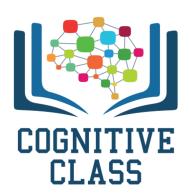


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# **Linear Regression Multiple Outputs**

## **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:

### In [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:

### In [2]:

```
# Set the random seed to 1.
torch.manual_seed(1)
```

### Out[2]:

<torch.\_C.Generator at 0x7f67884f8ed0>

Use this function for plotting:

```
# 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.min(), x2.min(), x2.min(), x3.max(), 0.05), np.arange(x3.min(), 0
\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:

```
In [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:

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

```
# Create the dataset object
data_set = Data2D()
```

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

Create a customized linear regression module:

```
In [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:

tensor([0.3026], requires\_grad=True)]

#### In [7]:

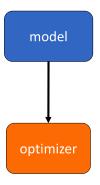
constructor.

```
# 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:
```

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



### In [8]:

```
# Create the optimizer

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

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

```
In [9]:
```

```
# Create the cost function
criterion = nn.MSELoss()
```

Create a data loader object. Set the batch\_size equal to 2:

```
In [10]:
```

```
# Create the data loader
train_loader = DataLoader(dataset=data_set, batch_size=2)
```

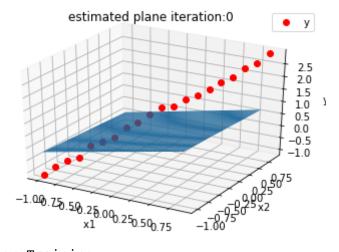
# **Train the Model via Mini-Batch Gradient Descent**

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:

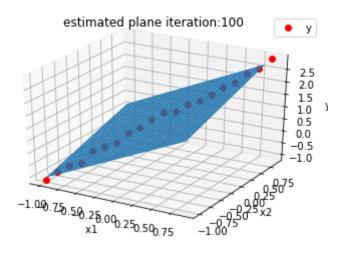
#### In [11]:

```
# 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:



### After Training:



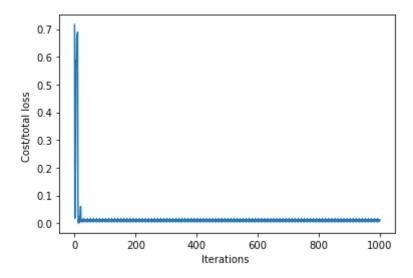
## In [12]:

```
# Plot out the Loss and iteration diagram

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

### Out[12]:

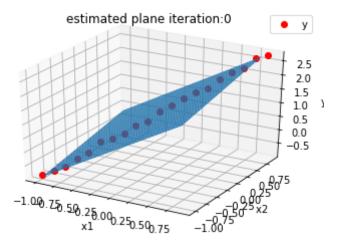
Text(0, 0.5, 'Cost/total loss ')



## **Practice**

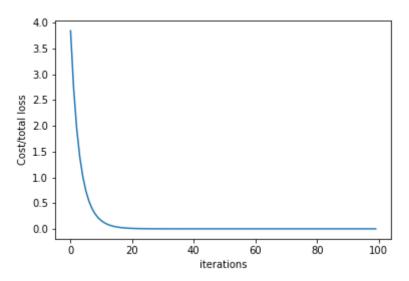
Create a new model1 . Train the model with a batch size 30 and learning rate 0.1, store the loss or total cost in a list LOSS1, and plot the results.

```
# 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.
data_set = Data2D()
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 = modell(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')
```



### Out[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:

#### In [16]:

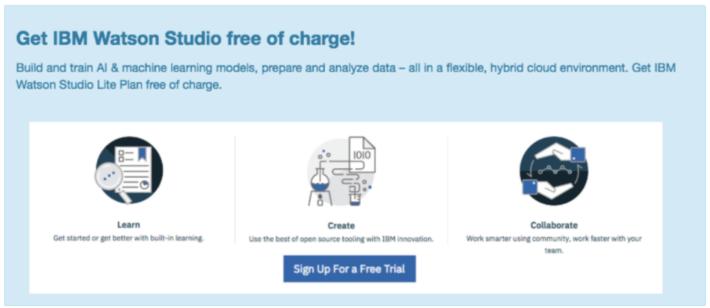
```
torch.manual_seed(2)

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(0.0092, grad_fn=<MseLossBackward >)
```

Double-click here for the solution.



(http://cocl.us/pytorch\_link\_bottom)

## **About the Authors:**

<u>Joseph Santarcangelo (https://www.linkedin.com/in/joseph-s-50398b136/)</u> 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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