
PyTorch

1.0 release + next steps

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Deep learning framework

~~Deep learning framework~~

~~Deep learning framework~~

NumPy

```
import numpy as np

a = np.array([[1, 2, 3],
              [4, 5, 6]], dtype=np.float)
b = np.array(2, dtype=np.float)

c = a + b

d = c[:, [0, 2]]

assert d.shape == (2, 2)

e = d @ np.random.normal(size=(2, 2))
```

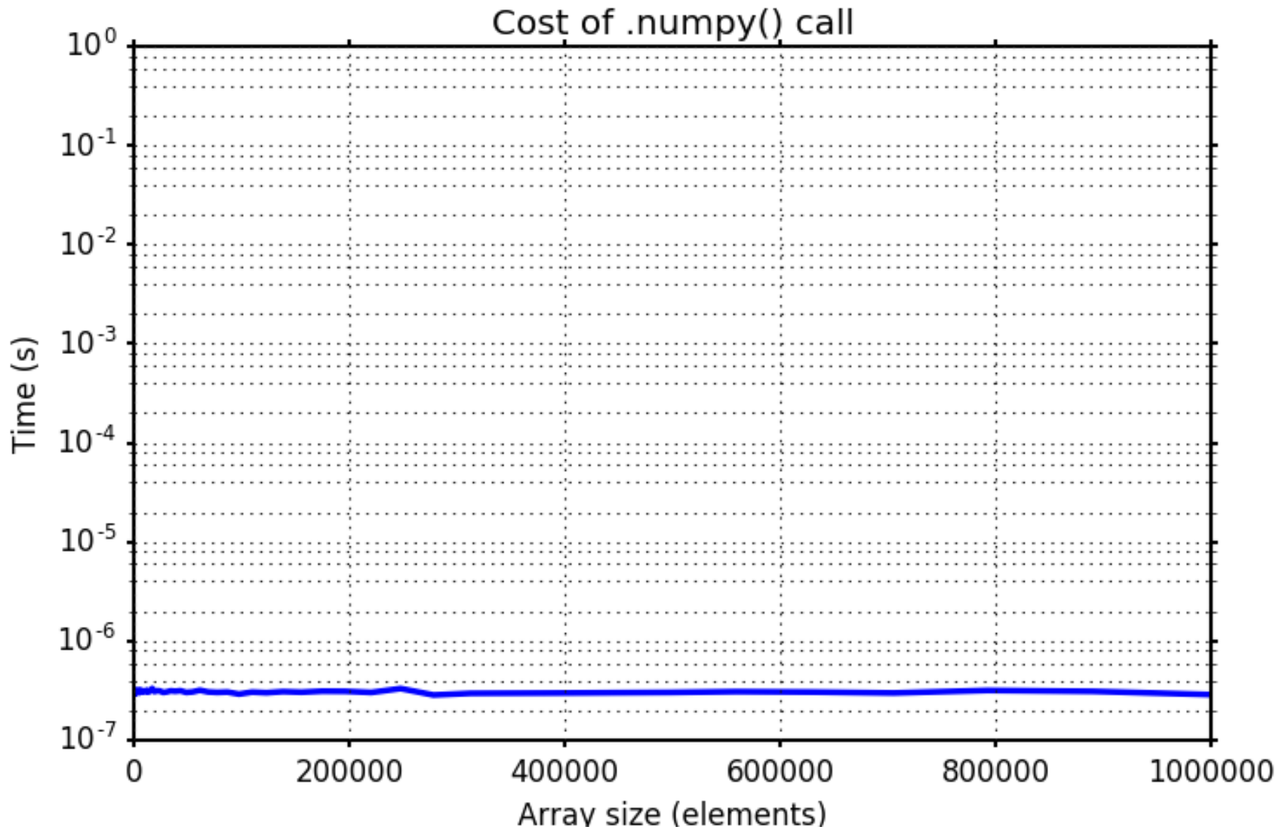
```
import torch

a = torch.tensor([[1, 2, 3],
                  [4, 5, 6]], dtype=torch.float)
b = torch.tensor(2, dtype=torch.float)

c = a + b

d = c[:, [0, 2]]

assert d.shape == (2, 2)

e = d @ torch.randn(2, 2, dtype=torch.float)
```

~~Deep learning framework~~

NumPy + ???

NumPy integration

```
import torch

x = torch.ones((2, 2), dtype=torch.double)
print(x)
# tensor([[ 1., 1.]
#         [ 1., 1.]], dtype=torch.float64)

y = x.numpy()
print(y)
# array([[ 1.,  1.],
#        [ 1.,  1.]])

z = torch.from_numpy(y)
print(z)
# tensor([[ 1., 1.]
#         [ 1., 1.]], dtype=torch.float64)
```

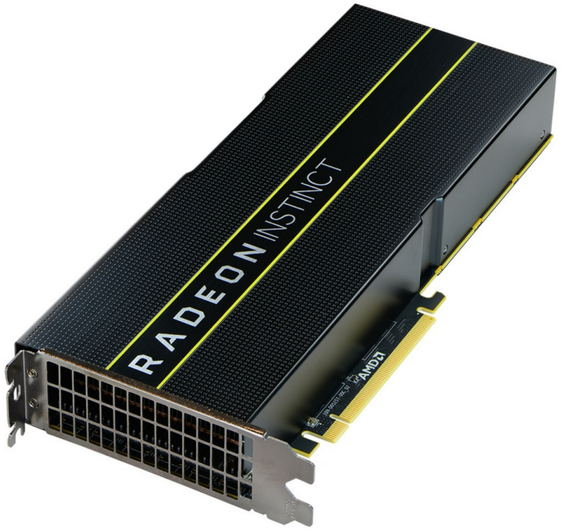

Cost of .numpy() call
Time (s)
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
0
200000
400000
600000
800000
1000000
Array size (elements)

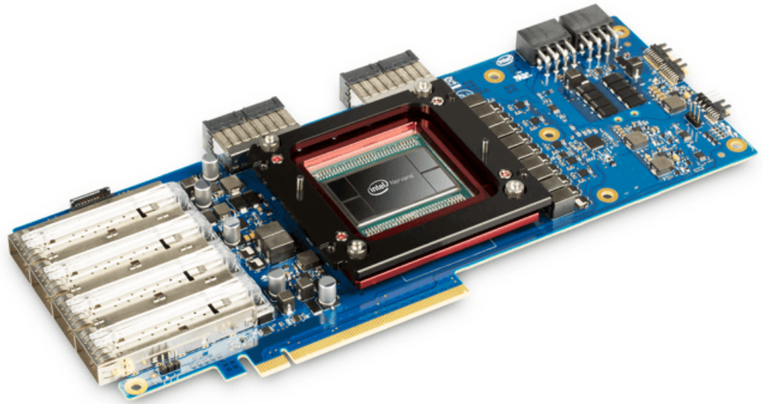
5 µs!

```
x += 1
print(arr)

# array([[ 2.,  2.],
#        [ 2.,  2.]])

np.add(arr, 1, out=arr)
print(x)

# tensor([[ 3., 3.]
#         [ 3., 3.]], dtype=torch.float64)
```

✅ Accelerator support


RTX 2080Ti
NVIDIA

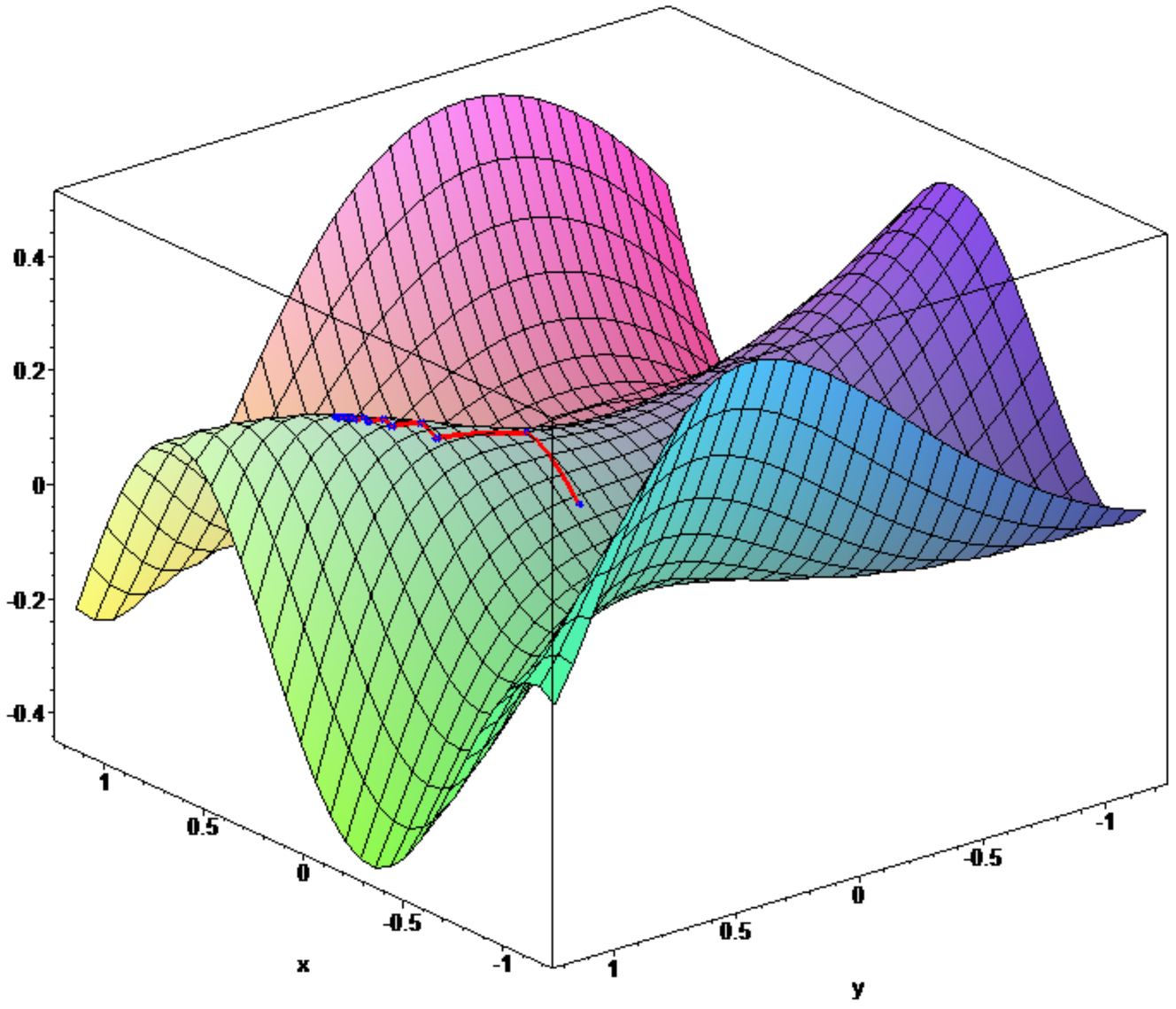

RADEON INSTINCT



```python
import torch



x = torch.randn((2, 2))
y = torch.randn((2, 2))

z = x + y

print(z)

# tensor([[1.4689,0.2254],
#         [1.3166,1.5713]])
```

```
import torch

dev = 'cuda:0' if torch.cuda.is_available() else 'cpu'

x = torch.randn((2, 2), device=dev)
y = torch.randn((2, 2)).to(x.device)

z = x + y # Runs on GPU!

print(z)

# tensor([[1.4689,0.2254],
#         [1.3166,1.5713]])
```

High-performance Automatic Differentiation


0.4
0.2
0
-0.2
-0.4
1
0.5
0
-0.5
-1
x
1
0.5
0
-0.5
-1
y

```python
import torch

x = torch.arange(4, requires_grad=True)

def poly(x):
    return x ** 2 + 5 * x + 2

# poly'(x) =  2x + 5
grad_x, = torch.autograd.grad(poly(x), x)

print(x)
# tensor([0., 1., 2., 3.])
print(grad_x)
# tensor([5., 7., 9., 11.])
```

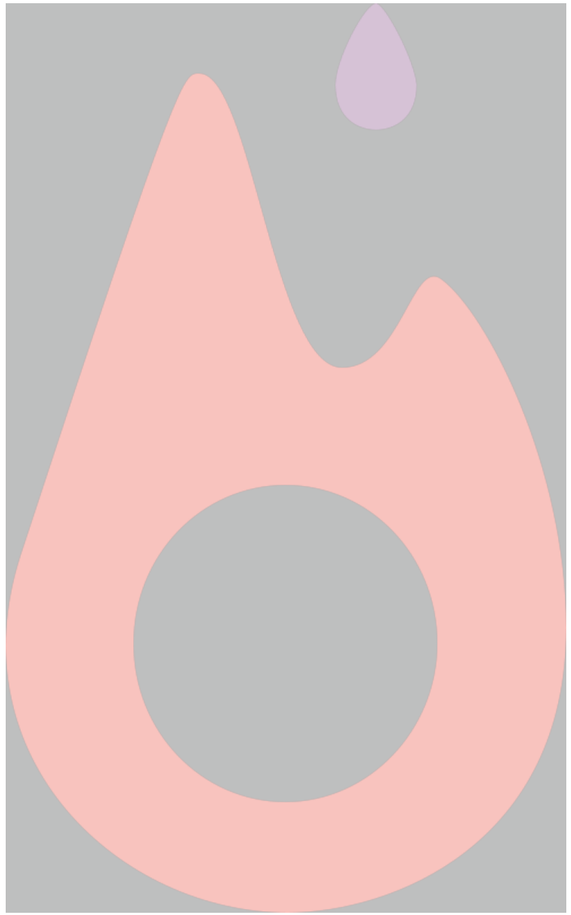
✅ High-level helpers for ML

```
import torch.nn as nn
import torch.nn.functional as F

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 10, kernel_size=5)
        self.conv2 = nn.Conv2d(10, 20, kernel_size=5)
        self.conv2_drop = nn.Dropout2d()
        self.fc1 = nn.Linear(320, 50)
        self.fc2 = nn.Linear(50, 10)

    def forward(self, x):
        x = F.relu(F.max_pool2d(self.conv1(x), 2))
        x = F.relu(F.max_pool2d(self.conv2_drop(self.conv2(x)), 2))
        x = x.view(-1, 320)
        x = F.relu(self.fc1(x))
        x = F.dropout(x, training=self.training)
        x = self.fc2(x)
        return F.log_softmax(x)
```

```
model.parameters()                                  # Iterator over parameters

model.state_dict()                                  # Weight serialization
model.load_state_dict(serialized_weights)           # and loading

model.eval()                                        # Train/eval mode toggle
model.train()

model.half()                                        # Type casts

model.zero_grad()                                   # Gradient management

model.cuda()                                        # Device changes

model = nn.DataParallel(model)                      # Multi-GPU

model = DistributedDataParallel(model)              # Multi-GPU + Multi-Node
```

✅ Data loading

- Vision
  - MNIST
  - Fashion MNIST
  - COCO (captioning and detection)
  - LSUN Classification
  - ImageFolder (generic classification dataset format)
  - Imagenet-12
  - CIFAR10 and CIFAR100
  - STL10
  - SVHN
  - PhotoTour
- Text
  - SST (sentiment analysis)
  - IMDb (sentiment analysis)
  - TREC (question classification)
  - SNLI (entailment)
  - Wikitext-2 (language modeling)
  - Abstract/generic support for machine translation



```
if opt.dataset in ['imagenet', 'folder', 'lfw']:
    dataset = dset.ImageFolder(root=opt.dataroot,
                               transform=transforms.Compose([
                                   transforms.Scale(opt.imageSize),
                                   transforms.CenterCrop(opt.imageSize),
                                   transforms.ToTensor(),
                                   transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
                               ]))
elif opt.dataset == 'lsun':
    dataset = dset.LSUN(db_path=opt.dataroot, classes=['bedroom_train'],
                        transform=transforms.Compose([
                            transforms.Scale(opt.imageSize),
                            transforms.CenterCrop(opt.imageSize),
                            transforms.ToTensor(),
                            transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
                        ]))
elif opt.dataset == 'cifar10':
    dataset = dset.CIFAR10(root=opt.dataroot, download=True,
                           transform=transforms.Compose([
                               transforms.Scale(opt.imageSize),
                               transforms.ToTensor(),
                               transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
                           ]))
elif opt.dataset == 'fake':
    dataset = dset.FakeData(image_size=(3, opt.imageSize, opt.imageSize),
                            transform=transforms.ToTensor())
```

```
class MNIST(torch.utils.data.Dataset):
    def __init__(self, root, train=True, transform=None, target_transform=None):
        self.root = os.path.expanduser(root)
        self.transform = transform
        self.target_transform = target_transform

        self.download()
        self.data, self.labels = torch.load(
            os.path.join(self.root, self.processed_folder, MNIST.training_file))

    def __getitem__(self, index):
        img, target = self.data[index], self.labels[index]

        # doing this so that it is consistent with all other datasets to return a PIL Image
        img = Image.fromarray(img.numpy(), mode='L')

        if self.transform is not None:
            img = self.transform(img)
        if self.target_transform is not None:
            target = self.target_transform(target)

        return img, target

    def __len__(self):
        return len(self.data)
```

```
train_loader = torch.utils.data.DataLoader(
        train_dataset, batch_size=args.batch_size, shuffle=True,
        num_workers=args.workers, pin_memory=True)

for data_batch, label_batch in train_loader:
  ...  # train!
```

A single class for:

- multiprocess parallel data loading
- shuffling
- batching
- memory locking (for faster CUDA transfers)


PyTorch 1.0

Research ➡ Deployment

But what *deployment* really is?

PyTorch *Eager mode*

✅ Simple to write

✅ Simple to debug

❌ Hard to *deploy*

PyTorch *Script mode*

✅ Still Python

✅ Exportable

✅ Optimizable

⚠️ Only a subset

What works:

- ✅ Tensors
- ✅ Integral and floating-point scalars
- ✅ `if/while/for`
- ✅ `print`
- ✅ Strings
- ✅ Tuples
- ✅ Lists
- ✅ Function calls
- 🚧 ... much more coming

PyTorch *Eager*

`torch.jit.trace/script`

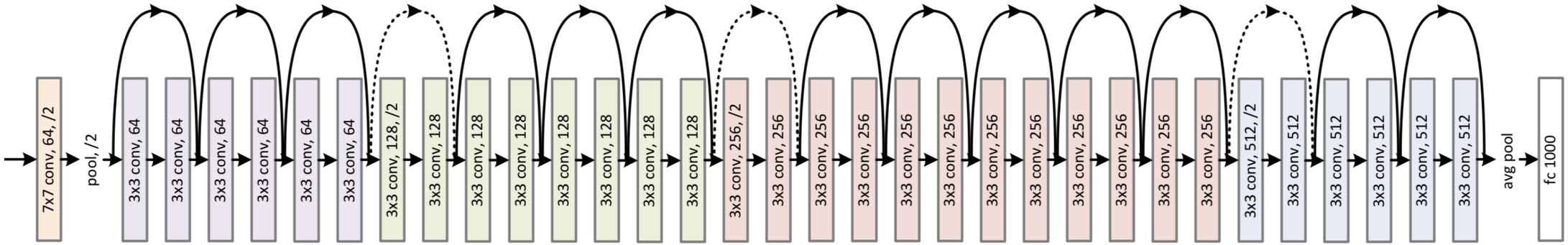
PyTorch *Script*

`torch.jit.trace`

✅ No code changes required

⚠️ Has to run your code on an example

⚠️ Control flow is inlined



Deep Residual Learning for Image Recognition, Kaiming He et al. https://arxiv.org/abs/1512.03385

```
convolutions = [
  nn.Conv2d(64, 64, kernel_size=3),
  nn.Conv2d(64, 64, kernel_size=3),
  nn.Conv2d(64, 128, kernel_size=3, stride=2),
  nn.Conv2d(128, 128, kernel_size=3, stride=2),
]

def model(x):
    for conv in convolutions:
        x = torch.relu(conv(x))
    return x
```

```
convolutions = [
  nn.Conv2d(64, 64, kernel_size=3),
  nn.Conv2d(64, 64, kernel_size=3),
  nn.Conv2d(64, 128, kernel_size=3, stride=2),
  nn.Conv2d(128, 128, kernel_size=3, stride=2),
]

def model(x):
    x = torch.relu(convolutions[0](x))
    x = torch.relu(convolutions[1](x))
    x = torch.relu(convolutions[2](x))
    x = torch.relu(convolutions[3](x))
    return x
```

```
import torchvision


model = torch.jit.trace(
    torchvision.models.resnet50(pretrained=True),
    args=(torch.randn(1, 3, 224, 224),))
```

`torch.jit.script`

✅ Program just as if you were writing Python

✅ Control flow is recovered correctly

⚠️ Restricted to a subset

```
@torch.jit.script
def lstm(x : Tensor,
         hidden : (Tensor, Tensor),
         w_ih : Tensor,
         w_hh : Tensor) -> (Tensor, (Tensor, Tensor)):

  outputs = []
  hx, cx = hidden

  for step in range(x.size(0)):
    hx, cx = lstm_cell(x[step], (hx, cx), w_ih, w_hh)
    outputs.append(hx)

  return torch.stack(outputs, dim=0), (hx, cx)
```

`trace` and `script` mix seamlessly …

`trace` and `script` mix seamlessly ...

and still allow you to call back to Python!

All *TorchScript* programs can be exported and run from native C++ environments!

```
auto model = torch::jit::load(path);
auto input = torch::randn({1, 3, 224, 224});
auto output = model->forward(inputs).toTensor();
```

Performance optimizations

Once a builtin doesn't fit what you're doing the perf drops ~5x

For an LSTM variant

23ms ➡ `torch.jit.script` ➡ 6ms

For an LSTM variant

23ms ➡ `torch.jit.script` ➡ 6ms

3.5x speedup!

C++ extensions/interface (beta!)

```
#include <torch/extension.h>


torch::Tensor compute(torch::Tensor x, torch::Tensor y) {
  auto z = torch::empty_like(x);
  x.mul_(2);
  compute_kernel<<<2, 4>>>(x.data<float>(),
                           y.data<float>(),
                           z.data<float>());
  return z;
}

PYBIND11_MODULE(TORCH_EXTENSION_NAME, m) {
  m.def("compute", &compute);
}
```

Setuptools

```
from setuptools import setup
from torch.utils.cpp_extension import BuildExtension, CUDAExtension

setup(
    name='extension',
    packages=['extension'],
    ext_modules=[CUDAExtension(
        'extension', ['extension.cpp', 'extension.cu']
    )],
    cmdclass=dict(build_ext=BuildExtension))
```

JIT loading

```
module = torch.utils.cpp_extension.load(
    name='extension',
    sources=['extension.cpp', 'extension.cu'])

module.compute(
    torch.ones(3, 4, device='cuda'), torch.randn(4, 5, device='cuda'))
```

```
import torch

class Net(torch.nn.Module):
    def __init__(self):
        self.fc1 = torch.nn.Linear(8, 64)
        self.fc2 = torch.nn.Linear(64, 1)


    def forward(self, x):
        x = torch.relu(self.fc1.forward(x))
        x = torch.dropout(x, p=0.5)
        x = torch.sigmoid(self.fc2.forward(x))
        return x
```

```
#include <torch/torch.h>

struct Net : torch::nn::Module {
  Net() : fc1(8, 64), fc2(64, 1) {
    register_module("fc1", fc1);
    register_module("fc2", fc2);
  }

  torch::Tensor forward(torch::Tensor x) {
    x = torch::relu(fc1->forward(x));
    x = torch::dropout(x, /*p=*/0.5);
    x = torch::sigmoid(fc2->forward(x));
    return x;
  }

  torch::nn::Linear fc1, fc2;
};
```

```
net = Net()

data_loader = torch.utils.data.DataLoader(
    torchvision.datasets.MNIST('./data'))

optimizer = torch.optim.SGD(net.parameters())

for epoch in range(1, 11):
    for data, target in data_loader:
        optimizer.zero_grad()
        prediction = net(data)
        loss = F.nll_loss(prediction, target)
        loss.backward()
        optimizer.step()



    if epoch % 2 == 0:
        torch.save(net, "net.pt")
```

```
Net net;

auto data_loader = torch::data::data_loader(
  torch::data::datasets::MNIST("./data"));

torch::optim::SGD optimizer {net.parameters()};

for (size_t epoch = 1; epoch <= 10; ++epoch) {
    for (auto batch : data_loader) {
        optimizer.zero_grad();
        auto prediction = net.forward(batch.data);
        auto loss = torch::nll_loss(prediction, batch.label);
        loss.backward();
        optimizer.step();
    }
    if (epoch % 2 == 0) {
        torch::save(net, "net.pt");
    }
}
```

torch::nn

torch::optim

torch::data

torch::serialize

torch::python

torch::jit

Distributed

New abstractions

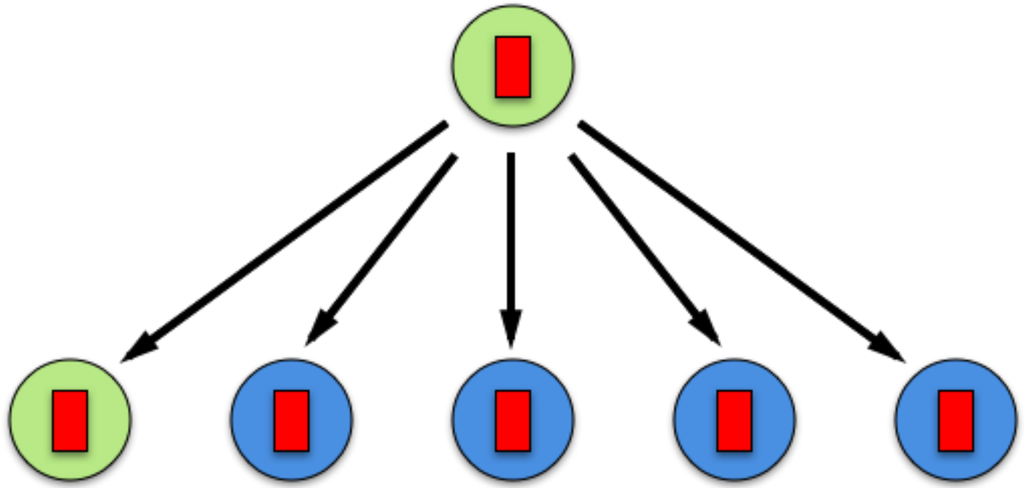
Asynchronous operation

Independent groups

Performance improvements

Fault tolerance

Elastic sizing



Caffe2

With ❤ from


facebook


NVIDIA


salesforce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