PyTorch 101

PyTorch vs Tensorflow

PyTorch

TensorFlow

KEY FEATURES & CAPABILITIES

See all Features >

Production Ready

Transition seamlessly between eager and graph modes with TorchScript, and accelerate the path to production with TorchServe.

Distributed Training

Scalable distributed training and performance optimization in research and production is enabled by the torch.distributed backend.

Robust Ecosystem

A rich ecosystem of tools and libraries extends PyTorch and supports development in computer vision, NLP and more.

Cloud Support

PyTorch is well supported on major cloud platforms, providing frictionless development and easy scaling.

Easy model building

Build and train ML models easily using intuitive high-level APIs like Keras with eager execution, which makes for immediate model iteration and easy debugging.

Robust ML production anywhere

Easily train and deploy models in the cloud, on-prem, in the browser, or on-device no matter what language you use.

Powerful experimentation for research

A simple and flexible architecture to take new ideas from concept to code, to state-of-the-art models, and to publication faster.

Source: horace.io

PyTorch vs Tensorflow

- PyTorch
  - Dynamic graph by default
- Tensorflow
  - Static graph by default (pre-2.0)

Static graph

- Once the graph is built, you can serialize and run it without the code
- The graph cannot be modified after compilation

Dynamic graph

- You always need to have the code around
- It offers the programmer better access to the inner workings of the network

Deep learning frameworks

- Caffe
- Torch / PyTorch
- Theano
- TensorFlow
- MatConvNet
- MXNet

PyTorch example

- Train a 2-layer network on random data
- The networks are usually far more complex, but the principles remain the same

```
import torch

device = torch.device('cpu')

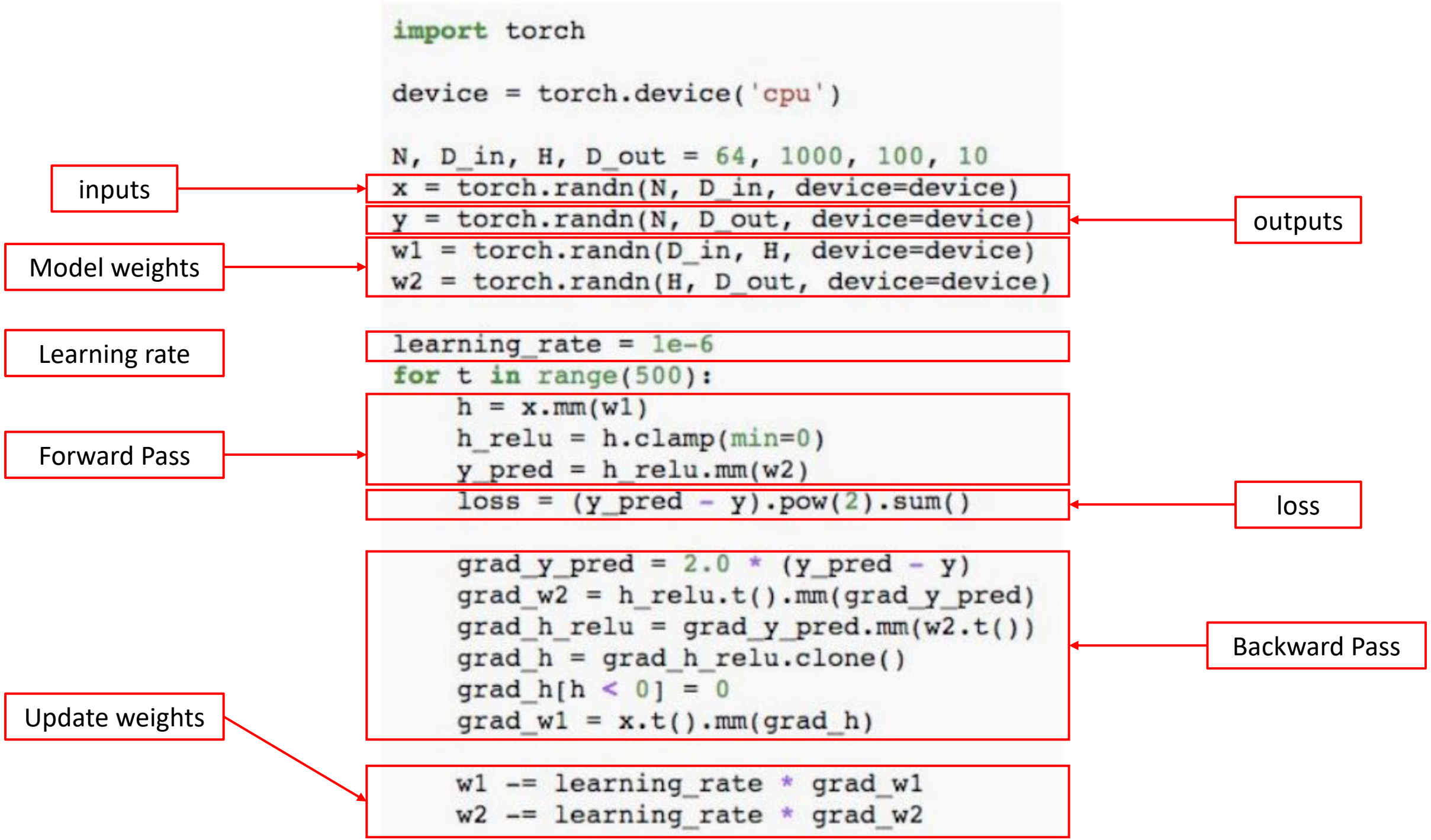
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred - y)
    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
```

Code credit: Fei-Fei Li


import torch
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grad_h[h < 0] = 0
grad_w1 = x.t().mm(grad_h)
w1 -= learning_rate * grad_w1
w2 -= learning_rate * grad_w2
inputs
Model weights
Learning rate
Forward Pass
Update weights
outputs
loss
Backward Pass

PyTorch example

Automatic differentiation

- **PyTorch** has the ability to perform automatic differentiation for all operations on Tensors.

```
grad_y_pred = 2.0 * (y_pred - y)
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)
```

```
loss.backward()
```

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

Code credit: Fei-Fei Li

Model Weights (Set requires_grad=True for tensors to be updated)

```
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N, D_in, H, D_out = 64, 1000, 100, 10
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w2 = torch.randn(H, D_out, requires_grad=True)

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    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
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        w1.grad.zero_()
        w2.grad.zero_()
```

Forward Pass

Backward Pass

Update Weights

Reset gradients

PyTorch
Higher-level wrapper

- PyTorch has higher-level wrappers to make things even easier

TORCH.NN

These are the basic building block for graphs

torch.nn

- Containers
- Convolution Layers
- Pooling layers
- Padding Layers
- Non-linear Activations (weighted sum, nonlinearity)
- Non-linear Activations (other)
- Normalization Layers
- Recurrent Layers
- Transformer Layers
- Linear Layers
- Dropout Layers
- Sparse Layers
- Distance Functions
- Loss Functions
- Vision Layers

TORCH.OPTIM

`torch.optim` is a package implementing various optimization algorithms. Most commonly used methods are already supported, and the interface is general enough, so that more sophisticated ones can be also easily integrated in the future.

How to use an optimizer

To use `torch.optim` you have to construct an optimizer object, that will hold the current state and will update the parameters based on the computed gradients.

Constructing it

To construct an `Optimizer` you have to give it an iterable containing the parameters (all should be `Variable` s) to optimize. Then, you can specify optimizer-specific options such as the learning rate, weight decay, etc.

• NOTE

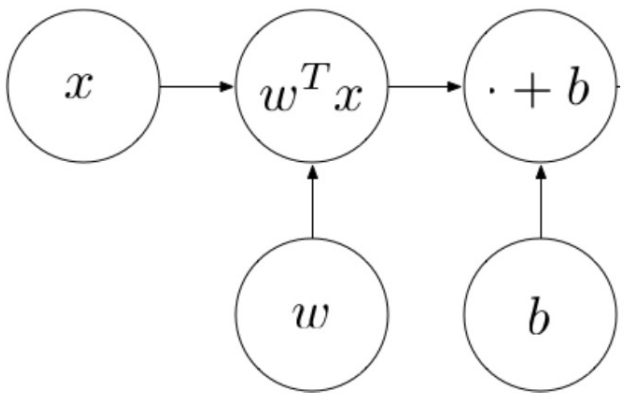
If you need to move a model to GPU via `.cuda()`, please do so before constructing optimizers for it. Parameters of a model after `.cuda()` will be different objects with those before the call.

In general, you should make sure that optimized parameters live in consistent locations when optimizers are constructed and used.

PyTorch

Higher-level wrapper

- torch.nn.Linear contains many commonly used layers



CLASS `torch.nn.Linear(in_features: int, out_features: int, bias: bool = True)` [SOURCE]

Applies a linear transformation to the incoming data: $\mathrm{y} = \mathrm{x}\mathrm{A}^{\mathrm{T}} + \mathrm{b}$

Parameters

- **in_features** – size of each input sample
- **out_features** – size of each output sample
- **bias** – If set to `False`, the layer will not learn an additive bias. Default: `True`

Shape:

- Input: $(\mathrm{N}, *, \mathrm{H}_{\mathrm{in}})$ where $*$ means any number of additional dimensions and $\mathrm{H}_{\mathrm{in}} = \mathrm{in\_features}$
- Output: $(\mathrm{N}, *, \mathrm{H}_{\mathrm{out}})$ where all but the last dimension are the same shape as the input and $\mathrm{H}_{\mathrm{out}} = \mathrm{out\_features}$.

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device = torch.device('cpu')

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y = torch.randn(N, D_out, device=device)
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for t in range(500):
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    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
```

```python
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

Code credit: Fei-Fei Li

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Code credit: Fei-Fei Li

PyTorch example

torch.optim

- You can use the optimizers in torch.optim to update weights

```
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x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))

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    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

```
import torch

class ParallelBlock(torch.nn.Module):
    def __init__(self, D_in, D_out):
        super(ParallelBlock, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, D_out)
        self.linear2 = torch.nn.Linear(D_in, D_out)
    def forward(self, x):
        h1 = self.linear1(x)
        h2 = self.linear2(x)
        return (h1 * h2).clamp(min=0)

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
            ParallelBlock(D_in, H),
            ParallelBlock(H, H),
            torch.nn.Linear(H, D_out))

optimizer = torch.optim.Adam(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Code credit: Fei-Fei Li

환경설정 및 Reference

- Python 3.7
- Pip install torch torchvision
- Pip install transformers
- Reference: https://data-newbie.tistory.com/425