# Tutorial: Training a Classifier

Friday, July 17, 2020 4:32 PM

Data

For this tutorial

### Steps for Training an image classifier

- 1. Loading and normalizing CIFAR10
- 2. Define a Convolutional Neural Network
- 3. Define a Loss Function and Optimizer
- 4. Train the Network
- 5. Test the network on the test data

### Training on GPU

Training on multiple GPUs

### Data

You can use standard <u>python</u> packages that load data into a **numpy array** 

- Then you can **convert** this array into a torch.\*Tensor
- Python Packages:
- For images => can use Pillow and OpenCV
- For audio => can use scipy and librosa
- For text => can use:
  - either raw Python or Cython based loading
  - o or *NLTK* and *SpaCy*

### For vision, use the package => torchvision

- It has data loaders for common datasets such as *Imagenet*, *CIFAR10*, *MNIST*, etc. and data transformers for images, visualizations
  - o torchvision.datasets and torch.utils.data.DataLoader

----- ------ ------ ------ ------

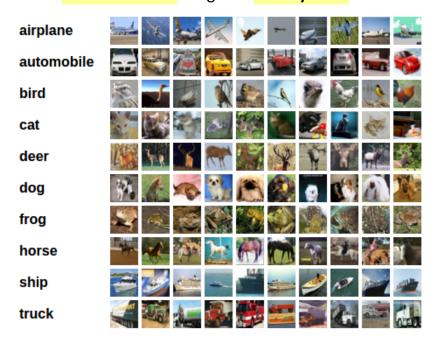
## For this tutorial

#### **Tutorial Link:**

- <a href="https://pytorch.org/tutorials/beginner/blitz/cifar10\_tutorial.html#sphx-glr-beginner-blitz-cifar10-tutorial-py">https://pytorch.org/tutorials/beginner/blitz/cifar10\_tutorial.html#sphx-glr-beginner-blitz-cifar10-tutorial-py</a>

#### Uses the **CIFAR10** dataset:

- It has the classes: 'airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck'.
- The *images* in *CIFAR-10* are of size 3x32x32
  - o <u>Example</u>:
    - 3-channel color images of 32x32 pixels in size.



# Steps for Training an image classifier

### We will do the following steps in order:

- Load and normalizing the CIFAR10 training and test datasets using torchvision
- 2. **Define** a **Convolutional Neural Network** (**CNN**)
- 3. **Define** a *loss* function

- 4. Train the network on the training data
- 5. Test the network on the test data

----- ----- ----- ----- ----- -----

# 1. Loading and normalizing CIFAR10

The **output** of *torchvision datasets* are **PILImage** images of **range** [0, 1].

Need to transform them to Tensors of normalized range [-1, 1].

#### **STEPS:**

- a. Create the transform function.
  - This creates tensors and normalizes the data.
- b. **Get** the **training** set **data** from torchvision.datasets.
  - Set argument train=True
  - Set transform function to transform argument
- c. **Pass** the **training set** to the **DataLoader** using torch.utils.data.DataLoader.
  - This adds the batch size and num\_workers, etc.
- d. **Repeat** *step b and c* for **test set**.
- e. **Create** the **list of classes** for the dataset as a *python tuple*.

# 2. Define a Convolutional Neural Network

- <u>Example:</u>
  - Takes 3 channels images

```
import torch.nn as nn
import torch.nn.functional as F

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
```

```
self.fc2 = nn.Linear(120, 84)
self.fc3 = nn.Linear(84, 10)

def forward(self, x):
    x = self.pool(F.relu(self.conv1(x)))
    x = self.pool(F.relu(self.conv2(x)))
    x = x.view(-1, 16 * 5 * 5)
    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = self.fc3(x)
    return x
```

# 3. Define a Loss Function and Optimizer

### **USE:**

- Loss function => Classification Cross-Entropy loss
- Optimizer => SGD with momentum
  - Updates the weights
  - Need to set a learning rate (example: lr=0.001)
  - Need to set momentum (example: momentum=0.9)
    - 323

# 4. Train the Network

Model loops over the data iterator, and feeds the inputs to the network and optimize.

- Each loop is called an epoch
- GOAL is to lower the loss.
  - By mini batches. (<u>example</u>: loss for every 2000 samples)
- Then save the trained model.
  - More details on saving PyTorch models:
    - https://pytorch.org/docs/stable/notes/serialization.html
  - Example:

```
PATH = './cifar_net.pth'
torch.save(net.state_dict(), PATH)
```

----- ----- ----- ----- ----- -----

### 5. Test the network on the test data

Need to **check if the network** has **learnt** anything at all.

- A. By predicting the class label that the neural network outputs,
- B. and by checking it against the ground-truth (test dataset)
- If the prediction is correct, we **add the sample to the list of correct predictions**.

### STEPS:

- 1. Check and view a few images and corresponding labels from the test dataset.
- 2. Load back saved model.
- Note:
  - Saving and re-loading the model is only necessary is its going be open elsewhere:

```
net = Net()
net.load state dict(torch.load(PATH))
```

- 3. **Run testing images** through model.
- 4. **Get** the **index** of the **highest** *energy*:
  - The outputs are energies for the 10 classes.
  - The higher the energy for a class, the more the network thinks that the image is of the particular class.
- 5. **Look at how** the network performs on the **whole dataset** by checking the *accuracy*.
- 6. **Check** the performance (*accurancy*) of every class.

-----

# **Training on GPU**

Just like how you transfer a Tensor onto the GPU, you transfer the neural net onto the GPU.

- First **define our device** as the *first visible cuda device* **if we have CUDA available**:

device = torch.device("cuda:0" if torch.cuda.is\_available() else "cpu")
# Assuming that we are on a CUDA machine, this should print a CUDA device:
print(device)

- The rest of this section assumes that device is a CUDA device.
- Then these **methods** will recursively go **over all modules** and **convert** their **parameters** and **buffers** to CUDA tensors:

net.to(device)

- You will have to send the inputs and targets at every step to the GPU too:

inputs, labels = data[0].to(device), data[1].to(device)

- To increase the speedup on the model:
  - Try increasing the width of the network.
    - By changing argument 2 of the first nn.Conv2d,
    - and argument 1 of the second nn.Conv2d,
    - they need to be the same number!

**Training on multiple GPUs** 

For **more** even more speedup **using all of your GPUs**, please check out:

doc: data parallel tutorial