4.2.multiple_linear_regression_training_v2

March 28, 2022

Linear Regression Multiple Outputs

Objective

How to create a complicated models using pytorch build in functions.

Table of Contents

In this lab, you will create a model the PyTroch way. This will help you more complicated models.

Make Some Data

Create the Model and Cost Function the PyTorch way

Train the Model: Batch Gradient Descent

Estimated Time Needed: 20 min

Preparation

We'll need the following libraries:

[1]:
```
# Import the libraries we need for this lab

from torch import nn,optim
import torch
import numpy as np
import matplotlib.pyplot as plt

from mpl_toolkits.mplot3d import Axes3D
from torch.utils.data import Dataset, DataLoader
```

Set the random seed:

[2]:
```
# Set the random seed to 1.

torch.manual_seed(1)
```

[2]:
```
<torch._C.Generator at 0x7f209c53f2f0>
```

Use this function for plotting:

[3]:
```
# The function for plotting 2D

```

```
def Plot_2D_Plane(model, dataset, n=0):
    w1 = model.state_dict()['linear.weight'].numpy()[0][0]
    w2 = model.state_dict()['linear.weight'].numpy()[0][1]
    b = model.state_dict()['linear.bias'].numpy()

    # Data
    x1 = data_set.x[:, 0].view(-1, 1).numpy()
    x2 = data_set.x[:, 1].view(-1, 1).numpy()
    y = data_set.y.numpy()

    # Make plane
    X, Y = np.meshgrid(np.arange(x1.min(), x1.max(), 0.05), np.arange(x2.min(),
 ↪x2.max(), 0.05))
    yhat = w1 * X + w2 * Y + b

    # Plotting
    fig = plt.figure()
    ax = fig.gca(projection='3d')

    ax.plot(x1[:, 0], x2[:, 0], y[:, 0],'ro', label='y') # Scatter plot

    ax.plot_surface(X, Y, yhat) # Plane plot

    ax.set_xlabel('x1 ')
    ax.set_ylabel('x2 ')
    ax.set_zlabel('y')
    plt.title('estimated plane iteration:' + str(n))
    ax.legend()

    plt.show()
```

Make Some Data

Create a dataset class with two-dimensional features:

[4]:
```
# Create a 2D dataset

class Data2D(Dataset):

    # Constructor
    def __init__(self):
        self.x = torch.zeros(20, 2)
        self.x[:, 0] = torch.arange(-1, 1, 0.1)
        self.x[:, 1] = torch.arange(-1, 1, 0.1)
        self.w = torch.tensor([[1.0], [1.0]])
        self.b = 1
        self.f = torch.mm(self.x, self.w) + self.b
        self.y = self.f + 0.1 * torch.randn((self.x.shape[0],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:

[5]:
```
# Create the dataset object

data_set = Data2D()
```

Create the Model, Optimizer, and Total Loss Function (Cost)

Create a customized linear regression module:

[6]:
```
# Create a customized linear

class linear_regression(nn.Module):

    # Constructor
    def __init__(self, input_size, output_size):
        super(linear_regression, self).__init__()
        self.linear = nn.Linear(input_size, output_size)

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

Create a model. Use two features: make the input size 2 and the output size 1:

[7]:
```
# Create the linear regression model and print the parameters

model = linear_regression(2,1)
print("The parameters: ", list(model.parameters()))
```

```
The parameters:  [Parameter containing:
tensor([[ 0.6209, -0.1178]], requires_grad=True), Parameter containing:
tensor([0.3026], requires_grad=True)]
```

Create an optimizer object. Set the learning rate to 0.1. Don't forget to enter the model parameters in the constructor.

[8]:
```
# Create the optimizer

optimizer = optim.SGD(model.parameters(), lr=0.1)
```

Create the criterion function that calculates the total loss or cost:

[9]:
```
# Create the cost function

criterion = nn.MSELoss()
```

Create a data loader object. Set the batch_size equal to 2:

[10]:
```
# Create the data loader

train_loader = DataLoader(dataset=data_set, batch_size=2)
```

Train the Model via Mini-Batch Gradient Descent

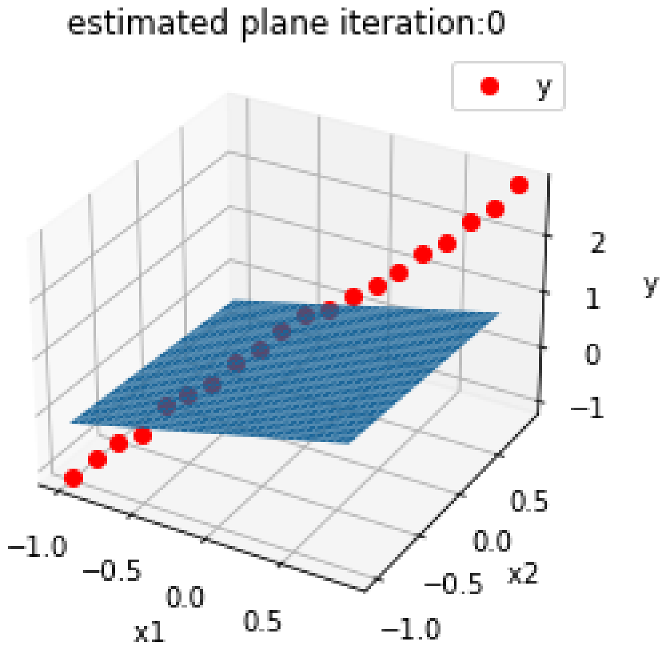
Run 100 epochs of Mini-Batch Gradient Descent and store the total loss or cost for every iteration. Remember that this is an approximation of the true total loss or cost:

[11]:
```
# Train the model

LOSS = []
print("Before Training: ")
Plot_2D_Plane(model, data_set)
epochs = 100

def train_model(epochs):
    for epoch in range(epochs):
        for x,y in train_loader:
            yhat = model(x)
            loss = criterion(yhat, y)
            LOSS.append(loss.item())
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
train_model(epochs)
print("After Training: ")
Plot_2D_Plane(model, data_set, epochs)
```

```
Before Training:
```

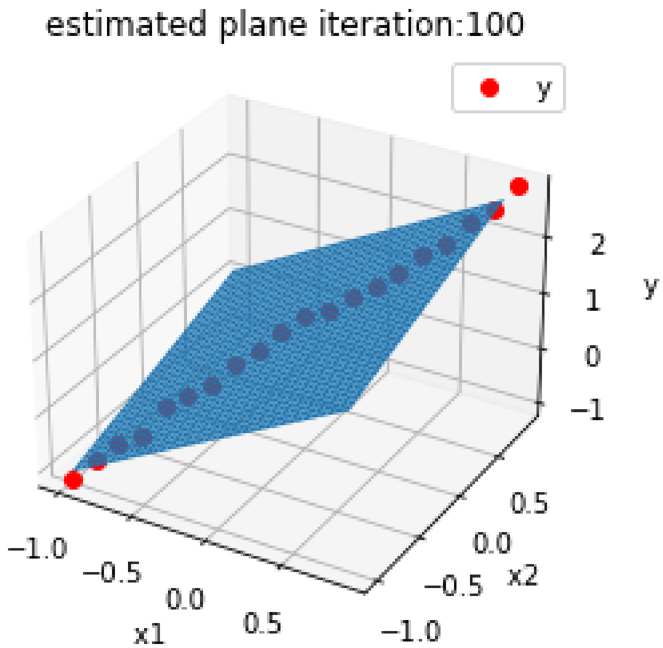
```
/home/jupyterlab/conda/envs/python/lib/python3.7/site-
packages/ipykernel_launcher.py:19: MatplotlibDeprecationWarning: Calling gca()
with keyword arguments was deprecated in Matplotlib 3.4. Starting two minor
releases later, gca() will take no keyword arguments. The gca() function should
only be used to get the current axes, or if no axes exist, create new axes with
default keyword arguments. To create a new axes with non-default arguments, use
```

plt.axes() or plt.subplot().



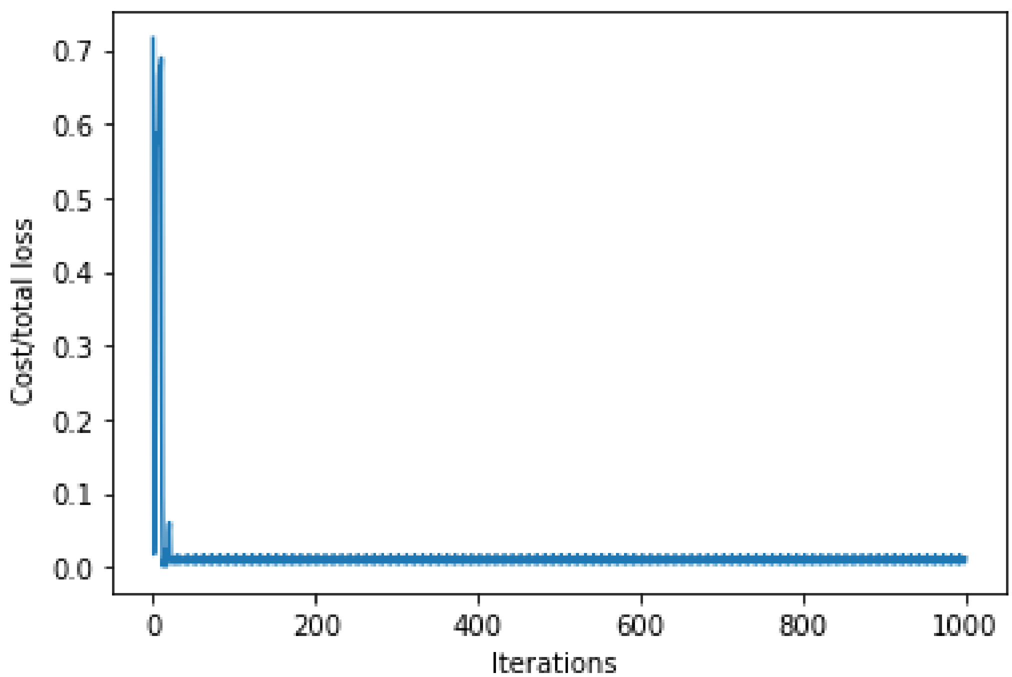
After Training:

/home/jupyterlab/conda/envs/python/lib/python3.7/site-packages/ipykernel_launcher.py:19: MatplotlibDeprecationWarning: Calling gca() with keyword arguments was deprecated in Matplotlib 3.4. Starting two minor releases later, gca() will take no keyword arguments. The gca() function should only be used to get the current axes, or if no axes exist, create new axes with default keyword arguments. To create a new axes with non-default arguments, use plt.axes() or plt.subplot().



[12]:
```
# Plot out the Loss and iteration diagram

plt.plot(LOSS)
plt.xlabel("Iterations ")
plt.ylabel("Cost/total loss ")
```

[12]: Text(0, 0.5, 'Cost/total loss ')



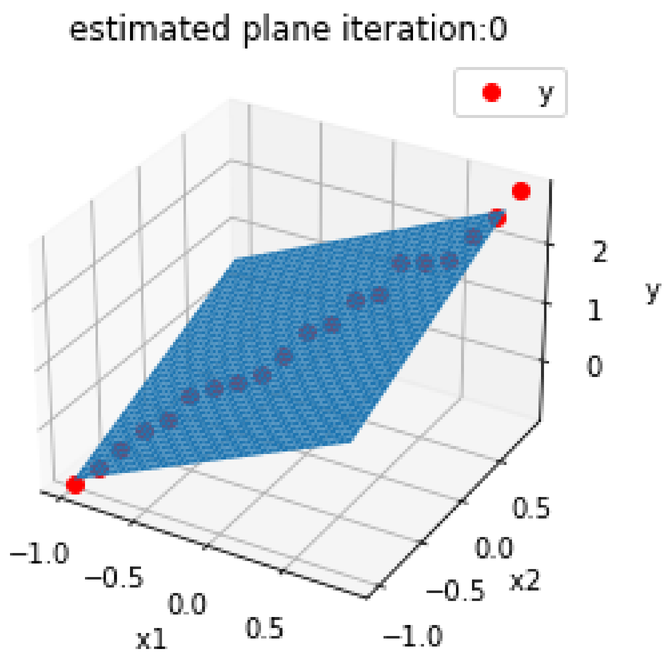
Practice

Create a new model1. Train the model with a batch size 30 and learning rate 0.1, store the loss or total cost in a list LOSS1, and plot the results.

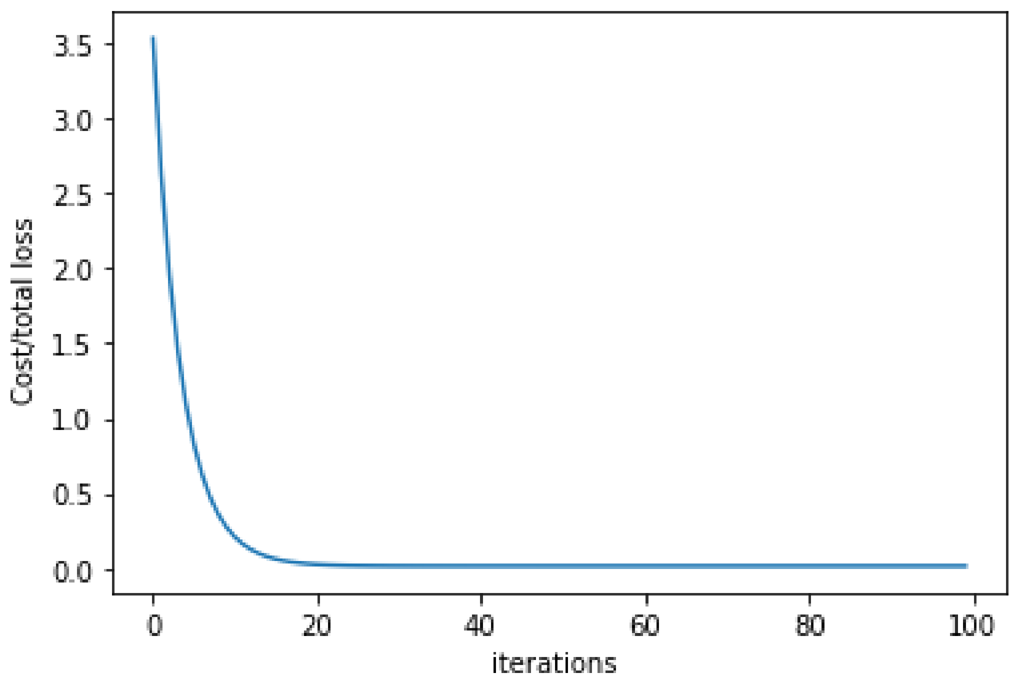
[14]:
```
# Practice create model1. Train the model with batch size 30 and learning rate
↪0.1, store the loss in a list <code>LOSS1</code>. Plot the results.

train_loader = DataLoader(dataset = data_set, batch_size = 30)
model1 = linear_regression(2, 1)
optimizer = optim.SGD(model1.parameters(), lr = 0.1)
LOSS1 = []
epochs = 100
def train_model(epochs):
    for epoch in range(epochs):
        for x,y in train_loader:
            yhat = model1(x)
            loss = criterion(yhat,y)
            LOSS1.append(loss.item())
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
train_model(epochs)
Plot_2D_Plane(model1 , data_set)
plt.plot(LOSS1)
```

```
plt.xlabel("iterations ")
plt.ylabel("Cost/total loss ")
```

```
/home/jupyterlab/conda/envs/python/lib/python3.7/site-
packages/ipykernel_launcher.py:19: MatplotlibDeprecationWarning: Calling gca()
with keyword arguments was deprecated in Matplotlib 3.4. Starting two minor
releases later, gca() will take no keyword arguments. The gca() function should
only be used to get the current axes, or if no axes exist, create new axes with
default keyword arguments. To create a new axes with non-default arguments, use
plt.axes() or plt.subplot().
```




```
[14]: Text(0, 0.5, 'Cost/total loss ')
```



Double-click here for the solution.

Use the following validation data to calculate the total loss or cost for both models:

[15]:
```
torch.manual_seed(2)

validation_data = Data2D()
Y = validation_data.y
X = validation_data.x
print("total loss or cost for model: ",criterion(model(X),Y))
print("total loss or cost for model: ",criterion(model1(X),Y))
```

```
total loss or cost for model:  tensor(0.0081, grad_fn=<MseLossBackward>)
total loss or cost for model:  tensor(0.0108, grad_fn=<MseLossBackward>)
```

Double-click here for the solution.

About the Authors:

Joseph Santarcangelo 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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0.1 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

##