



mini-batch

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

数据点
↓ mini-batch

Terminology: Epoch, Batch-Size, Iterations

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

Definition: Epoch

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

Definition: Batch-Size

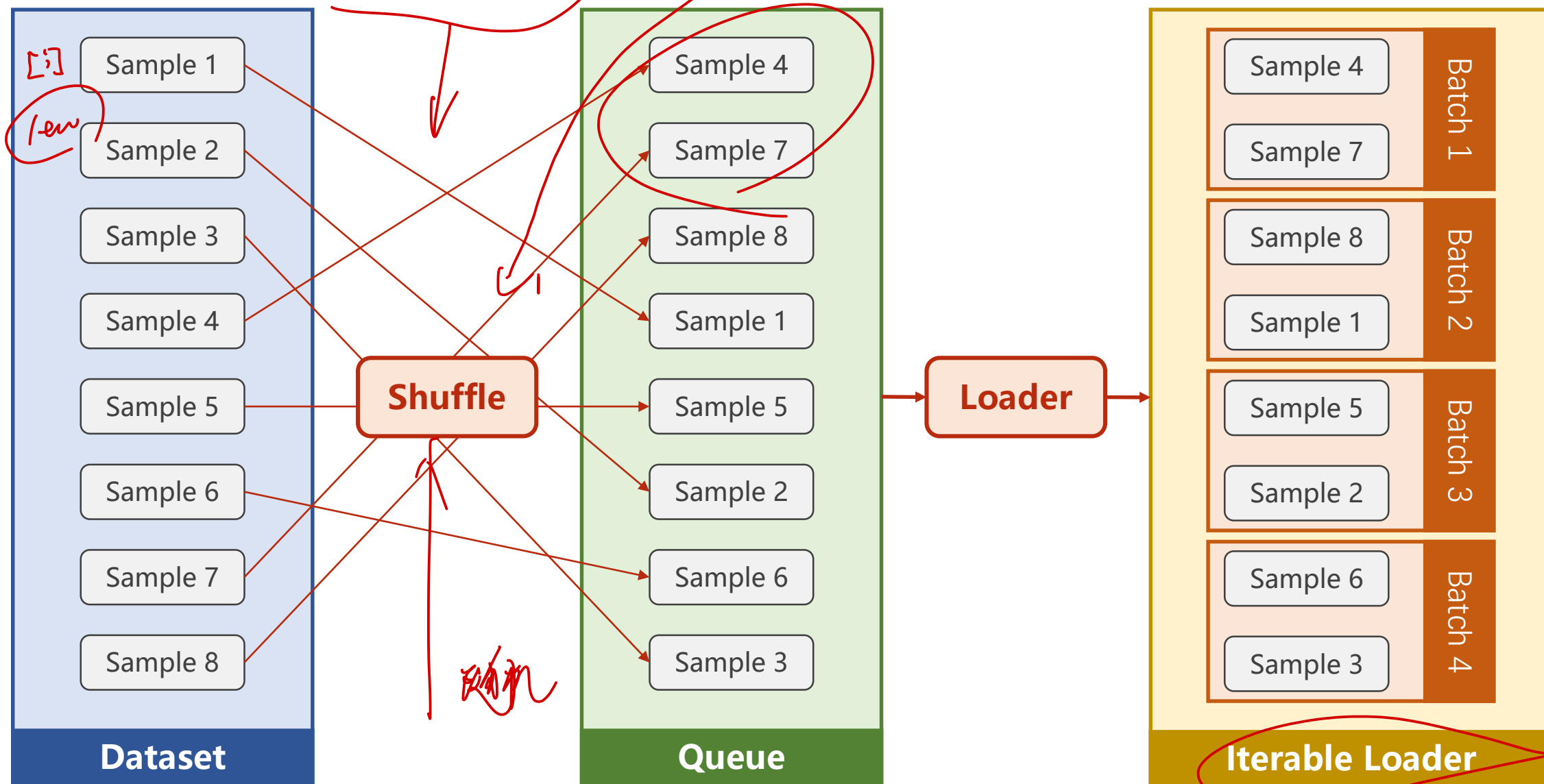
The **number of training examples** in one forward backward pass.

Definition: Iteration

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

10000
iterations
↓
10

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)
```

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

↓ 只能被继承

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                           batch_size=32,
                           shuffle=True,
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```

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

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dataset = DiabetesDataset()
train_loader = DataLoader(dataset=dataset,
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```

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

↓ 下标操作

len()

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

init -

1. All data / $[i]$ (1. 数据)

2. $\begin{bmatrix} \text{---} \\ \text{---} \\ \text{---} \end{bmatrix}$

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

X 文件

2. $\begin{bmatrix} \text{---} \\ \text{---} \\ \text{---} \end{bmatrix}$

2. \rightarrow 每次 getitem 处理

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)
```

This magic function returns length of dataset.

多线程:

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)
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This magic function returns length of dataset.

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):
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    def __getitem__(self, index):
        pass

    def __len__(self):
        pass

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

Construct DiabetesDataset object.

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)
```

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)
```

Handwritten notes:

- $(N, 9)$ next to `xy.shape[0]`
- 元组 (tuple) next to the `return` statement in `__getitem__`
- (x, y) next to the `return` statement in `__getitem__`

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

```
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)
```

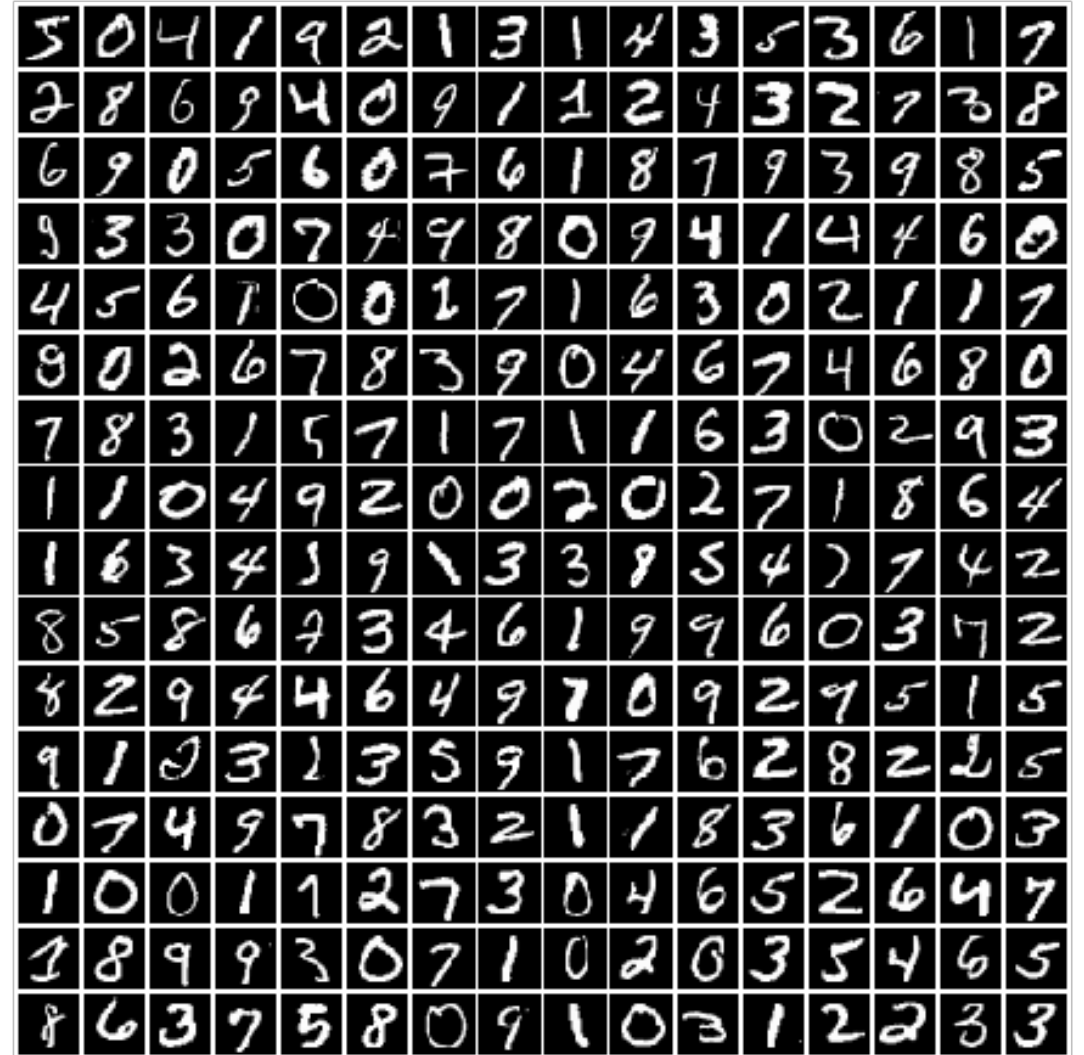
Example: MNIST Dataset

```
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)

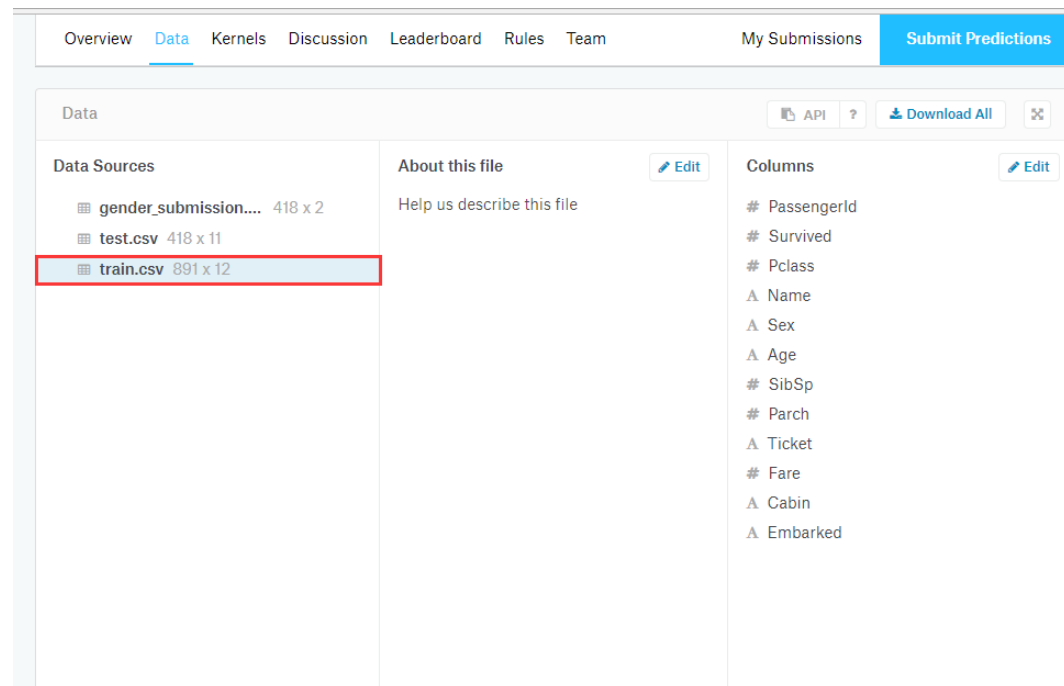
train_loader = DataLoader(dataset=train_dataset,
                          batch_size=32,
                          shuffle=True)
test_loader = DataLoader(dataset=test_dataset,
                         batch_size=32,
                         shuffle=False)

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





PyTorch Tutorial

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