A Complete Guide to Using TensorBoard with PyTorch

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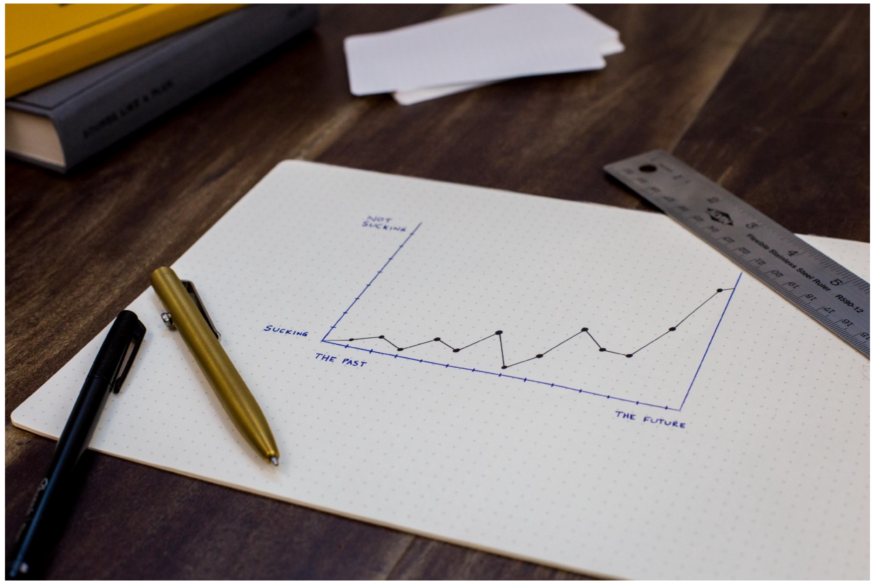


Photo by Isaac Smith on Unsplash

In this article, we will be integrating TensorBoard into our **PyTorch** project. **TensorBoard** is a suite of web applications for inspecting and understanding your model runs and graphs. TensorBoard currently supports five visualizations: **scalars, images, audio, histograms, and graphs**. In this guide, we will be covering all five except audio and also learn how to use TensorBoard for efficient hyperparameter analysis and tuning.

Installation Guide:

```
import torch
print(torch.__version__)
```

2. There are two package managers to install TensordBoard — **pip or Anaconda**. Depending on your python version use any of the following:

Pip installation command:

```
pip install tensorboard
```

Anaconda Installation Command:

```
conda install -c conda-forge tensorboard
```

Note: Having **TensorFlow** installed is not a prerequisite to running TensorBoard, although it is a product of the TensorFlow ecosystem, TensorBoard by itself can be used with PyTorch.

Introduction:

In this guide, we will be using the **FashionMNIST** dataset (60,000 clothing images and 10 class labels for different clothing types) which is a popular dataset inbuilt in the **torch vision** library. It consists of images of clothes, shoes, accessories, etc. along with an integer label corresponding to each category. We will create a simple CNN classifier and then draw inferences from it. Nonetheless, this guide will help you extend the power of TensorBoard to any project in PyTorch that you might be working on including ones that are created using Custom Datasets.

Note that in this guide we will not go into details of implementing the **CNN** model and setting up the training loops. Instead, the focus of the article will be on the bookkeeping aspect of Deep Learning projects to get visuals of the inner workings of the models(weights and biases) and the evaluation metrics(**loss, accuracy, num_correct_predictions**) along with hyperparameter tuning. If you are new to the PyTorch framework take a look at my other article on Implementing CNN in PyTorch(**working with datasets, moving data to GPU, creating models and training loops**) before moving forward.

Importing Libraries and Helper Functions:

```
import torch.optim as opt
torch.set_printoptions(linewidth=120)
import torch.nn.functional as F
import torchvision
import torchvision.transforms as transforms
from torch.utils.tensorboard import SummaryWriter
```

The last command is the one which enables us to import the Tensorboard class. We will be creating instances of **"SummaryWriter"** and then add our model's evaluation features like loss, the number of correct predictions, accuracy, etc. to it. One of the novel features of TensorBoard is that we simply have to feed our output tensors to it and it displays the plot of all those metrics, in this way TensorBoard can take care of all the plotting for us.

```
def get_num_correct(preds, labels):
    return preds.argmax(dim=1).eq(labels).sum().item()
```

This line of code helps us to get the number of correct labels after training of the model and applying the trained model to the test set. **"argmax "** gets the index corresponding to the highest value in a tensor. It's taken across the dim=1 because dim=0 corresponds to the batch of images.**"eq"** compares the predicted labels to the True labels in the batch and returns 1 if matched and 0 if unmatched. Finally, we take the **sum** of the 1's to get total number of correct predictions. After performing operations on tensors the output is also returned as a tensor. **"item"** converts the one dimensional tensor of correct_predictions to a floating point value so that it can be appended to a list(total_correct) for plotting in TensorBoard(Tensors if appended to a list cannot be plotted in TensorBoard, hence we need to convert them to floating point values, append them to a list and then pass this list to TensorBoard for plotting).

CNN Model:

We create a simple CNN model by passing the images through two Convolution layers followed by a set of fully connected layers. Finally we will use a **Softmax** Layer at the end to predict the class labels.

```
class CNN(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=6,
kernel_size=5)
        self.conv2 = nn.Conv2d(in_channels=6, out_channels=12,
kernel_size=5)

        self.fc1 = nn.Linear(in_features=12*4*4, out_features=120)
```

```
    def forward(self, x):
        x = F.relu(self.conv1(x))
        x = F.max_pool2d(x, kernel_size = 2, stride = 2)
        x = F.relu(self.conv2(x))
        x = F.max_pool2d(x, kernel_size = 2, stride = 2)
        x = torch.flatten(x,start_dim = 1)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.out(x)

        return x
```

Importing data and creating the train loader:

```
train_set = torchvision.datasets.FashionMNIST(root="./data",
train = True,
 download=True,
transform=transforms.ToTensor())

train_loader = torch.utils.data.DataLoader(train_set,batch_size =
100, shuffle = True)
```

Displaying Images And Graphs with TensorBoard:

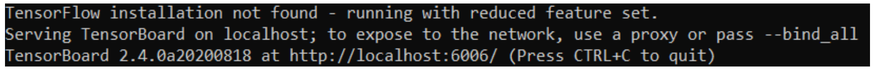
```
tb = SummaryWriter()
model = CNN()
images, labels = next(iter(train_loader))
grid = torchvision.utils.make_grid(images)
tb.add_image("images", grid)
tb.add_graph(model, images)
tb.close()
```

We create an instance 'tb' of the **SummaryWriter** and add images to it by using the **tb.add_image** function. It takes two main arguments, one for the **heading** of the image and another for the **tensor of images**. In this case, we have created a batch of **100** images and passed them to a **grid** which is then added to the tb instance. To the **tb.add_graph** function, we pass our CNN model and a single batch of input images to generate a graph of the model. After running the code a **"runs"** folder will be created in the project directory. All runs going ahead will be sorted in the folder by **date**. This way you have an efficient log of all runs which can be viewed and compared in TensorBoard.

Now use the command line(I use Anaconda Prompt) to redirect into your project directory where the runs folder is present and run the following command:

```
tensorboard --logdir runs
```

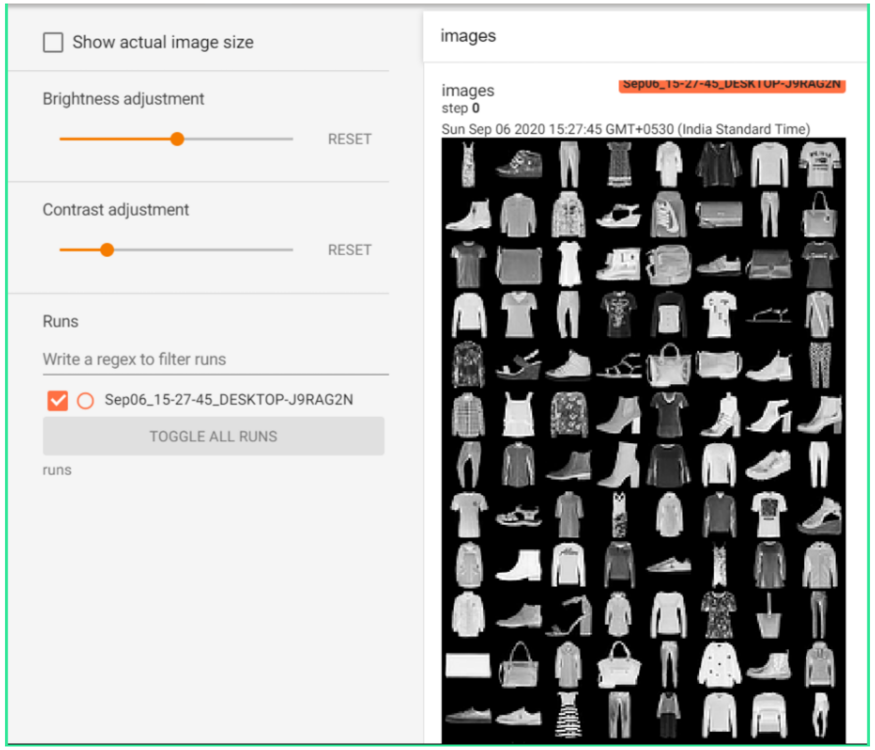
It will then server TensorBoard on the localhost, the link for which will be displayed in the terminal:



```
TensorFlow installation not found - running with reduced feature set.
Serving TensorBoard on localhost; to expose to the network, use a proxy or pass --bind_all
TensorBoard 2.4.0a20200818 at http://localhost:6006/ (Press CTRL+C to quit)
```

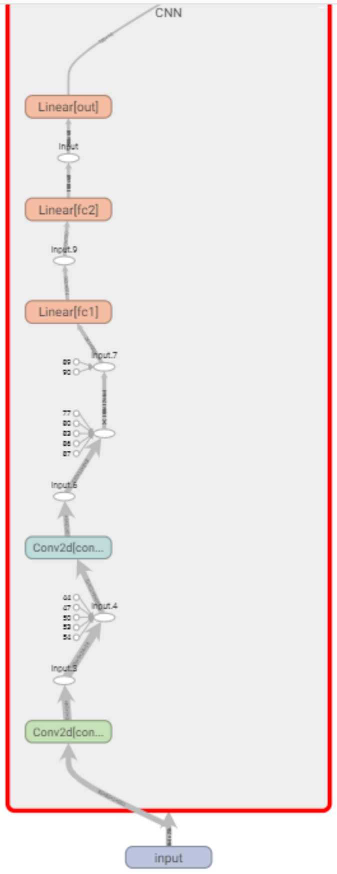
"TensorFlow not installed" warning can be ignored

After opening the link we will be able to see all our runs. The Images are visible under the **"Images"** tab. We can use regex to filter through the runs and tick those that we are interested in visualizing.


Show actual image size
Brightness adjustment
RESET
Contrast adjustment
RESET
Runs
Write a regex to filter runs
Sep06_15-27-45_DESKTOP-J9RAG2N
TOGGLE ALL RUNS
runs
images
images
step 0
Sep06_15-27-45_DESKTOP-J9RAG2N
Sun Sep 06 2020 15:27:45 GMT+0530 (India Standard Time)

Grid Plot of Images in TensorBoard

Under the **"Graphs"** tab you will find the graph for the model. It gives details of the entire pipeline of how the dimensions of the batch of images changes after every convolution and linear layer operations. Just double click on any of the icons to grab more information from the graph. It also gives the dimensions of all the weight and bias matrices by double-clicking on any of the Conv2d or Linear layers.



Graph Generated Using TensorBoard For CNN Model

Training Loop to visualize Evaluation:

```
device = ("cuda" if torch.cuda.is_available() else cpu)
model = CNN().to(device)
train_loader = torch.utils.data.DataLoader(train_set,batch_size =
100, shuffle = True)
optimizer = opt.Adam(model.parameters(), lr= 0.01)
criterion = torch.nn.CrossEntropyLoss()

tb = SummaryWriter()

for epoch in range(10):

    total_loss = 0
    total_correct = 0

    for images, labels in train_loader:
        loss = criterion(preds, labels)
        total_loss+= loss.item()
        total_correct+= get_num_correct(preds, labels)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    tb.add_scalar("Loss", total_loss, epoch)
    tb.add_scalar("Correct", total_correct, epoch)
    tb.add_scalar("Accuracy", total_correct/ len(train_set), epoch)

    tb.add_histogram("conv1.bias", model.conv1.bias, epoch)
    tb.add_histogram("conv1.weight", model.conv1.weight, epoch)
    tb.add_histogram("conv2.bias", model.conv2.bias, epoch)
    tb.add_histogram("conv2.weight", model.conv2.weight, epoch)

    print("epoch:", epoch, "total_correct:", total_correct,
"loss:",total_loss)

tb.close()
```

Alternatively, we can also use a for loop to iterate through all the model parameters including the **fc** and **softmax** layers:

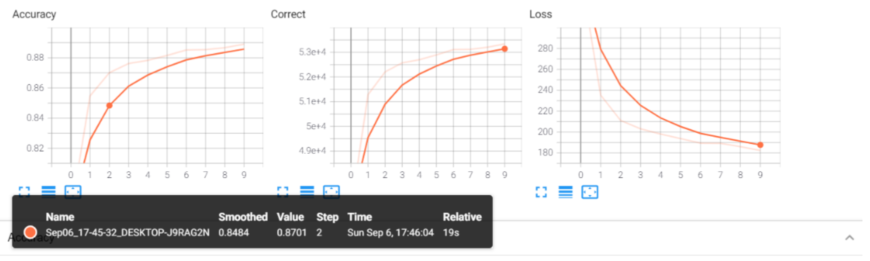
```
for name, weight in model.named_parameters():
    tb.add_histogram(name,weight, epoch)
    tb.add_histogram(f'{name}.grad',weight.grad, epoch)
```

We run the loop for **10 epochs** and at the end of the training loop, we pass augments to the tb variable we created. We have created **total_loss** and **total_correct** variable to keep track of the **loss** and **correct predictions** at the end of each epoch. Note that every "tb" takes three arguments, one for the string which will be the **heading** of the line chart/histogram, then the tensors containing the **values** to be plotted, and finally a **global step**. Since we are doing an epoch wise analysis, we have set it to epoch. Alternatively, it can also be set to the **batch id** by shifting the tb commands inside the for loop for a batch by using "enumerate" and set the step to **batch_id** as follows:

```
for batch_id, (images, labels) in enumerate(train_loader):
......
    tb.add_scalar("Loss", total_loss, batch_id)
```

As seen below running the command mentioned earlier to run TensorBoard will display the line graph and the histograms for the **loss, num_correct_predictions**, and **accuracy.**

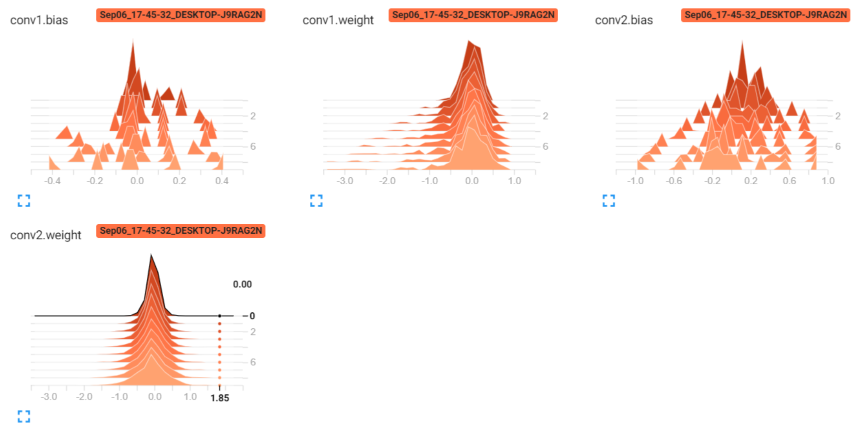
metric(Accuracy/Correct/Loss) for that particular **epoch**.



Name	Smoothed	Value	Step	Time	Relative
Sep06_17-45-32_DESKTOP-J9RAG2N	0.8484	0.8701	2	Sun Sep 6, 17:46:04	19s

Line Plot Generated By TensorBoard

Histograms:



Histograms generated by TensorBoard

Hyperparameter Tuning:

Firstly we need to change the **batch_size, learning_rate, shuffle** to dynamic variables. We do that by creating a dictionary as follows:

```
from itertools import product
parameters = dict(
    lr = [0.01, 0.001],
    batch_size = [32,64,128],
    shuffle = [True, False]
)

param_values = [v for v in parameters.values()]
print(param_values)
```

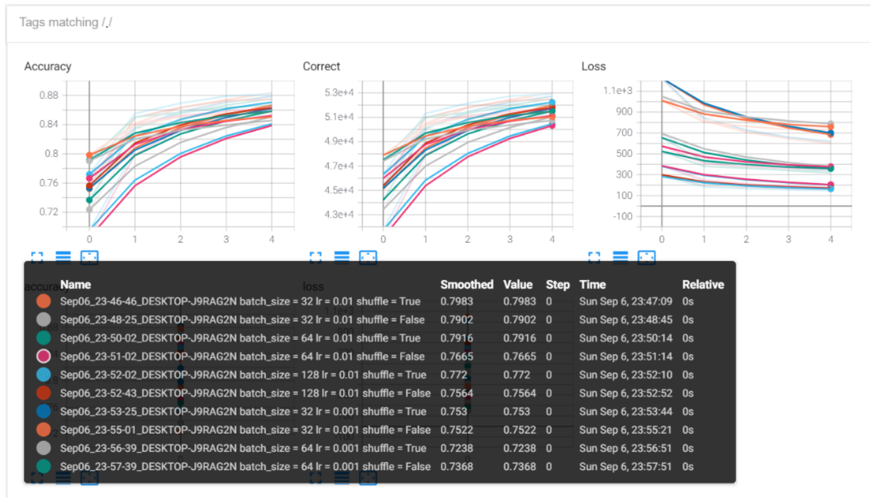
This will allow us to get tuples of three, corresponding to all combinations of the **three hyperparameters** and then call a for loop on them before running each epoch loop. In this way, we will be able to have **12** runs(2(learning_rates)*3(batch_sizes)*2(shuffles)) of all the different hyperparameter combinations and compare them on TensorBoard. We will modify the training loop as follows:

Modified Training Loop:

```
for run_id, (lr,batch_size, shuffle) in
enumerate(product(*param_values)):
    print("run id:", run_id + 1)
    model = CNN().to(device)
    train_loader = torch.utils.data.DataLoader(train_set,batch_size =
batch_size, shuffle = shuffle)
    optimizer = opt.Adam(model.parameters(), lr= lr)
    criterion = torch.nn.CrossEntropyLoss()
    comment = f' batch_size = {batch_size} lr = {lr} shuffle =
{shuffle}'
    tb = SummaryWriter(comment=comment)
    for epoch in range(5):
        total_loss = 0
        total_correct = 0
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device)
            preds = model(images)

            loss = criterion(preds, labels)
            total_loss+= loss.item()
            total_correct+= get_num_correct(preds, labels)

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

        tb.add_scalar("Loss", total_loss, epoch)
        tb.add_scalar("Correct", total_correct, epoch)
        tb.add_scalar("Accuracy", total_correct/ len(train_set),
epoch)

        print("batch_size:",batch_size, "lr:",lr,"shuffle:",shuffle)
        print("epoch:", epoch, "total_correct:", total_correct,
"loss:",total_loss)

print("__________________________________________________________")

    tb.add_hparams(
            {"lr": lr, "bsize": batch_size, "shuffle":shuffle},
            {
                "accuracy": total_correct/ len(train_set),
                "loss": total_loss,
            },
        )

tb.close()
```

combinations of hyperparameters and at each run, we have to re-instantiate the **model** as well as reload the **batches** of the dataset. **"comment"** allows us to create different folders inside the runs folder depending on specified hyperparameters. We pass this comment as an argument to the **SummaryWriter**. Note that we will be able to see all the runs together and draw comparative analysis across all hyperparameters in TensorBoard. **tb.add_scalar** is the same as earlier just that we have it displayed for all runs this time. **tb.add_hparams** allows us to add **hyperparameters** inside as arguments to keep track of the training progress. It takes two dictionaries as inputs, one for the hyperparameters and another for the evaluation metrics to be analyzed. The results are mapped across all these hyperparameters. It will be clear from the graph mapping diagram at the bottom.

Combined Plots:

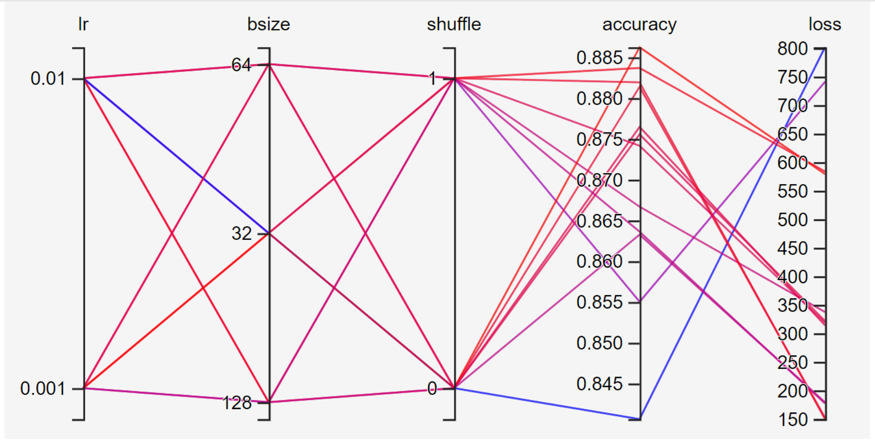


	Name	Smoothed	Value	Step	Time	Relative
●	Sep06_23-46-46_DESKTOP-J9RAG2N batch_size = 32 lr = 0.01 shuffle = True	0.7983	0.7983	0	Sun Sep 6, 23:47:09	0s
●	Sep06_23-48-25_DESKTOP-J9RAG2N batch_size = 32 lr = 0.01 shuffle = False	0.7902	0.7902	0	Sun Sep 6, 23:48:45	0s
●	Sep06_23-50-02_DESKTOP-J9RAG2N batch_size = 64 lr = 0.01 shuffle = True	0.7916	0.7916	0	Sun Sep 6, 23:50:14	0s
●	Sep06_23-51-02_DESKTOP-J9RAG2N batch_size = 64 lr = 0.01 shuffle = False	0.7665	0.7665	0	Sun Sep 6, 23:51:14	0s
●	Sep06_23-52-02_DESKTOP-J9RAG2N batch_size = 128 lr = 0.01 shuffle = True	0.772	0.772	0	Sun Sep 6, 23:52:10	0s
●	Sep06_23-52-43_DESKTOP-J9RAG2N batch_size = 128 lr = 0.01 shuffle = False	0.7564	0.7564	0	Sun Sep 6, 23:52:52	0s
●	Sep06_23-53-25_DESKTOP-J9RAG2N batch_size = 32 lr = 0.001 shuffle = True	0.753	0.753	0	Sun Sep 6, 23:53:44	0s
●	Sep06_23-55-01_DESKTOP-J9RAG2N batch_size = 32 lr = 0.001 shuffle = False	0.7522	0.7522	0	Sun Sep 6, 23:55:21	0s
●	Sep06_23-56-39_DESKTOP-J9RAG2N batch_size = 64 lr = 0.001 shuffle = True	0.7238	0.7238	0	Sun Sep 6, 23:56:51	0s
●	Sep06_23-57-39_DESKTOP-J9RAG2N batch_size = 64 lr = 0.001 shuffle = False	0.7368	0.7368	0	Sun Sep 6, 23:57:51	0s

Plots of 12 Runs for combined Visualization

As seen above we can filter any runs that we want or have all of them plotted on the same graph. In this way, we can draw a comparative study of the performance of the model across several hyperparameters and tune the model to the ones which give us the best performance. All details like batch size, learning rate, shuffle, and corresponding accuracy values are visible in the pop-up box.

It is evident from the results that a batch size of 32, shuffle set to True, and a learning rate of 0.01 yields the best result. For demonstration purposes it's run for only 5 epochs. Increasing the number of epochs can very well affect the result, hence it's important to train and test with several values of epochs.



Hyperparameter Graph generated by TensorBoard

This graph has the combined logs of all 12 runs so that you can use the highest accuracy and lowest loss value and trace it back to the corresponding batch size and learning rate.

From the Hyperparameter Graph it is very clear that setting shuffle to False(0) tends to yield very poor results. Hence setting shuffle to always True is ideal for training as it adds randomization.

Conclusion:

Feel free to play around with TensorBoard, try to add more hyperparameters to the graph to gain as much information on the pattern of loss convergence and performance of the model given various hyperparameters. We could also potentially add a set of optimizers other than Adam and draw a comparative study. In cases of Sequence models like LSTMs, GRUs one can add the time-steps as well to the graph and draw insightful conclusions. Hope this article gave you a thorough insight into using TensorBoard with PyTorch.

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Link to code: https://github.com/ajinkya98/TensorBoard_PyTorch

Deep Learning Tensorboard Visualization Hyperparameter Tuning Pytorch