Chem 277B Spring 2024 Tutorial 4

Outline

- Installation & Introduction
- PyTorch Tensors and auto grads
- Building up neural network
- Optimizers

Installation & Introduction

- · Official Web site
- Installation

PyTorch is an open-source machine learning library widely used for deep learning applications. Developed by Facebook's AI Research lab (FAIR), it provides a flexible and intuitive framework for building and training neural networks. PyTorch is known for its ease of use, computational efficiency, and dynamic computational graph, making it a favorite among researchers and developers for both academic and industrial applications.

Key Features of PyTorch

- **Dynamic Computational Graph**: PyTorch uses a dynamic computation graph (also known as a define-by-run paradigm), meaning the graph is built on the fly as operations are performed. This makes it more intuitive and flexible, allowing for easy changes and debugging.
- **Eager Execution**: Operations in PyTorch are executed eagerly, meaning they are computed immediately without waiting for a compiled graph of operations. This allows for more interactive and dynamic development.
- **Pythonic Nature**: PyTorch is deeply integrated with Python, making it easy to use and familiar to those with Python experience. It leverages Python's features and libraries, allowing for seamless integration with the Python data science stack (e.g., NumPy, SciPy, Pandas).
- **Extensive Library Support**: PyTorch provides a wide range of libraries and tools for various tasks in deep learning, including computer vision (TorchVision), natural

2/25/24, 2:46 PM Sp24_Tutorial4_Hu

language processing (TorchText), and more. This ecosystem supports a vast array of algorithms, pre-trained models, and datasets to facilitate development and experimentation.

- **GPU Acceleration**: It supports CUDA, enabling it to leverage Nvidia GPUs for accelerated tensor computations. This makes training deep neural networks significantly faster compared to CPU-based training.
- Community and Support: PyTorch has a large and active community, contributing
 to a growing ecosystem of tools, libraries, and resources. It also enjoys robust
 support from major tech companies, ensuring continuous development and
 improvement.

Tensors

Tensors are data structure in PyTorch to manipulate data. It is very similar to numpy.ndarray, but with support for automatic differentiation and hardware acceleration (Nvidia GPU, Apple silicon)

```
In [ ]: import torch
In []: a = torch.tensor([[1, 2], [3, 4]], dtype=torch.float)
        print(type(a))
        а
       <class 'torch.Tensor'>
Out[]: tensor([[1., 2.],
                 [3., 4.]])
        Bridge with NumPy
In [ ]: import numpy as np
        arr = np.array([[1., 2.], [3., 4.]])
        arr_torch = torch.from_numpy(arr)
        arr torch
Out[]: tensor([[1., 2.],
                 [3., 4.]], dtype=torch.float64)
In [ ]: # detach() stops a tensor from tracking history in automatic differentiation
        arr_np = arr_torch.detach().numpy()
        Generate random numbers
In [ ]: # normal distribution
        torch.randn(4, 4)
```

2/25/24, 2:46 PM Sp24_Tutorial4_Hu

```
Out[]: tensor([[ 1.5061, 1.5521, -1.0470, 0.9524],
                 [0.1724, -0.8170, -0.4362, -1.7570],
                 [-0.9271, 0.5948, 0.5426, 0.6211],
                 [ 2.5317, -0.0726, 1.2755, -0.9024]])
In [ ]: # uniform distribution
        torch.rand(4, 4)
Out[]: tensor([[0.4538, 0.1356, 0.3053, 0.3966],
                 [0.7942, 0.2810, 0.5078, 0.0802],
                 [0.2853, 0.4896, 0.2016, 0.0923],
                 [0.2763, 0.8430, 0.4971, 0.7215]])
        Others
In []: # arange
        torch.arange(5)
Out[]: tensor([0, 1, 2, 3, 4])
In [ ]: # linspace
        torch.linspace(-4, 4, 10)
Out[]: tensor([-4.0000, -3.1111, -2.2222, -1.3333, -0.4444, 0.4444, 1.3333, 2.2
        222,
                 3.1111, 4.0000])
In []: # ones & zeros
        torch.ones(6)
Out[]: tensor([1., 1., 1., 1., 1., 1.])
In [ ]: torch.zeros(6)
Out[]: tensor([0., 0., 0., 0., 0., 0.])
        Attributes of tensors
In [ ]: tensor = torch.rand(3,4)
        # shape, dtype, device
        print(tensor.shape)
        print(tensor.dtype)
        print(tensor.device)
       torch.Size([3, 4])
       torch.float32
       cpu
        Single-element tensor can use .item() method to get a Python float object
In [ ]: a = torch.tensor([4.])
        print(type(a.item()))
```

```
<class 'float'>
```

PyTorch can work on different hardwares

```
In []: device = (
    "cuda"
    if torch.cuda.is_available()
    else "mps"
    if torch.backends.mps.is_available()
    else "cpu"
)

# send the tensor to device
tensor_device = tensor.to(device)

# send the tensor back to cpu
tensor_cpu = tensor.cpu()
```

Autograd

Build Neural Network with PyTorch

```
In [ ]: import torch.nn as nn
```

Activation Functions

```
In []: tensor = 5 * (torch.rand(3, 2) * 2 - 1)
    print(tensor)

# ReLU
    relu = nn.ReLU()
    print("ReLU:", relu(tensor))

# Tanh
    tanh = nn.Tanh()
    print("Tanh:", tanh(tensor))

# Sigmoid
    sigmoid = nn.Sigmoid()
    print("Sigmoid:", sigmoid(tensor))

# Softmax
```

```
softmax = nn.Softmax(dim=1)
 print('Softmax:', softmax(tensor))
tensor([[-4.4536, -3.6808],
        [ 4.2285, 0.9234],
        [-2.8912, 0.2049]
ReLU: tensor([[0.0000, 0.0000],
        [4.2285, 0.9234],
        [0.0000, 0.2049]])
Tanh: tensor([[-0.9997, -0.9987],
        [ 0.9996, 0.7275],
        [-0.9939, 0.2021]
Sigmoid: tensor([[0.0115, 0.0246],
        [0.9856, 0.7157],
        [0.0526, 0.5510]])
Softmax: tensor([[0.3159, 0.6841],
        [0.9646, 0.0354],
        [0.0433, 0.9567]])
```

Loss functions

```
In []: # mse
    mse = nn.MSELoss()
    a, b = torch.rand(5, 2), torch.rand(5, 2)
    print(mse(a, b))

# cross-entropy
    cross_entropy = nn.CrossEntropyLoss()
    a = torch.rand(10, 2)
    b = torch.randint(2, (10,))
    print(cross_entropy(a, b))

tensor(0.0510)
tensor(0.8622)
```

Neural Network

```
model = Net()
        model
Out[]: Net(
          (layers): Sequential(
            (0): Linear(in features=13, out features=3, bias=True)
            (2): Linear(in features=3, out features=3, bias=True)
            (3): Softmax(dim=1)
          )
        )
In []: for name, param in model.named parameters():
            print(f"Layer: {name} | Size: {param.size()} | Values : {param.data} \n"
       Layer: layers.0.weight | Size: torch.Size([3, 13]) | Values : tensor([[ 1.49
       70e-01, 1.9379e-01, -9.0148e-03, -1.7468e-01, -7.0514e-03,
                 2.5876e-01, -1.6496e-01, 3.2200e-02, 2.7713e-01, -7.9044e-02,
                 2.1192e-01, -1.1687e-01, -9.4473e-02],
               [-1.1988e-01, 2.6266e-01, -2.7326e-01, 3.7626e-02, 6.1010e-03,
                 1.1791e-01, 1.8273e-01, 2.6510e-02, 2.3690e-01, 1.5921e-01,
                -1.0735e-01, 1.0431e-01, -1.3671e-01],
               [-8.7143e-02, 6.0707e-02, 2.5314e-01, -1.8690e-04, -1.8122e-01,
               -2.6005e-01, 8.0267e-03, 9.1560e-02, 3.6584e-02, -1.1889e-01,
                 2.4024e-01, -7.0544e-03, -6.0306e-02]])
       Layer: layers.0.bias | Size: torch.Size([3]) | Values : tensor([0.1372, 0.12
       76, 0.1171])
       Layer: layers.2.weight | Size: torch.Size([3, 3]) | Values : tensor([[ 0.297
       3, 0.2046, 0.2851],
               [-0.1045, -0.3047, -0.0849],
               [ 0.4997, 0.4337, 0.5680]])
       Layer: layers.2.bias | Size: torch.Size([3]) | Values : tensor([0.0160, 0.36
       79, 0.2519])
In []: X = torch.rand(3, 13)
        y = model(X)
        print(y)
       tensor([[0.2821, 0.2517, 0.4662],
               [0.2887, 0.2284, 0.4829],
               [0.2880, 0.2503, 0.4617]], grad_fn=<SoftmaxBackward0>)
```

Optimization

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

df = pd.read_csv("wines.csv")
df.head()
```

2/25/24, 2:46 PM Sp24_Tutorial4_Hu

```
Out[ ]:
             Alcohol Malic
                                                                                    Proantho-
                             Ash Alkalinity Mg Phenols Flavanoids Phenols.1
                  %
                       Acid
                                                                                       cyanins in
               14.23
                                                                                          2.29
         0
                        1.71 2.43
                                        15.6 127
                                                        2.8
                                                                   3.06
                                                                              0.28
          1
               13.24
                       2.59
                             2.87
                                        21.0 118
                                                        2.8
                                                                   2.69
                                                                              0.39
                                                                                          1.82
          2
               14.83
                       1.64
                             2.17
                                        14.0
                                               97
                                                        2.8
                                                                   2.98
                                                                              0.29
                                                                                          1.98
          3
               14.12
                       1.48 2.32
                                        16.8
                                               95
                                                        2.2
                                                                   2.43
                                                                              0.26
                                                                                           1.57
          4
                       1.73 2.41
                                               89
                                                        2.6
                                                                   2.76
                                                                               0.29
               13.75
                                        16.0
                                                                                           1.81
```

```
In [ ]: features = df.drop(['Start assignment', 'ranking'], axis=1).values
        X = StandardScaler().fit_transform(features)
        X = torch.tensor(X, dtype=torch.float32)
        y = torch.tensor(df['ranking'].values - 1)
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
        # define loss
        loss func = nn.CrossEntropyLoss()
        # define optimizer
        optimizer = torch.optim.Adam(model.parameters(), lr=1E-3)
        epochs = 50
        for _ in range(epochs):
            y pred = model(X train)
            loss = loss_func(y_pred, y_train)
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            with torch.no grad():
                test_loss = loss_func(model(X_test), y_test)
                print(test_loss.item())
```

- 1.1370505094528198
- 1.1359128952026367
- 1.1347821950912476
- 1.1336588859558105
- 1.1325392723083496
- 1.1313978433609009
- 1.1302647590637207
- 1.1291391849517822
- 1.1280276775360107
- 1.1269327402114868
- 1,1258574724197388
- 1.1247683763504028
- 1.123687744140625
- 1.1226146221160889
- 1.1215488910675049
- 1.120490550994873
- 1.119441032409668
- 1.1184029579162598
- 1.1173787117004395
- 1.1163653135299683
- 1.115361213684082
- 1.114367127418518
- 1.113383412361145
- 1.1123921871185303
- 1.111432433128357
- 1.1104927062988281
- 1.1095753908157349
- 1.108666181564331
- 1,1077618598937988
- 1,1068756580352783
- 1.1060177087783813
- 1.1051641702651978
- 1.1042935848236084
- 1.1034016609191895
- 1.102513313293457
- 1,1016294956207275
- 1.1007494926452637
- 1.09987211227417
- 1.0990054607391357
- 1.0981426239013672
- 1,0972955226898193
- 1.09645414352417
- 1.0956145524978638
- 1.0947521924972534
- 1.0938698053359985
- 1.0929876565933228
- 1,0921039581298828
- 1.0912169218063354
- 1.0903290510177612
- 1.0894485712051392