# Deep Learning Software
## PyTorch

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Reference: Stanford CS231n

# Frameworks

TensorFlow

PyTorch

PaddlePaddle

Microsoft CNTK

Keras

torch

Chainer

Caffe2

DL4J

mxnet

Caffe

**And others……**

# Frameworks

**Most people use these**

TensorFlow

PyTorch

PaddlePaddle

Microsoft CNTK

Keras

torch

Chainer

Caffe2

DL4J

mxnet

Caffe

**And others……**

# Frameworks

**We will focus on this**

PyTorch

TensorFlow

PaddlePaddle

Microsoft CNTK

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torch

Chainer

Caffe2

DL4J

mxnet

Caffe

**And others……**

# Advantages of PyTorch

- Developing and testing new ideas are quickly
- Computing gradients automatically
- Running model structures on GPU is efficiently

**Please use PyTorch in this course !!**

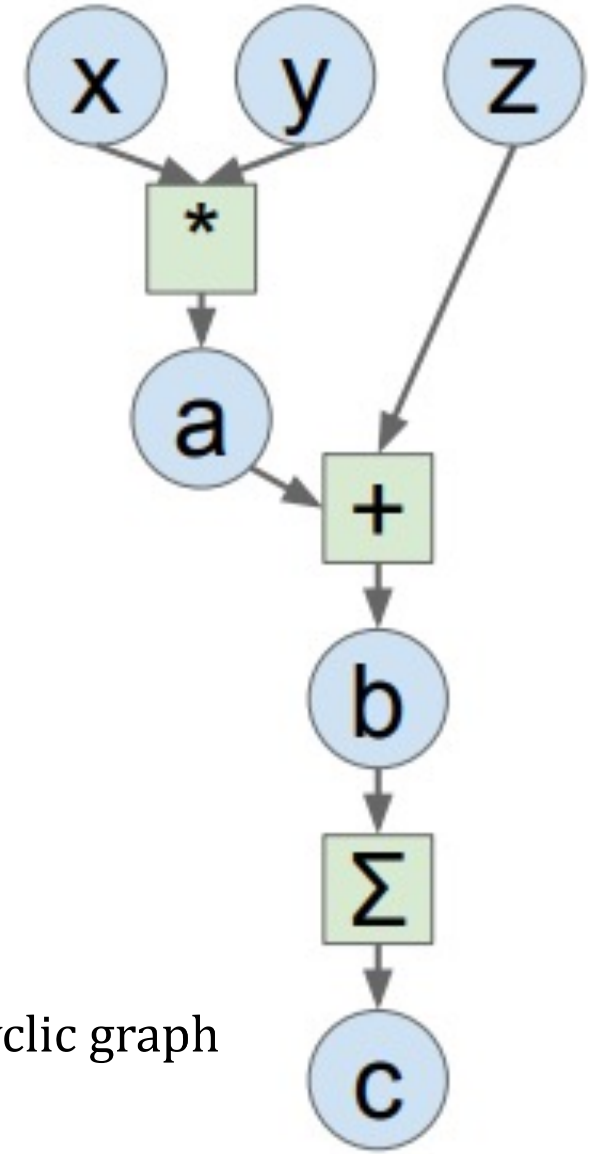
PyTorch PyTorch PyTorch

# Computational Graphs

## Numpy

```
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)
```

$x \times y + z$



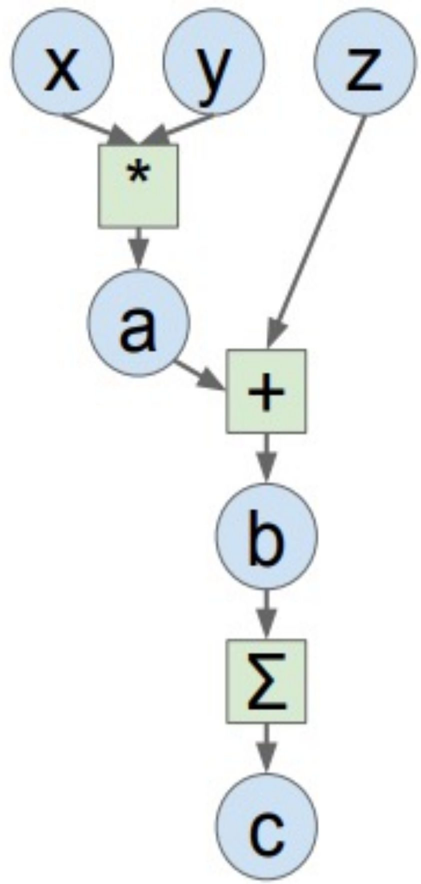

Neural network can be denoted as a directed acyclic graph

# Computational Graphs

## Numpy

```
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)

grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```

compute gradients



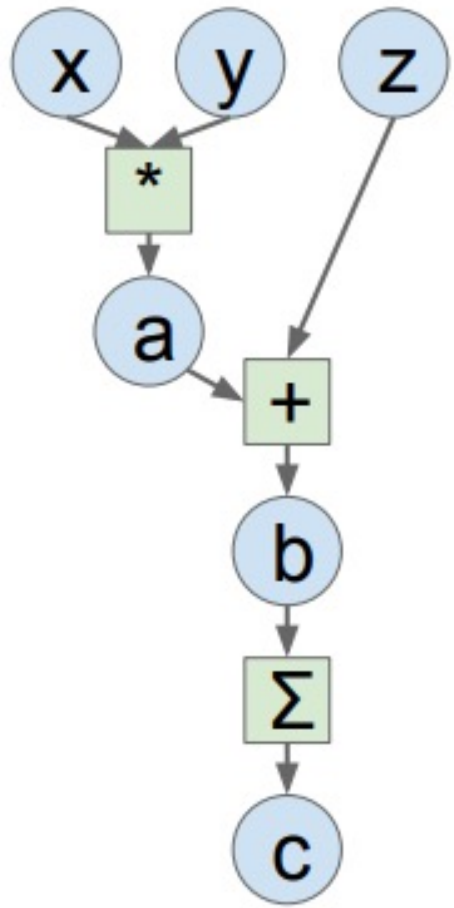

**Problems**:
- Can't run on GPU
- Have to compute our own gradients

# Computational Graphs

## Numpy

```
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)
```

```
grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```




## PyTorch

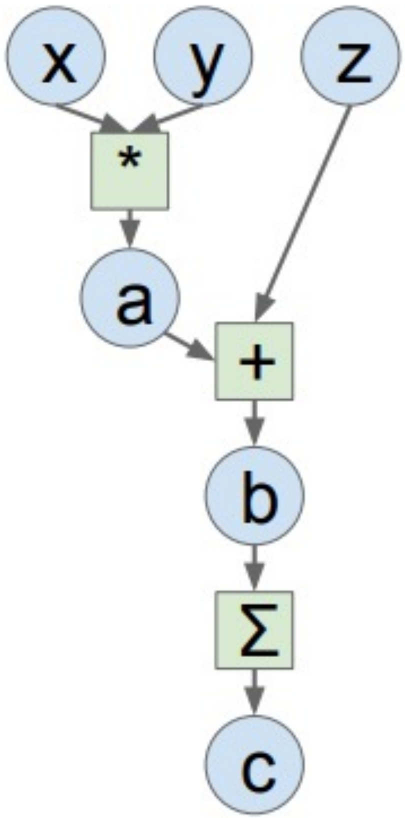
```
import torch

N, D = 3, 4
x = torch.randn(N, D)
y = torch.randn(N, D)
z = torch.randn(N, D)

a = x * y
b = a + z
c = torch.sum(b)
```

Looks exactly like numpy!

# Computational Graphs

## Numpy

```python
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)

grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```




## PyTorch

```python
import torch

N, D = 3, 4
x = torch.randn(N, D, requires_grad=True)
y = torch.randn(N, D)
z = torch.randn(N, D)

a = x * y
b = a + z
c = torch.sum(b)

c.backward()
print(x.grad)
```

PyTorch handles gradients for us!

.backward()   computes the gradient

# Computational Graphs

## Numpy

```
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
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c = np.sum(b)

grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```
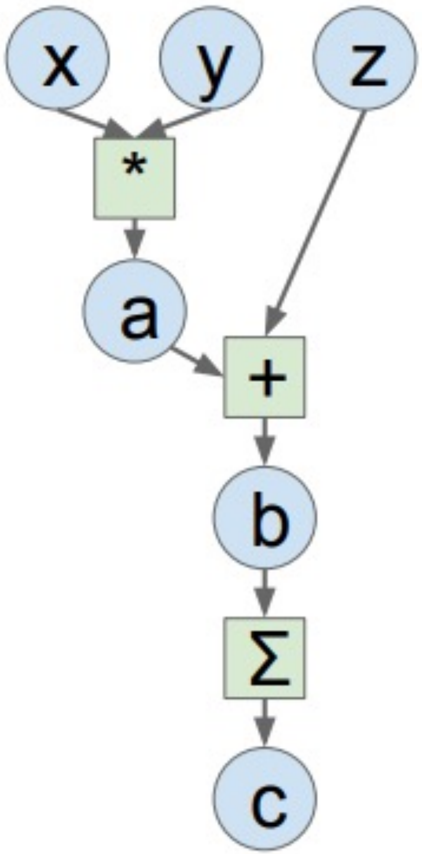



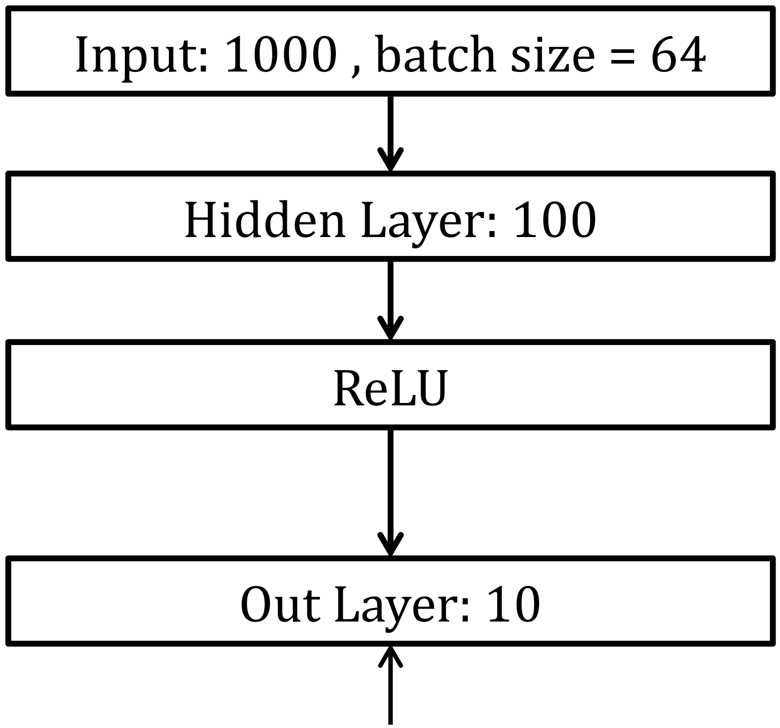

## PyTorch

```
import torch

device = 'cuda:0'
N, D = 3, 4
x = torch.randn(N, D, requires_grad=True,
                device=device)
y = torch.randn(N, D, device=device)
z = torch.randn(N, D, device=device)

a = x * y
b = a + z
c = torch.sum(b)

c.backward()
print(x.grad)
```

Trivial to run on GPU - just construct arrays on a different device!

# Example

- 2-layer network




x: 64×1000

w1: 1000×100

$$ReLU(x) = \begin{cases} x \; if \; x > 0 \\ 0 \; if \; x \le 0 \end{cases}$$

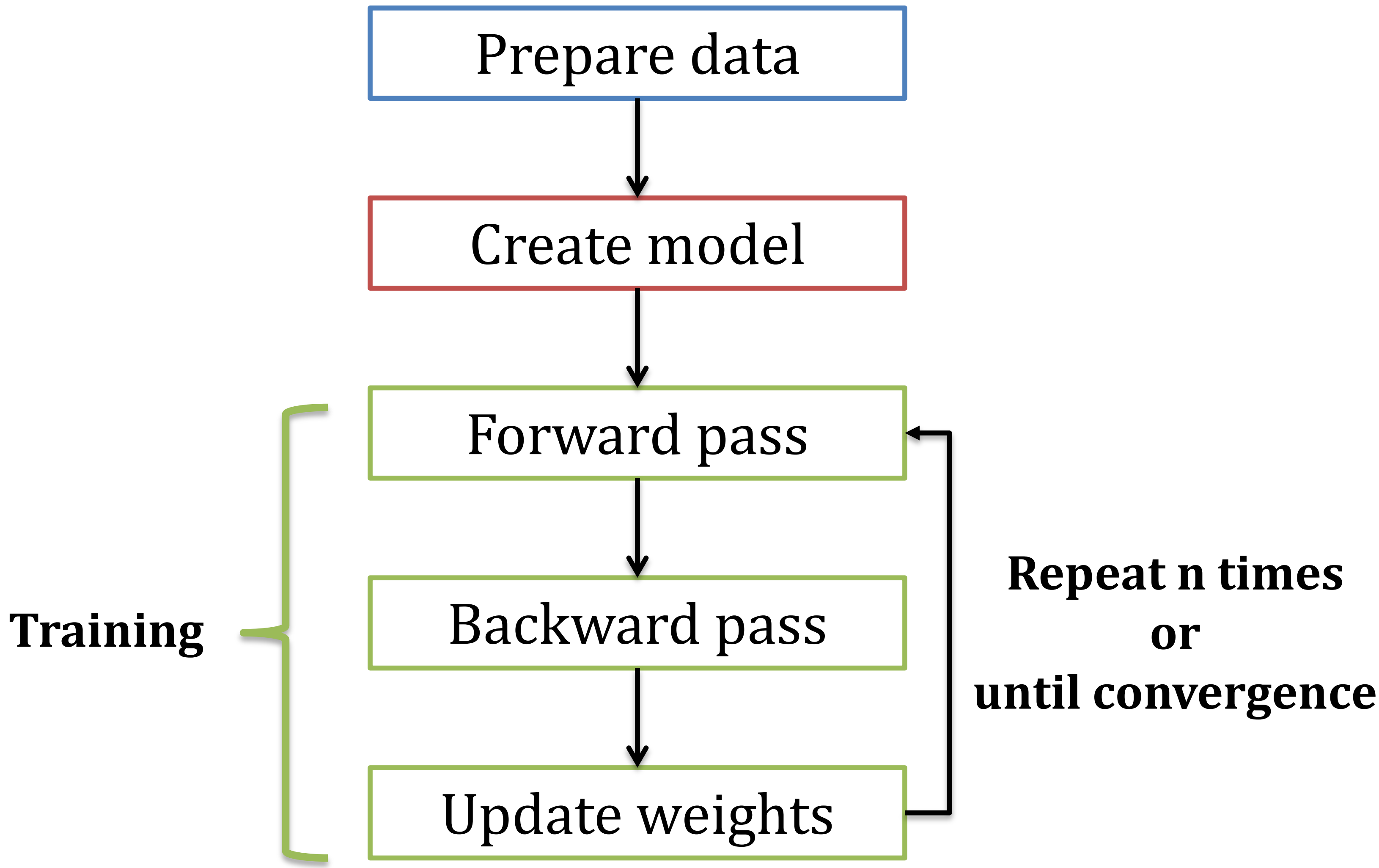
w2: 100×10

Loss : sum of square error

$$\sum(\boldsymbol{y} - \widehat{\boldsymbol{y}})^{\mathbf{2}}$$

y：64×10

# Flow Chart



Prepare data
Create model
Forward pass
Backward pass
Update weights
Training
Repeat n times
or
until convergence

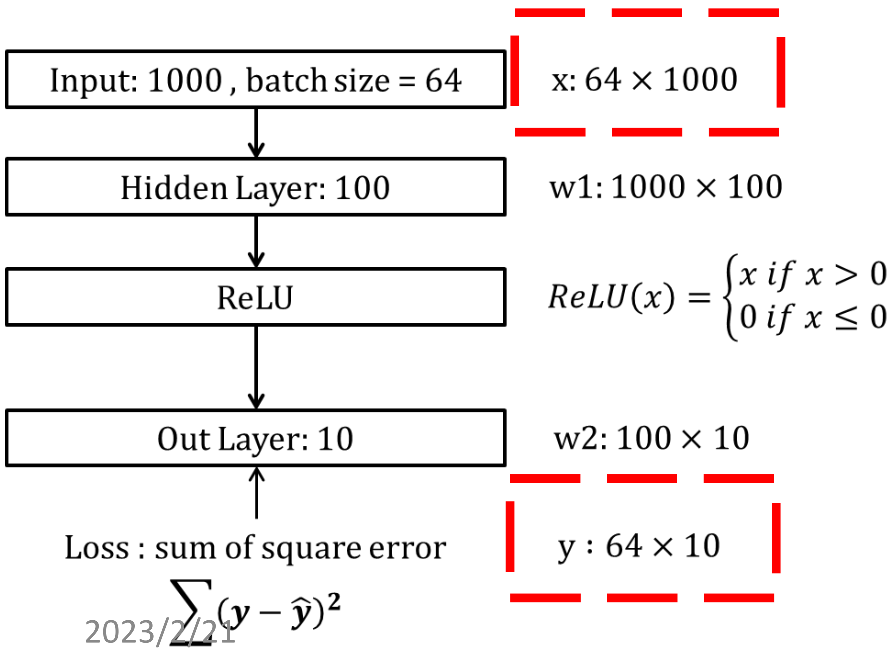
# Step1. Prepare Data

## PyTorch Tensors

Create random tensors as input and ground truth

To run on GPU, just use a different device, like a following:

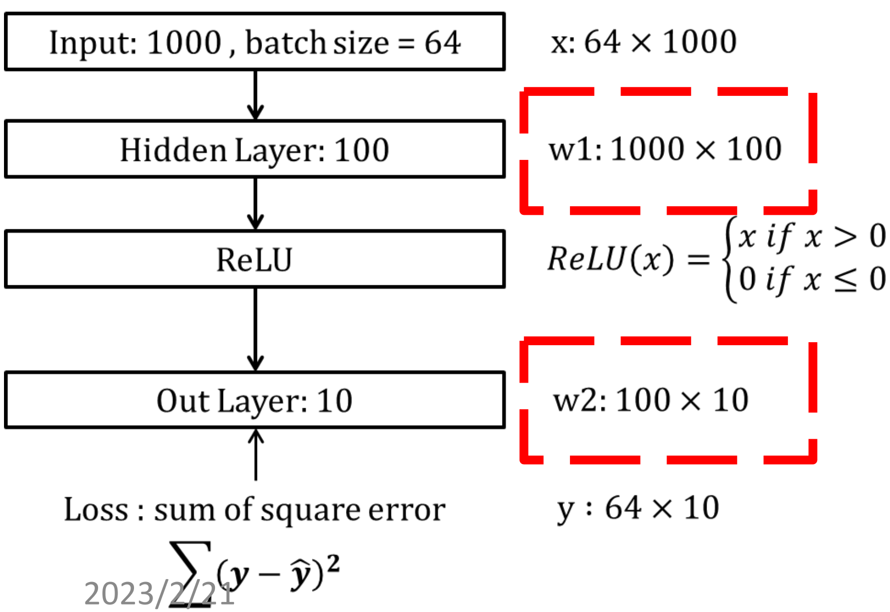
```
device = torch.device('cuda:0')
```




```
import torch

device = torch.device('cpu')
learning_rate = 1e-6

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)

w1 = torch.randn(1000, 100, device=device)
w2 = torch.randn(100, 10, device=device)

for t in range(300):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y)

    grad_y_pred = 2.0 * loss
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h<0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2

    print(loss.pow(2).sum())
```

# Step2. Create Model
## PyTorch Tensors

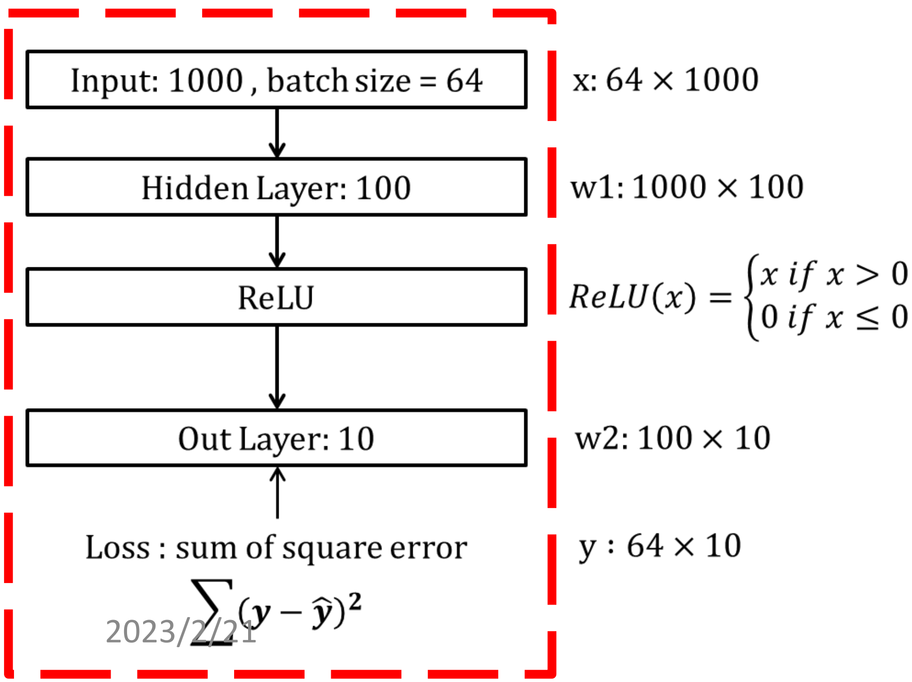
Create random tensors as layer weights




```
import torch

device = torch.device('cpu')
learning_rate = 1e-6

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)

w1 = torch.randn(1000, 100, device=device)
w2 = torch.randn(100, 10, device=device)

for t in range(300):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y)

    grad_y_pred = 2.0 * loss
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h<0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2

    print(loss.pow(2).sum())
```

# Step3. Forward pass
## PyTorch Tensors

Compute predictions and loss




```python
import torch

device = torch.device('cpu')
learning_rate = 1e-6

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)

w1 = torch.randn(1000, 100, device=device)
w2 = torch.randn(100, 10, device=device)

for t in range(300):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y)

    grad_y_pred = 2.0 * loss
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h<0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2

    print(loss.pow(2).sum())
```

# Step4. Backward pass

## PyTorch Tensors

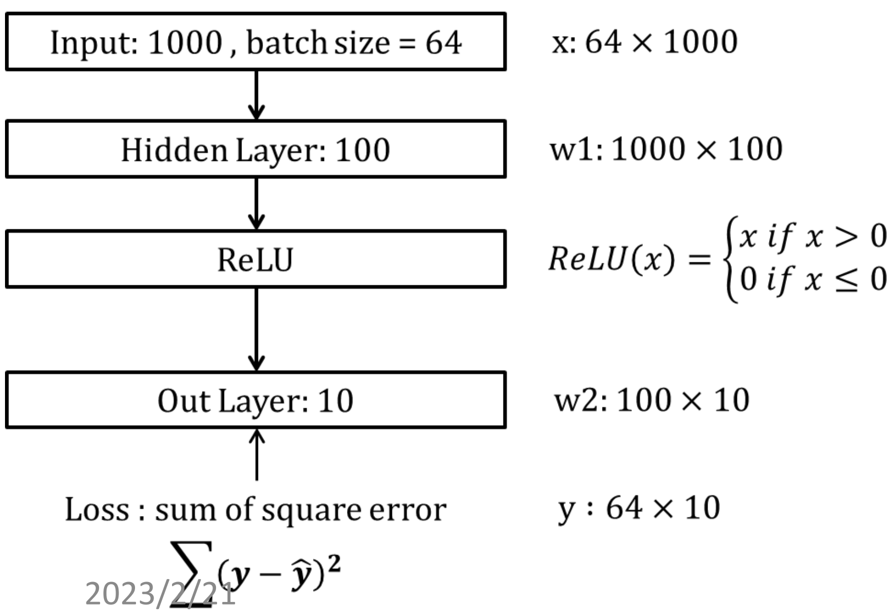
Manually compute gradients

| | |
|---|---|
| Input: 1000 , batch size = 64 | x: $64 \times 1000$ |
| Hidden Layer: 100 | w1: $1000 \times 100$ |
| ReLU | $ReLU(x) = \begin{cases} x \ if \ x > 0 \\ 0 \ if \ x \le 0 \end{cases}$ |
| Out Layer: 10 | w2: $100 \times 10$ |
| Loss : sum of square error $\sum (y - \hat{y})^2$ | y : $64 \times 10$ |

```python
import torch

device = torch.device('cpu')
learning_rate = 1e-6

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)

w1 = torch.randn(1000, 100, device=device)
w2 = torch.randn(100, 10, device=device)

for t in range(300):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y)

    grad_y_pred = 2.0 * loss
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h<0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2

    print(loss.pow(2).sum())
```

# Step5. Update Weights
## PyTorch Tensors

Gradient descent step on weights




```python
import torch

device = torch.device('cpu')
learning_rate = 1e-6

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)

w1 = torch.randn(1000, 100, device=device)
w2 = torch.randn(100, 10, device=device)

for t in range(300):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y)

    grad_y_pred = 2.0 * loss
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h<0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2

    print(loss.pow(2).sum())
```

# Implement your own DL model by using **PyTorch**

# Step1. Prepare Data

# PyTorch.utils.data

**DataLoader** wraps a **Dataset** and provides minibatches, shuffling, multithreading, for you

When you need to load custom data, just write your own Dataset class

Iterate over loader to form mini-batchs

*https://github.com/utkuozbulak/pytorch-custom-dataset-examples*

```python
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear_1 = torch.nn.Linear(D_in, H)
        self.linear_2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

# Step2. Create Model
# PyTorch.nn

Higher-level wrapper for working with neural nets

Use this ! It will make your life easier

A PyTorch Module is a neural net layer, it can contain weights or other modules

Define your whole model as a single module

```
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear_1 = torch.nn.Linear(D_in, H)
        self.linear_2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
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for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

# Step2. Create Model
## PyTorch.nn

Initializer sets up two children (Module can contain Modules)

```python
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear_1 = torch.nn.Linear(D_in, H)
        self.linear_2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

# Step2. Create Model
# PyTorch.nn

Define forward pass using child modules

No need to define backward – autograd will handle it

```python
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear_1 = torch.nn.Linear(D_in, H)
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    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

# Step3. Forward pass
## PyTorch.nn

Define forward pass using child modules

Feed data to model, and compute loss

nn.functional has useful helpers like loss functions

```
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
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    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

# Step4. Backward pass
# PyTorch.autograd

Forward pass looks exactly the same as before, but we don't need to track intermediate values

PyTorch keeps track of them for us in the computational graph

Compute gradient of loss with respect to all model weights (they have requires_grad=True)

```
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
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    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

# Step5. Update Weights
## PyTorch.optim

Use an **optimizer** for different update rules

After computing gradients, use optimizer to update each model parameters and reset gradients

```
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
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loader = DataLoader(TensorDataset(x, y), batch_size=8)

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    def forward(self, x):
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        y_pred = self.linear_2(h_relu)
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model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
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for epochs in range(50):
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        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```
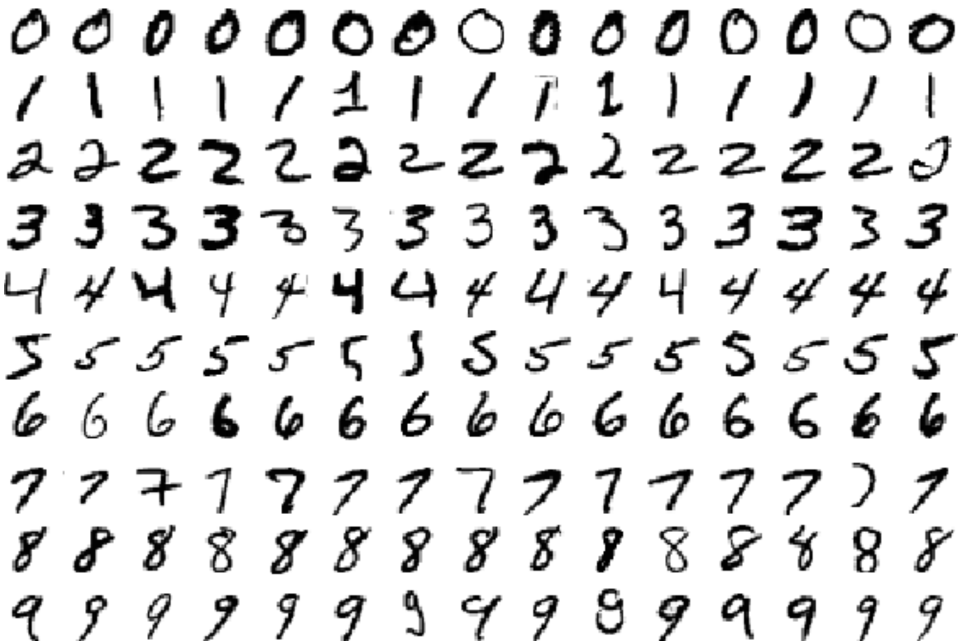

# Real Application

- MNIST example for PyTorch



- https://github.com/pytorch/examples/tree/master/mnist

# Build and train a CNN classifier

- Data Loader
- Define Network
- Define Optimizer/Loss function
- Learning rate scheduling
- Training
- Testing
- Run and Save model

# Set hyperparameters

```
    # Training settings
    parser = argparse.ArgumentParser(description='PyTorch MNIST Example')
    parser.add_argument('--batch-size', type=int, default=64, metavar='N',
                        help='input batch size for training (default: 64)')
    parser.add_argument('--test-batch-size', type=int, default=1000, metavar='N',
                        help='input batch size for testing (default: 1000)')
    parser.add_argument('--epochs', type=int, default=14, metavar='N',
                        help='number of epochs to train (default: 14)')
    parser.add_argument('--lr', type=float, default=1.0, metavar='LR',
                        help='learning rate (default: 1.0)')
    parser.add_argument('--gamma', type=float, default=0.7, metavar='M',
                        help='Learning rate step gamma (default: 0.7)')
    parser.add_argument('--no-cuda', action='store_true', default=False,
                        help='disables CUDA training')
    parser.add_argument('--dry-run', action='store_true', default=False,
                        help='quickly check a single pass')
    parser.add_argument('--seed', type=int, default=1, metavar='S',
                        help='random seed (default: 1)')
    parser.add_argument('--log-interval', type=int, default=10, metavar='N',
                        help='how many batches to wait before logging training status')
    parser.add_argument('--save-model', action='store_true', default=False,
                        help='For Saving the current Model')
    args = parser.parse_args()
```

# Data Loader

- Pytorch offers data loaders for popular dataset

The following datasets are available:

**Datasets**

- MNIST
- COCO
  - Captions
  - Detection
- LSUN
- ImageFolder
- Imagenet-12
- CIFAR
- STL10
- SVHN
- PhotoTour

# Data Loader

```
    transform=transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.1307,), (0.3081,))
        ])
    dataset1 = datasets.MNIST('../data', train=True, download=True,
                       transform=transform)
    dataset2 = datasets.MNIST('../data', train=False,
                       transform=transform)
    train_loader = torch.utils.data.DataLoader(dataset1,**train_kwargs)
    test_loader = torch.utils.data.DataLoader(dataset2, **test_kwargs)
```

# Define Network

```python
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 32, 3, 1)
        self.conv2 = nn.Conv2d(32, 64, 3, 1)
        self.dropout1 = nn.Dropout(0.25)
        self.dropout2 = nn.Dropout(0.5)
        self.fc1 = nn.Linear(9216, 128)
        self.fc2 = nn.Linear(128, 10)
```

```python
    def forward(self, x):
        x = self.conv1(x)
        x = F.relu(x)
        x = self.conv2(x)
        x = F.relu(x)
        x = F.max_pool2d(x, 2)
        x = self.dropout1(x)
        x = torch.flatten(x, 1)
        x = self.fc1(x)
        x = F.relu(x)
        x = self.dropout2(x)
        x = self.fc2(x)
        output = F.log_softmax(x, dim=1)
        return output
```

# Define Optimizer/Loss function

- Negative log likelihood loss

```
        loss = F.nll_loss(output, target)
```

- Adadelta

```
    optimizer = optim.Adadelta(model.parameters(), lr=args.lr)
```

# Learning rate scheduling

```
scheduler = StepLR(optimizer, step_size=1, gamma=args.gamma)
```

# Training

```
def train(args, model, device, train_loader, optimizer, epoch):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        data, target = data.to(device), target.to(device)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        if batch_idx % args.log_interval == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.item()))
            if args.dry_run:
                break
```

# Testing

```python
def test(model, device, test_loader):
    model.eval()
    test_loss = 0
    correct = 0
    with torch.no_grad():
        for data, target in test_loader:
            data, target = data.to(device), target.to(device)
            output = model(data)
            test_loss += F.nll_loss(output, target, reduction='sum').item()  # sum up batch loss
            pred = output.argmax(dim=1, keepdim=True)  # get the index of the max log-probability
            correct += pred.eq(target.view_as(pred)).sum().item()

    test_loss /= len(test_loader.dataset)

    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} ({:.0f}%)\n'.format(
        test_loss, correct, len(test_loader.dataset),
        100. * correct / len(test_loader.dataset)))
```

# Run and Save model

```
    for epoch in range(1, args.epochs + 1):
        train(args, model, device, train_loader, optimizer, epoch)
        test(model, device, test_loader)
        scheduler.step()

    if args.save_model:
        torch.save(model.state_dict(), "mnist_cnn.pt")
```