PyTorch Tutorial

08. Dataset and DataLoader

Revision: Manual data feed

```
xy = np.loadtxt( 'diabetes.csv.gz' , delimiter= ',' , dtype=np.float32)
x_data = torch.from_numpy(xy[:,:-1])
y_data = torch.from_numpy(xy[:, [-1]])

......

for epoch in range(100):
    # 1. Forward
    y_pred = model(x_data)
    loss = criterion(y_pred, y_data)
    print(epoch, loss.item())
    # 2. Backward
    optimizer.zero_grad()
    loss.backward()
    # 3. Update
    optimizer.step()
```

Use all of the data

Terminology: Epoch, Batch-Size, Iterations

使用mini-batch

批量随机梯度下降：他用了一些小样本来近似全部的，其本质就是竟然1个样本的近似不一定准，那就用更大的30个或50个样本来近似。将样本分成m个mini-batch，每个mini-batch包含n个样本；在每个mini-batch里计算每个样本的梯度，然后在这个mini-batch里求和取平均作为最终的梯度来更新参数；然后再用下一个mini-batch来计算梯度，如此循环下去直到m个mini-batch操作完就称为一个epoch结束。

```
# Training cycle
for epoch in range(training_epochs):
    # Loop over all batches
    for i in range(total_batch):
```

内层迭代batch

若有10000个样本，batch-size设置为1000，则iteration = 10。

Definition: Epoch

One forward pass and one backward pass of **all the training examples**.

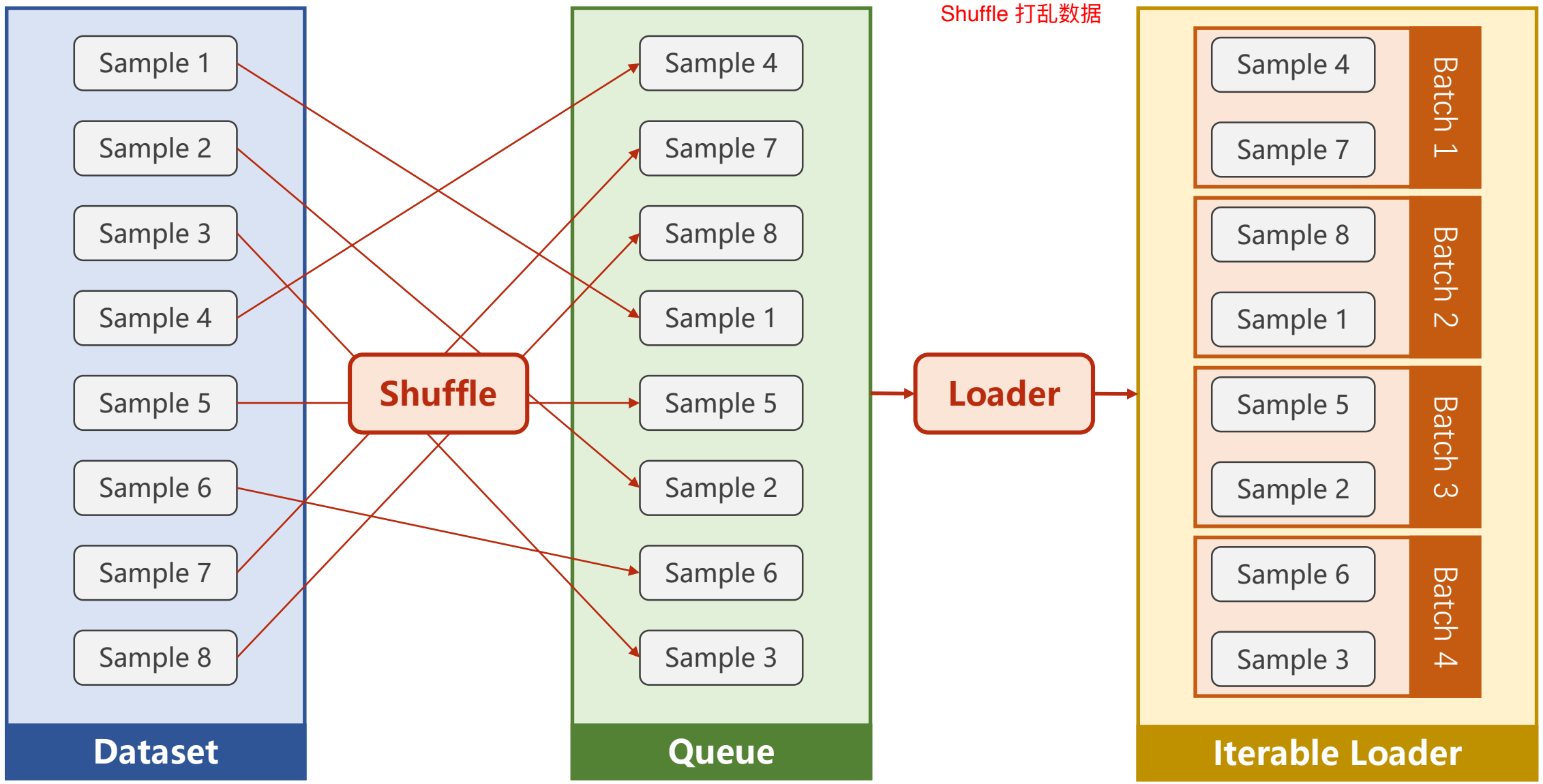
Definition: Batch-Size

The **number of training examples** in one forward backward pass.

Definition: Iteration

Number of passes, each pass using [**batch size**] number of examples.

DataLoader: batch_size=2, shuffle=True



How to define your Dataset

```
import torch
from torch.utils.data import Dataset
from torch.utils.data import DataLoader

class DiabetesDataset(Dataset):
    def __init__(self):
        pass

    def __getitem__(self, index):
        pass

    def __len__(self):
        pass

dataset = DiabetesDataset()
train_loader = DataLoader(dataset=dataset,
                          batch_size=32,
                          shuffle=True,
                          num_workers=2)
```

抽象类

具体类

Dataset is an **abstract** class. We can define our class inherited from this class.

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```

继承抽象类Dataset，需要实现__init__, __getitem__, __len__三个函数

```
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```

DataLoader is a class to help us loading data in PyTorch.

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train_loader = DataLoader(dataset=dataset,
                          batch_size=32,
                          shuffle=True,
                          num_workers=2)
```

DiabetesDataset is inherited from abstract class **Dataset**.

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train_loader = DataLoader(dataset=dataset,
                          batch_size=32,
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                          num_workers=2)
```

The expression, **dataset[index]**, will call this magic function.

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```

This magic function returns length of dataset.

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    def __len__(self):
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train_loader = DataLoader(dataset=dataset,
                          batch_size=32,
                          shuffle=True,
                          num_workers=2)
```

Construct DiabetesDataset object.

How to define your Dataset

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from torch.utils.data import DataLoader

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        pass

    def __len__(self):
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dataset = DiabetesDataset()
train_loader = DataLoader(dataset=dataset,
                          batch_size=32,
                          shuffle=True,
                          num_workers=2)
```

Initialize loader with batch-size, shuffle, process number.

Extra: *num_workers* in Windows

```
train_loader = DataLoader(dataset=dataset,
                          batch_size=32,
                          shuffle=True,
                          num_workers=2)
......
for epoch in range(100):
    for i, data in enumerate(train_loader, 0):
        ......
```

So we have to **wrap** the code with an if-clause to protect the code from executing multiple times.

The implementation of multiprocessing is different on Windows, which uses **spawn** instead of **fork**.

So left code will cause:

RuntimeError:

An attempt has been made to start a new process before the current process has finished its bootstrapping phase.

This probably means that you are not using fork to start your child processes and you have forgotten to use the proper idiom in the main module:

```
if __name__ == '__main__':
    freeze_support()
    ...
```

The "freeze_support()" line can be omitted if the program is not going to be frozen to produce an executable.

Extra: *num_workers* in Windows

```
train_loader = DataLoader(dataset=dataset,
                          batch_size=32,
                          shuffle=True,
                          num_workers=2)
......
if __name__ == '__main__':
    for epoch in range(100):
        for i, data in enumerate(train_loader, 0):
            # 1. Prepare data
```

So we have to **wrap** the code with an if-clause to protect the code from executing multiple times.

Example: Diabetes Dataset

```
class DiabetesDataset(Dataset):
    def __init__(self, filepath):
        xy = np.loadtxt(filepath, delimiter=',', dtype=np.float32)
        self.len = xy.shape[0]
        self.x_data = torch.from_numpy(xy[:, :-1])
        self.y_data = torch.from_numpy(xy[:, [-1]])

    def __getitem__(self, index):
        return self.x_data[index], self.y_data[index]

    def __len__(self):
        return self.len

dataset = DiabetesDataset('diabetes.csv.gz')
train_loader = DataLoader(dataset=dataset, batch_size=32, shuffle=True, num_workers=2)
```

Example: Using DataLoader

```
for epoch in range(100):
    for i, data in enumerate(train_loader, 0):
        # 1. Prepare data
        inputs, labels = data
        # 2. Forward
        y_pred = model(inputs)
        loss = criterion(y_pred, labels)
        print(epoch, i, loss.item())
        # 3. Backward
        optimizer.zero_grad()
        loss.backward()
        # 4. Update
        optimizer.step()
```

Classifying Diabetes

```python
import numpy as np
import torch
from torch.utils.data import Dataset, DataLoader

class DiabetesDataset(Dataset):
    def __init__(self, filepath):
        xy = np.loadtxt(filepath, delimiter=',', dtype=np.float32)
        self.len = xy.shape[0]
        self.x_data = torch.from_numpy(xy[:, :-1])
        self.y_data = torch.from_numpy(xy[:, [-1]])

    def __getitem__(self, index):
        return self.x_data[index], self.y_data[index]

    def __len__(self):
        return self.len

dataset = DiabetesDataset('diabetes.csv.gz')
train_loader = DataLoader(dataset=dataset,
                          batch_size=32,
                          shuffle=True,
                          num_workers=2)

class Model(torch.nn.Module):
    def __init__(self):
        super(Model, self).__init__()
        self.linear1 = torch.nn.Linear(8, 6)
        self.linear2 = torch.nn.Linear(6, 4)
        self.linear3 = torch.nn.Linear(4, 1)
        self.sigmoid = torch.nn.Sigmoid()

    def forward(self, x):
        x = self.sigmoid(self.linear1(x))
        x = self.sigmoid(self.linear2(x))
        x = self.sigmoid(self.linear3(x))
        return x

model = Model()

criterion = torch.nn.BCELoss(size_average=True)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)

for epoch in range(100):
    for i, data in enumerate(train_loader, 0):
        # 1. Prepare data
        inputs, labels = data
        # 2. Forward
        y_pred = model(inputs)
        loss = criterion(y_pred, labels)
        print(epoch, i, loss.item())
        # 3. Backward
        optimizer.zero_grad()
        loss.backward()
        # 4. Update
        optimizer.step()
```

1. **Prepare dataset**
   Dataset and Dataloader
2. **Design model using Class**
   inherit from nn.Module
3. **Construct loss and optimizer**
   using PyTorch API
4. **Training cycle**
   forward, backward, update

The following dataset loaders are available

- MNIST
- Fashion-MNIST
- EMNIST
- COCO
- LSUN
- ImageFolder
- DatasetFolder
- Imagenet-12
- CIFAR
- STL10
- PhotoTour

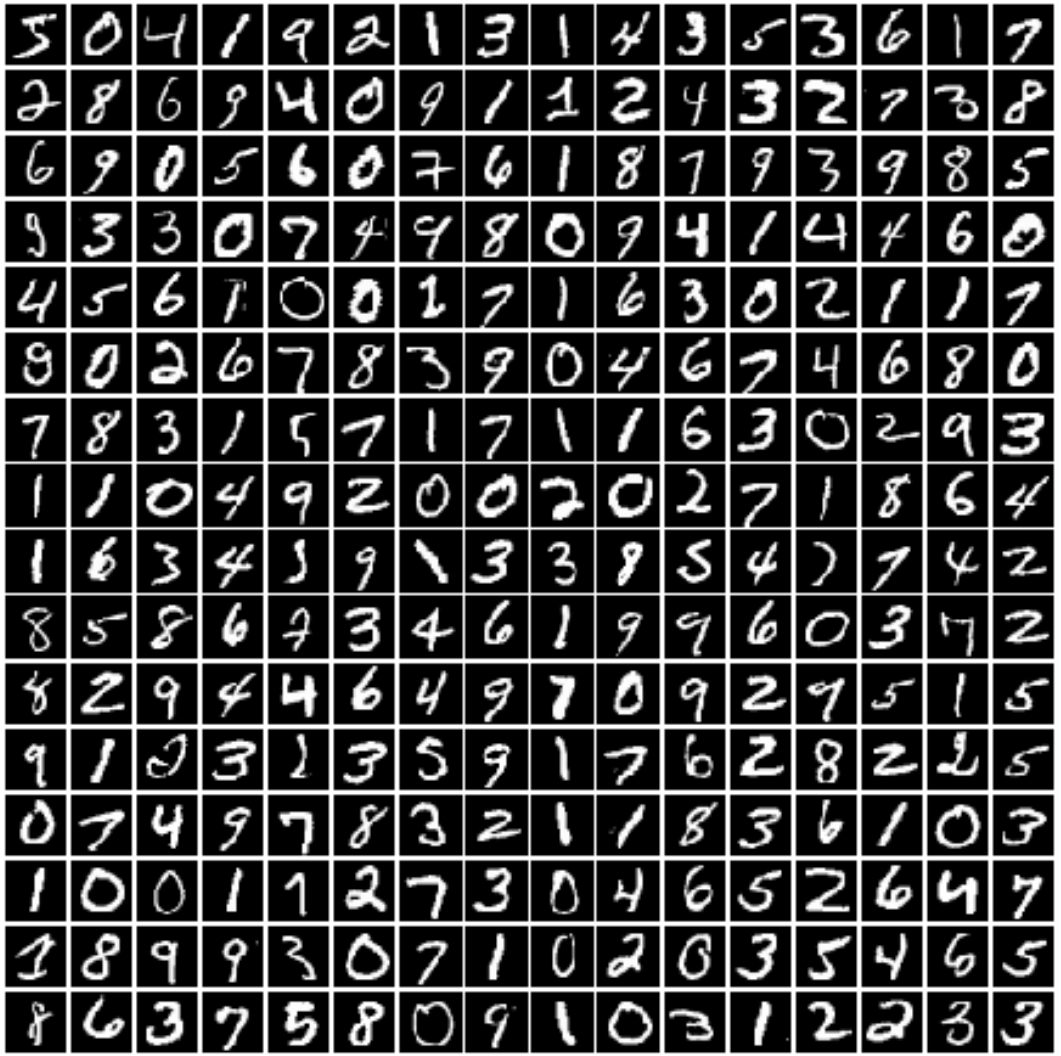
torchvision.datasets

All datasets are subclasses of `torch.utils.data.Dataset` i.e, they have `__getitem__` and `__len__` methods implemented. Hence, they can all be passed to a `torch.utils.data.DataLoader` which can load multiple samples parallelly using `torch.multiprocessing` workers. For example:

```
imagenet_data = torchvision.datasets.ImageFolder('path/to/imagenet_root/')
data_loader = torch.utils.data.DataLoader(imagenet_data,
                                          batch_size=4,
                                          shuffle=True,
                                          num_workers=args.nThreads)
```

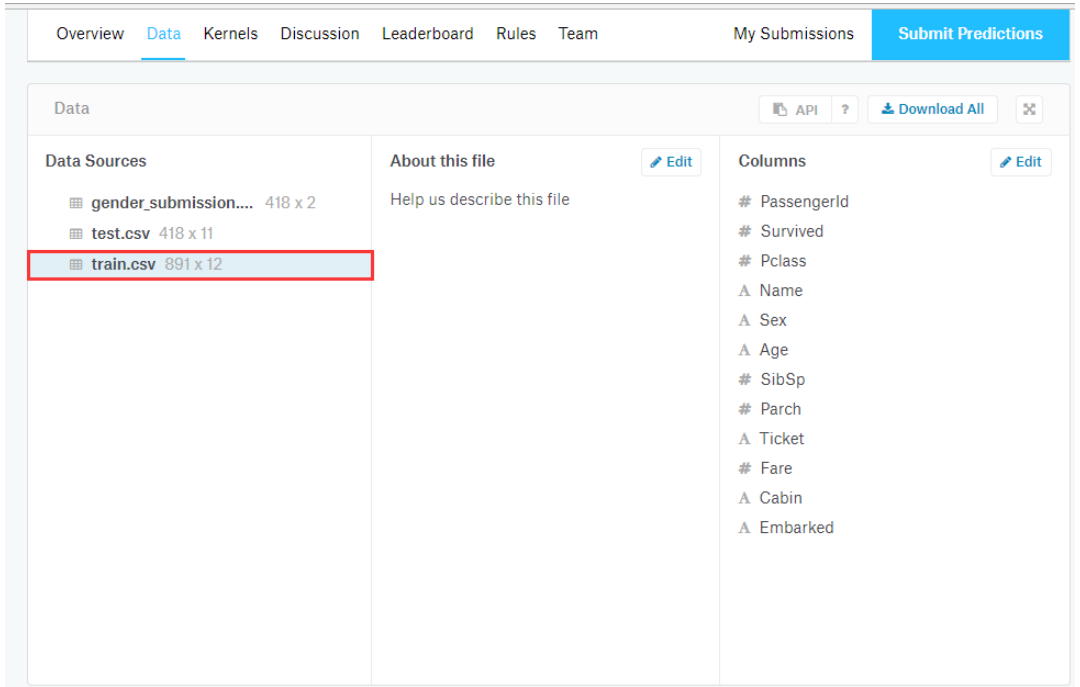
Example: MINST Dataset

```
import torch
from torch.utils.data import DataLoader
from torchvision import transforms
from torchvision import datasets

train_dataset = datasets.MNIST(root='../dataset/mnist',
                               train=True,
                               transform= transforms.ToTensor(),
                               download=True)
test_dataset = datasets.MNIST(root='../dataset/mnist',
                              train=False,
                              transform= transforms.ToTensor(),
                              download=True)

train_loader = DataLoader(dataset=train_dataset,
                          batch_size=32,
                          shuffle=True)
test_loader = DataLoader(dataset=test_dataset,
                         batch_size=32,
                         shuffle=False) 测试时一般不shuffle，没有必要

for batch_idx, (inputs, target) in enumerate(train_loader):
    ......
```



Exercise 8-1

- Build DataLoader for
  - Titanic dataset: https://www.kaggle.com/c/titanic/data
- Build a classifier using the DataLoader



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