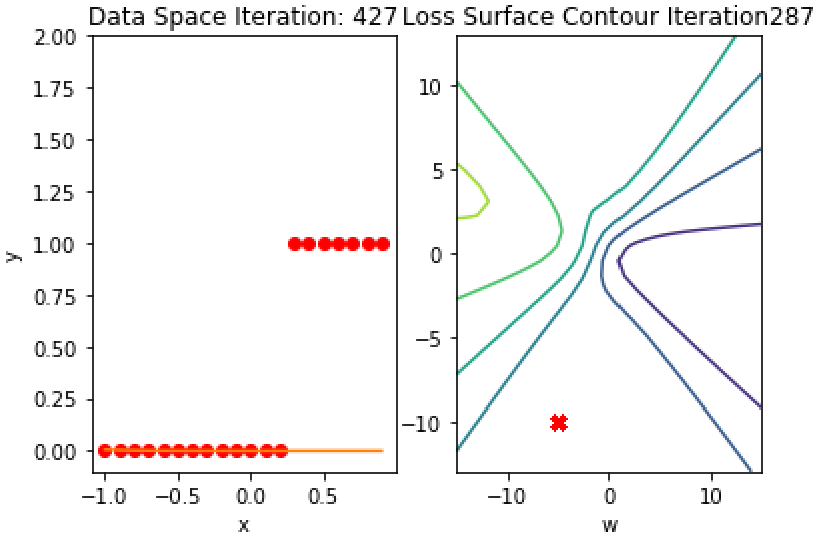
In [11]:

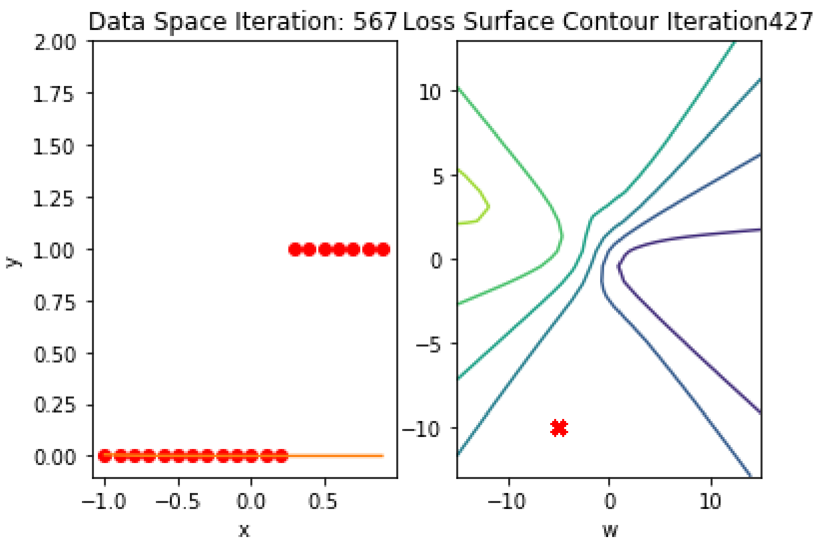
```
# Train the model

def train_model(epochs):
    for epoch in range(epochs):
        for x, y in trainloader:
            yhat = model(x)
            loss = criterion_rms(yhat, y)
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            get_surface.set_para_loss(model, loss.tolist())
        if epoch % 20 == 0:
            get_surface.plot_ps()

train_model(100)
```

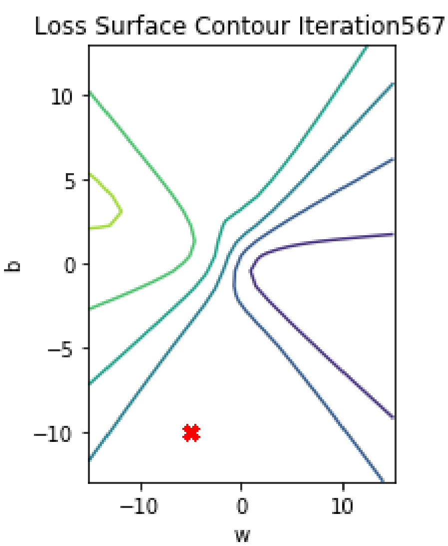

Data Space Iteration: 7
y
x


Data Space Iteration: 147
y
x
Loss Surface Contour Iteration7
w


Data Space Iteration: 287
y
x
Loss Surface Contour Iteration147
w







Get the actual class of each sample and calculate the accuracy on the test data:

In [12]:

```
# Make the Prediction

yhat = model(data_set.x)
label = yhat > 0.5
print("The accuracy: ", torch.mean((label == data_set.y.type(torch.ByteTensor)).typ
e(torch.float)))
```

```
The accuracy:  tensor(0.6500)
```

Accuracy is 60% compared to 100% in the last lab using a good Initialization value.

About the Authors:

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