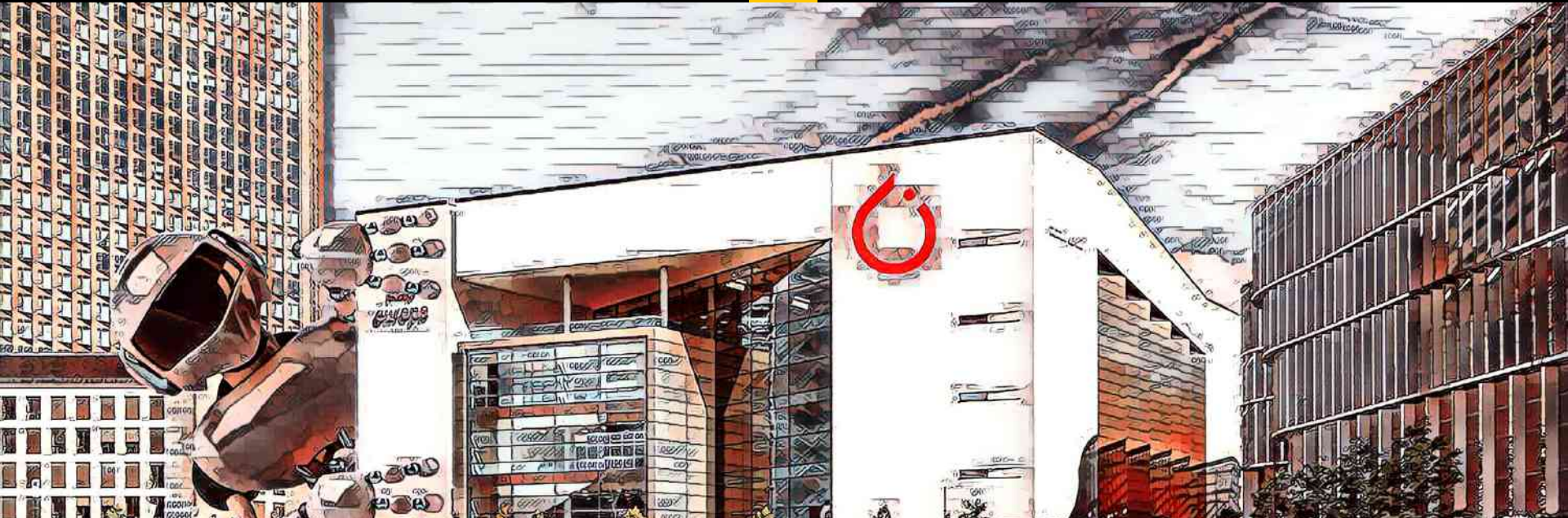


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Neuronale Netze mit PyTorch
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Neuronal Networks with PyTorch

Topics today

- Background of PyTorch
- Tensors
- Computational graphs
- Building an neural net in PyTorch
- Debugging
- Serialization





Origins of PyTorch



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Background of PyTorch

- 2017
- Open Source
- Facebook AI & huge community
- Build on Torch, made it popular with Python





Strongsuits



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Strongsuits of PyTorch

- Easy to learn
- Intuitive
- Integrated with NumPy and SciKit-Learn
- Easy to debug
- Dynamic graphs
- Well documented
- Keeping release schedule





Let's go



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GET STARTED

Select preferences and run the command to install PyTorch locally, or get started quickly with one of the supported cloud platforms.

Start Locally

Start via Cloud Partners

Previous PyTorch Versions

Mobile

Shortcuts

Prerequisites

Supported Linux Distributions

Python

Package Manager

Installation

Anaconda

pip

Verification

Building from source

Prerequisites

START LOCALLY

Select your preferences and run the install command. Stable represents the most currently tested and supported version of PyTorch. This should be suitable for many users. Preview is available if you want the latest, not fully tested and supported, 1.3 builds that are generated nightly. Please ensure that you have met the prerequisites below (e.g., numpy), depending on your package manager. Anaconda is our recommended package manager since it installs all dependencies. You can also [install previous versions of PyTorch](#). Note that LibTorch is only available for C++.

PyTorch Build:	Stable (1.3)	Preview (Nightly)			
Your OS:	Linux	Mac	Windows		
Package:	Conda	Pip	LibTorch	Source	
Language:	Python 2.7	Python 3.5	Python 3.6	Python 3.7	C++
CUDA:	9.2	10.1	None		
Run this Command:	<pre>conda install pytorch torchvision cudatoolkit=10.1 -c pytorch</pre>				

<https://pytorch.org/>

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Tensor Basics

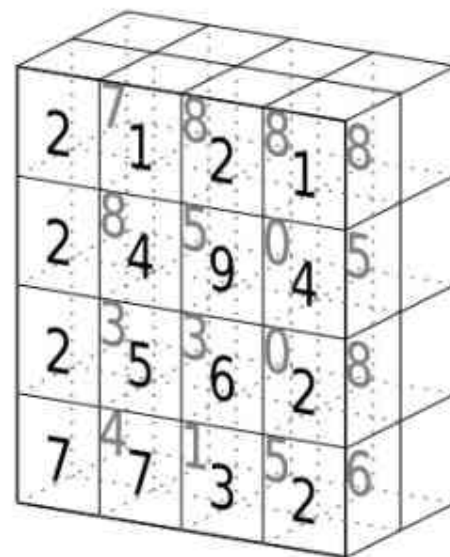
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't'
'e'
'n'
's'
'o'
'r'

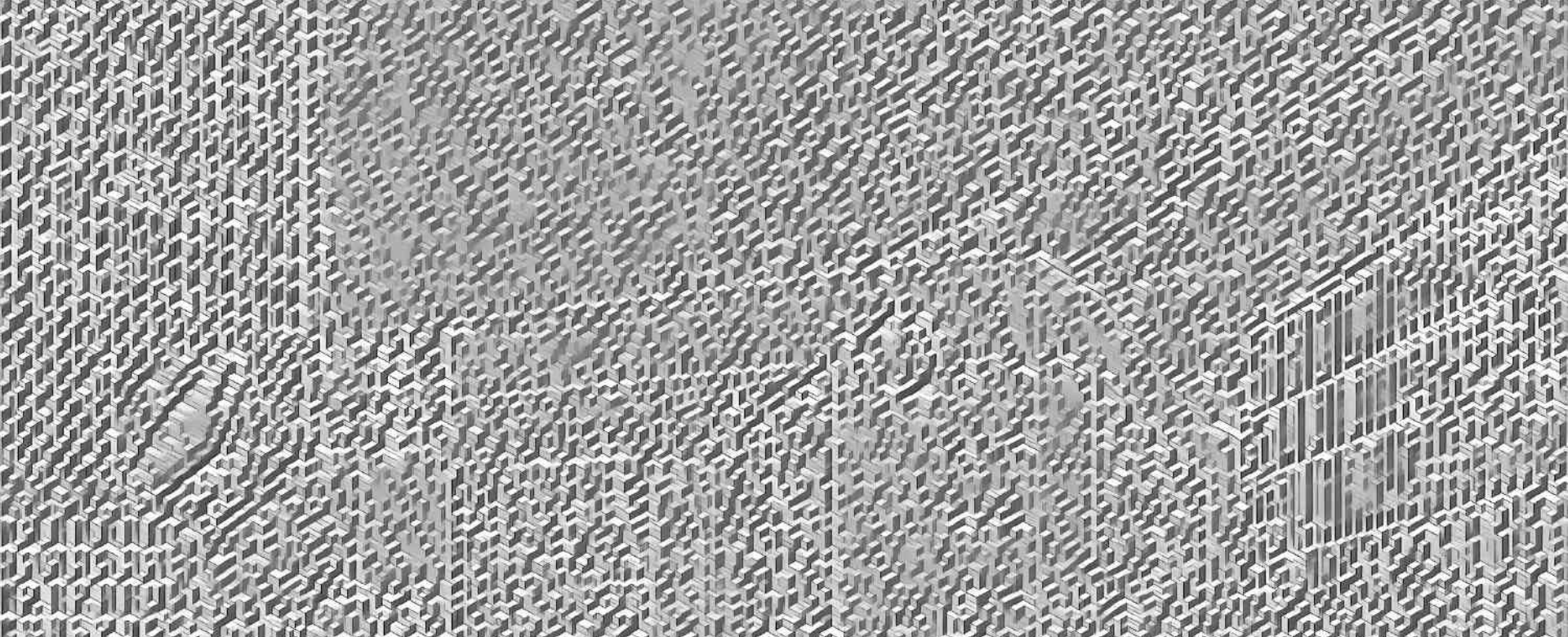
tensor of dimensions [6]
(vector of dimension 6)

3	1	4	1
5	9	2	6
5	3	5	8
9	7	9	3
2	3	8	4
6	2	6	4

tensor of dimensions [6,4]
(matrix 6 by 4)



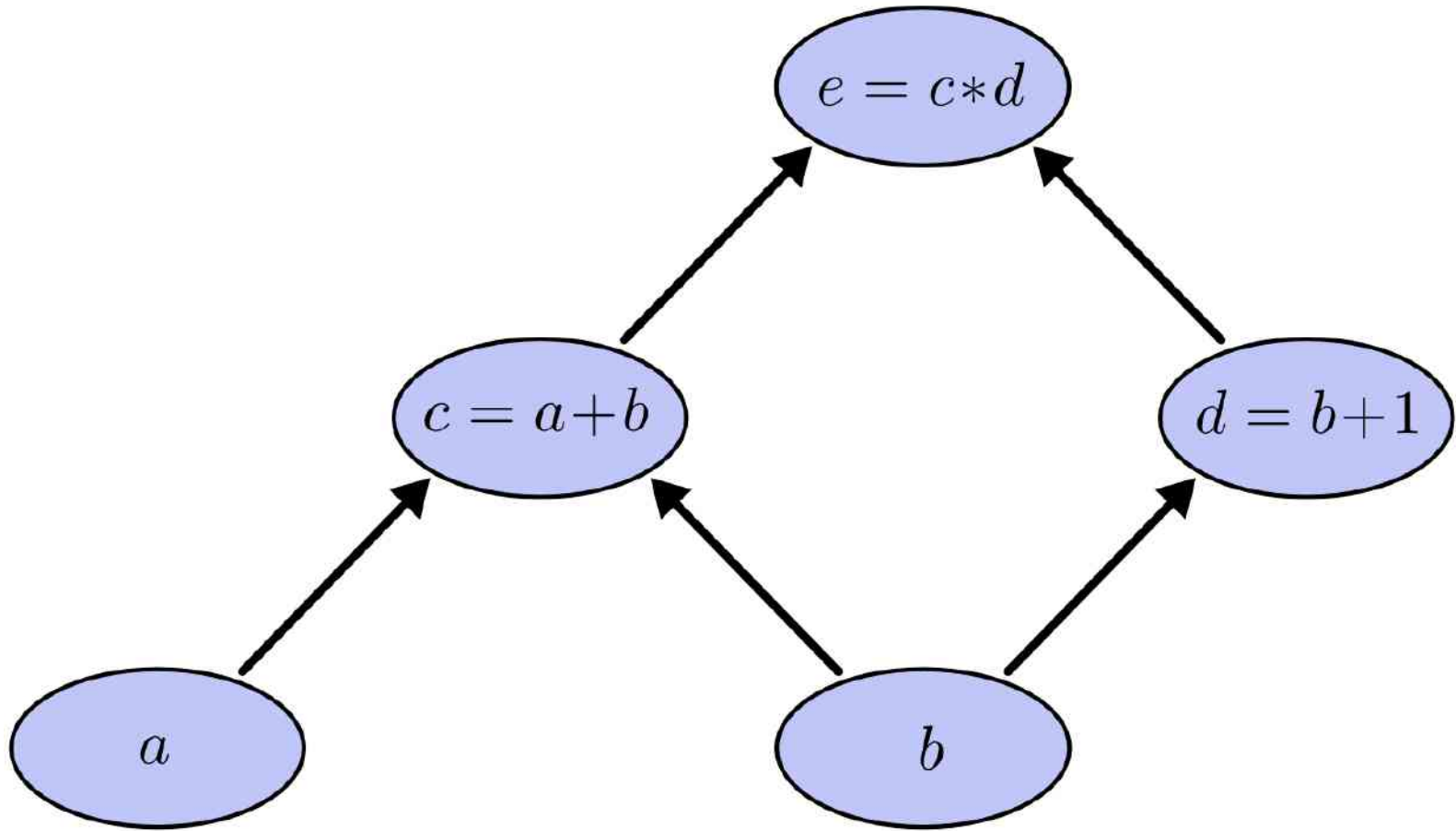
tensor of dimensions [4,4,2]



Computational Graphs



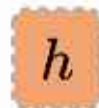
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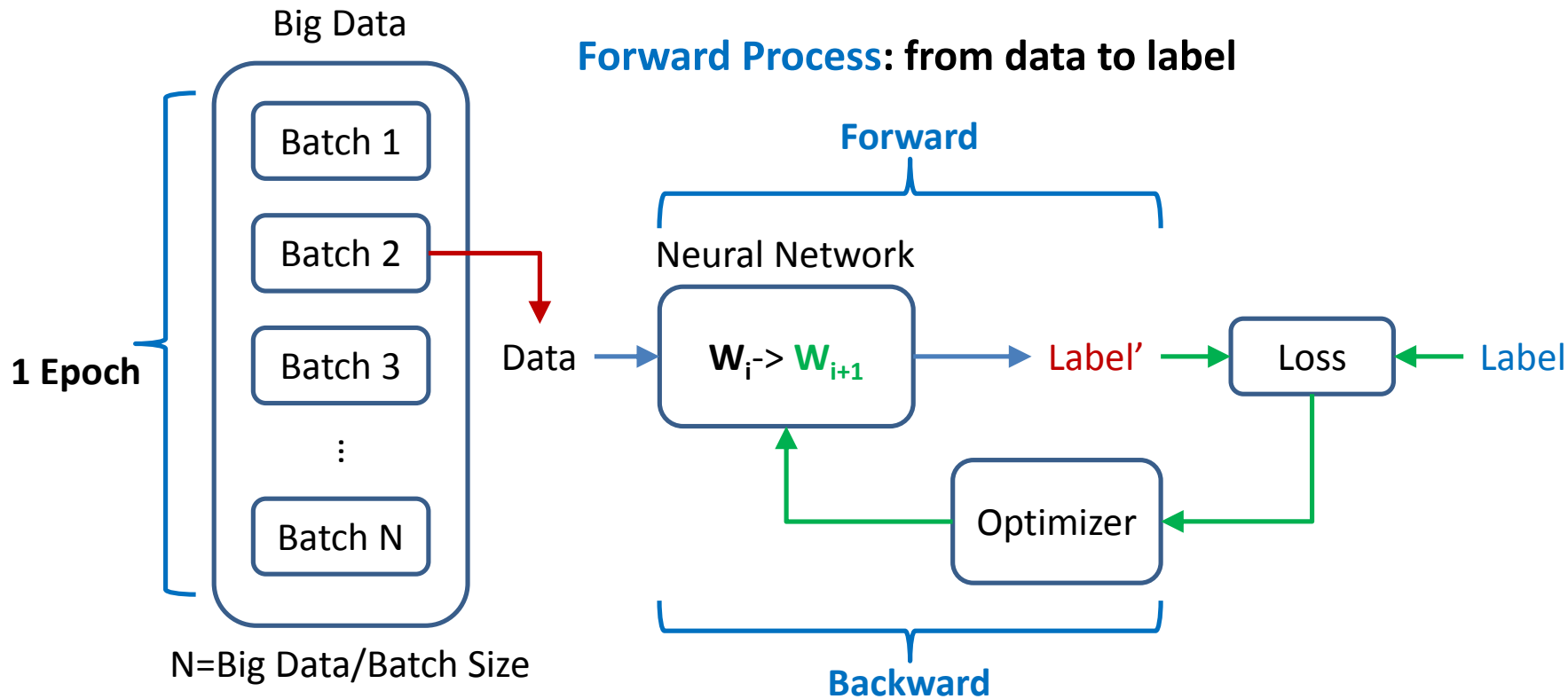


A graph is created on the fly

```
from torch.autograd import Variable

x = Variable(torch.randn(1, 10))
prev_h = Variable(torch.randn(1, 20))
W_h = Variable(torch.randn(20, 20))
W_x = Variable(torch.randn(20, 10))
```

A variable W_h represented as a brown square with a scalloped border.A variable h represented as a brown square with a scalloped border.A variable W_x represented as a brown square with a scalloped border.A variable x represented as a brown square with a scalloped border.



Backward Process: update the parameters

A graph is created on the fly

```
from torch.autograd import Variable

x = Variable(torch.randn(1, 10))
prev_h = Variable(torch.randn(1, 20))
W_h = Variable(torch.randn(20, 20))
W_x = Variable(torch.randn(20, 10))
```

A variable W_h represented as a brown square with a scalloped border.A variable h represented as a brown square with a scalloped border.A variable W_x represented as a brown square with a scalloped border.A variable x represented as a brown square with a scalloped border.

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

```
class Net(nn.Module):
```

```
    def __init__(self):
        super(Net, self).__init__()
        # 1 input image channel, 6 output channels, 3x3 square convolution
        # kernel
        self.conv1 = nn.Conv2d(1, 6, 3)
        self.conv2 = nn.Conv2d(6, 16, 3)
        # an affine operation: y = Wx + b
        self.fc1 = nn.Linear(16 * 6 * 6, 120) # 6*6 from image dimension
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)
```

```
    def forward(self, x):
        # Max pooling over a (2, 2) window
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        # If the size is a square you can only specify a single number
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = x.view(-1, self.num_flat_features(x))
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

Define modules

Build network

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

```
class Net(nn.Module):
```

```
    def __init__(self):
```

```
        super(Net, self).__init__()
```

```
        # 1 input image channel, 6 output channels, 3x3 square convolution
        # kernel
```

```
        self.conv1 = nn.Conv2d(1, 6, 3)
```

```
        self.conv2 = nn.Conv2d(6, 16, 3)
```

```
        # an affine operation:  $y = Wx + b$ 
```

```
        self.fc1 = nn.Linear(16 * 6 * 6, 120) # 6*6 from image dimension
```

```
        self.fc2 = nn.Linear(120, 84)
```

```
        self.fc3 = nn.Linear(84, 10)
```

```
    def forward(self, x):
```

```
        # Max pooling over a (2, 2) window
```

```
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
```

```
        # If the size is a square you can only specify a single number
```

```
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
```

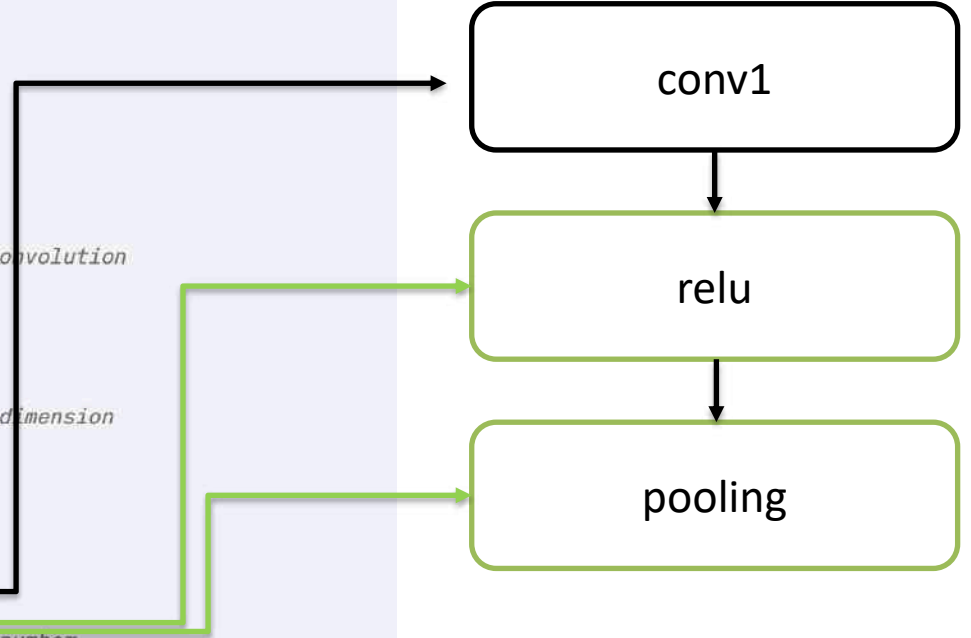
```
        x = x.view(-1, self.num_flat_features(x))
```

```
        x = F.relu(self.fc1(x))
```

```
        x = F.relu(self.fc2(x))
```

```
        x = self.fc3(x)
```

```
        return x
```



```
import torch.optim as optim
```

```
criterion = nn.CrossEntropyLoss()
```

```
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
```

```
net = Net()
```

Init Network

```
for epoch in range(2): # loop over the dataset multiple times
```

```
    running_loss = 0.0
```

```
    for i, data in enumerate(trainloader, 0):
```

```
        # get the inputs; data is a list of [inputs, labels]
```

```
        inputs, labels = data
```

```
        # zero the parameter gradients
```

```
        optimizer.zero_grad()
```

```
        # forward + backward + optimize
```

```
        outputs = net(inputs)
```

```
        loss = criterion(outputs, labels)
```

```
        loss.backward()
```

```
        optimizer.step()
```

```
    # print statistics
```

```
    running_loss += loss.item()
```

```
    if i % 2000 == 1999: # print every 2000 mini-batches
```

```
        print('[%d, %5d] loss: %.3f' %
```

```
              (epoch + 1, i + 1, running_loss / 2000))
```

```
    running_loss = 0.0
```

Parameter update

Train

Monitor Progress

```
print('Finished Training')
```




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Packages

- torch a Tensor library like Numpy, with strong GPU support
- torch.autograd a tape based automatic differentiation library that supports all differentiable Tensor operations in torch
- torch.nn a neural networks library deeply integrated with autograd designed for maximum flexibility
- torch.optim an optimization package to be used with torch.nn with standard optimization methods such as SGD, RMSProp, LBFGS, Adam etc.
- torch.multiprocessing python multiprocessing, but with magical memory sharing of torch Tensors across processes. Useful for data loading and hogwild training.
- torch.utils DataLoader, Trainer and other utility functions for convenience



GPU / CPU

- Well integrated with CUDA
- Control where to put the data CPU / GPU
`torch.device(dev)`
- Release data from GPU
`torch.cuda.empty_cache()`
- `torch.cuda.is_available()`



Saving Models

- Pickle
- `torch.save(the_model.state_dict(), optimizer_state_dict, PATH)`
- Requires the code to load 🤖
- ONNX





TensorFlow vs. PyTorch



Comparison with TensorFlow

Properties	TensorFlow	PyTorch
Graph	Static Dynamic (TensorFlow Fold)	Dynamic
Ramp-up Time	-	Win
Graph Creation and Debugging	-	Win
Feature Coverage	Win	Catch up quickly
Documentation	Tie	Tie
Serialization	Win (support other lang.)	-
Deployment	Win (Cloud & Mobile)	-
Data Loading	-	Win
Device Management	Win	Need .cuda()
Custom Extensions	-	Win

Summarized from <https://awni.github.io/pytorch-tensorflow/>



Wrap Up



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Vielen Dank für Ihre
Aufmerksamkeit.
Fragen & Antworten



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