

SMOKE TEST

Optimized PyTorch

Date Prepared: April 2020





Document Information

Project Name	EPIC Accelerator Deployment & Integration Services			
Project Owner		Document Version No	0.1	
Quality Review Method				
Prepared By	Prasad Adireddi	Preparation Date	April 2020	
Reviewed By		Review Date		



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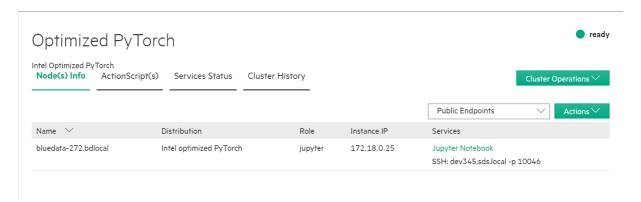
NO TABLE OF FIGURES ENTRIES FOUND.



1 LOGIN TO JUPYTERHUB WEB UI

Login to the JupyterHub Web UI, using the following steps:

1. From the Cluster page under Services, click on Jupyter Notebook



2. It will open-up a new tab with JupyterHub login page, login using your credentials







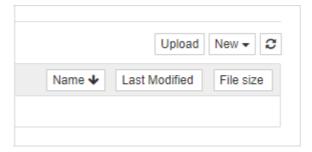
2 CREATE NOTEBOOK

To create a new notebook, in JupyterHub use the following steps:

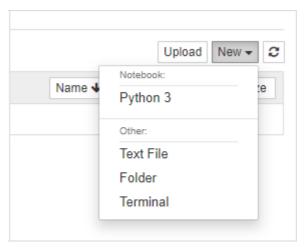
1. Once you log into JupyterHub, you will get the dashboard like below:



2. Click on New drop-down button, to create a new notebook



3. Select Python3, for upcoming tasks





3 REGRESSION WITH NEURAL NETWORKS

In this section, we are testing a Regression with Neural Networks example:

1. In Python3 notebook, add the following code in the code cell:

```
Import torch
from torch.autograd import Variable
import torch.nn.functional as F
import torch.utils.data as Data
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import imageio
torch.manual seed(1) # reproducible
x = torch.unsqueeze(torch.linspace(-1, 1, 100), dim=1) # x data (tensor),
shape=(100, 1)
y = x.pow(2) + 0.2*torch.rand(x.size())
                                                      # noisy y data
(tensor), shape=(100, 1)
# torch can only train on Variable, so convert them to Variable
x, y = Variable(x), Variable(y)
# view data
plt.figure(figsize=(10,4))
plt.scatter(x.data.numpy(), y.data.numpy(), color = "orange")
plt.title('Regression Analysis')
plt.xlabel('Independent varible')
plt.ylabel('Dependent varible')
plt.show()
# this is one way to define a network
class Net(torch.nn.Module):
   def init (self, n feature, n hidden, n output):
        super(Net, self).__init__()
        self.hidden = torch.nn.Linear(n_feature, n_hidden) # hidden layer
        self.predict = torch.nn.Linear(n hidden, n output)
                                                             # output layer
   def forward(self, x):
        x = F.relu(self.hidden(x))
                                       # activation function for hidden layer
        x = self.predict(x)
                                       # linear output
       return x
```

```
net = Net(n feature=1, n hidden=10, n output=1) # define the network
# print(net) # net architecture
optimizer = torch.optim.SGD(net.parameters(), lr=0.2)
loss_func = torch.nn.MSELoss() # this is for regression mean squared loss
my_images = []
fig, ax = plt.subplots(figsize=(12,7))
# train the network
for t in range(200):
   prediction = net(x) # input x and predict based on x
   loss = loss_func(prediction, y)  # must be (1. nn output, 2. target)
   optimizer.zero_grad() # clear gradients for next train
   loss.backward()
                         # backpropagation, compute gradients
   optimizer.step()
                         # apply gradients
   # plot and show learning process
   plt.cla()
   ax.set_title('Regression Analysis', fontsize=35)
   ax.set_xlabel('Independent variable', fontsize=24)
   ax.set_ylabel('Dependent variable', fontsize=24)
   ax.set_xlim(-1.05, 1.5)
   ax.set_ylim(-0.25, 1.25)
   ax.scatter(x.data.numpy(), y.data.numpy(), color = "orange")
   ax.plot(x.data.numpy(), prediction.data.numpy(), 'g-', lw=3)
   ax.text(1.0, 0.1, 'Step = %d' % t, fontdict={'size': 24, 'color': 'red'})
   ax.text(1.0, 0, 'Loss = %.4f' % loss.data.numpy(),
           fontdict={'size': 24, 'color': 'red'})
```



```
Jupyter Untitled Last Checkpoint: in 4 minutes (unsaved changes)
File Edit
             View
                      Insert Cell Kernel Widgets Help
In [ ]: import torch
               from torch.autograd import Variable
               import torch.nn.functional as F
               import torch.utils.data as Data
               import matplotlib.pyplot as plt
               %matplotlib inline
               import numpy as np
               torch.manual_seed(1) # reproducible
               x = torch.unsqueeze(torch.linspace(-1, 1, 100), dim=1) # x data (tensor), shape=(100, 1)
               y = x.pow(2) + 0.2*torch.rand(x.size())
                                                                           # noisy y data (tensor), shape=(100, 1)
               # torch can only train on Variable, so convert them to Variable
               x, y = Variable(x), Variable(y)
               # view data
               plt.figure(figsize=(10,4))
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               # this is one way to define a network
               class Net(torch.nn.Module):
                   def __init__(self, n_feature, n_hidden, n_output):
    super(Net, self).__init__()
    self.hidden = torch.nn.Linear(n_feature, n_hidden)  # hidden layer
    self.predict = torch.nn.Linear(n_hidden, n_output)  # output layer
```

```
def forward(self, x):
       x = F.relu(self.hidden(x))  # activation function for hidden layer
x = self.predict(x)  # linear output
        x = self.predict(x)
        return x
net = Net(n_feature=1, n_hidden=10, n_output=1)
                                                     # define the network
# print(net) # net architecture
optimizer = torch.optim.SGD(net.parameters(), lr=0.2)
loss_func = torch.nn.MSELoss() # this is for regression mean squared loss
my_images = []
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    # plot and show learning process
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    ax.set_xlim(-1.05, 1.5)
ax.set_ylim(-0.25, 1.25)
    ax.scatter(x.data.numpy(), y.data.numpy(), color = "orange")
```

2. Click on Run, to view the output

