

# A Brief Introduction to PyTorch

(a deep learning library)

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[pytorch.org](https://pytorch.org)

# Outline

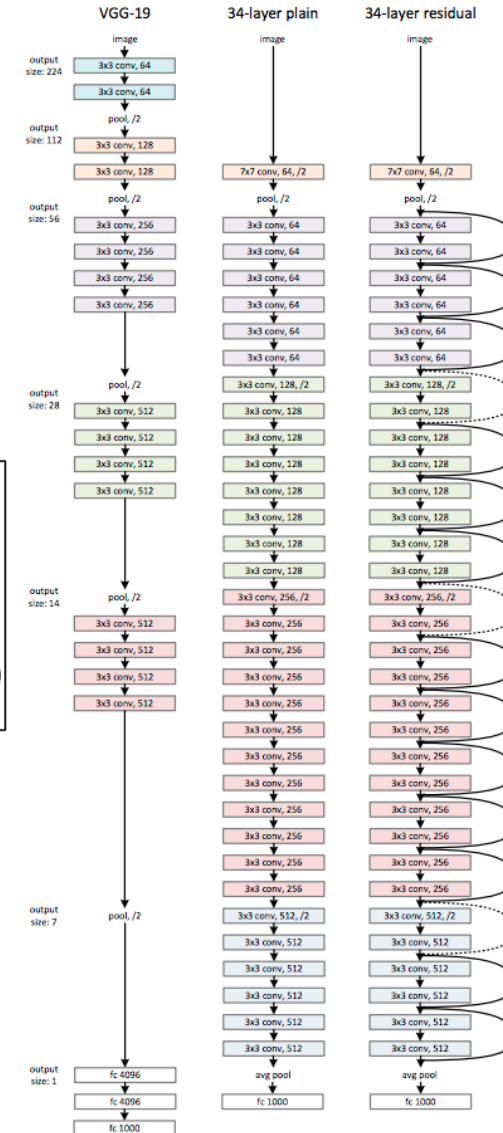
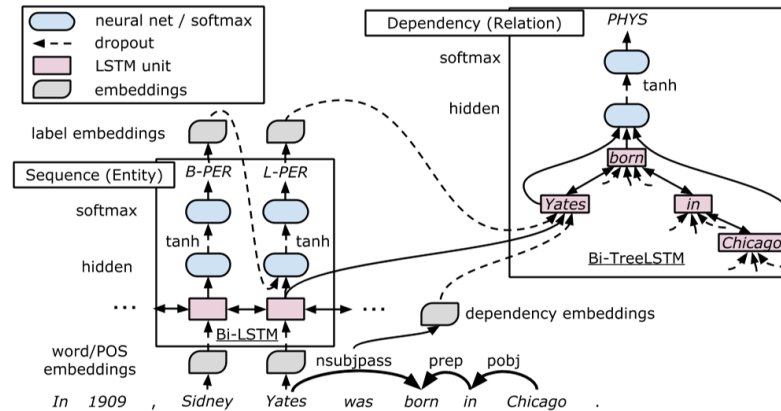
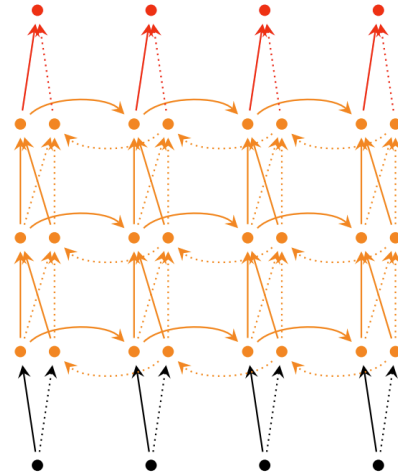
- ❑ **Why Deep Learning Libraries and Why PyTorch ?**
- ❑ **A Brief Introduction to PyTorch**
- ❑ **PyTorch in action**

# Outline

- ❑ **Why Deep Learning Libraries and Why PyTorch ?**
- ❑ A Brief Introduction to PyTorch
- ❑ PyTorch in action

# Why a DL Library is Necessary?

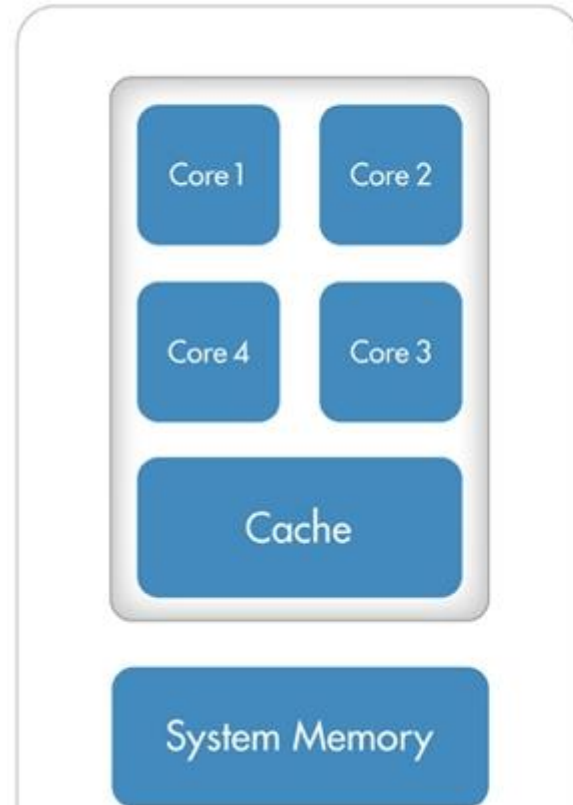
- Complicated DL architectures
  - Easily build big computational graphs
  - Easily compute gradients



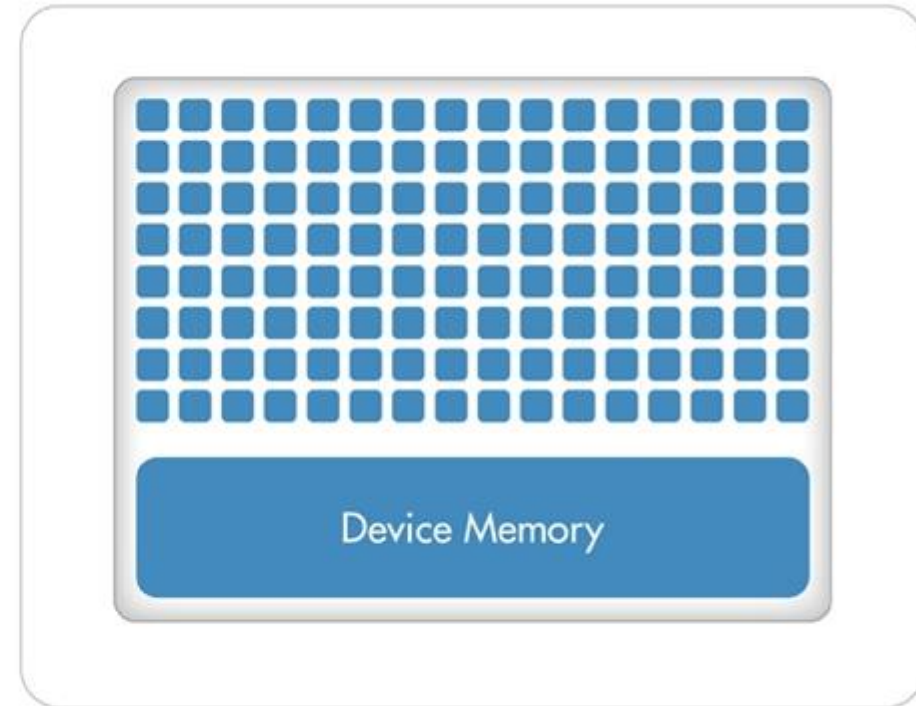
# Why a DL Library is Necessary?

- Run it all efficiently on GPU

**CPU (Multiple Cores)**



**GPU (Hundreds of Cores)**



# Popular Deep Learning Libraries

Caffe

 Microsoft  
CNTK

*dmlc*  
***mxnet***



**Caffe2**

  
TensorFlow

  
Chainer

theano

 torch



PYTORCH

 PaddlePaddle

# Why **PYTORCH**



**Andrej Karpathy** ✓

@karpathy

Following



I've been using PyTorch a few months now and I've never felt better. I have more energy. My skin is clearer. My eye sight has improved.

Life is short, you need **PYTORCH**

# Why PYTORCH

- Support Python
- Dynamic Graph
- Friendly API for research
- Easily debug
- Love all things [*Pythonic*]



# Outline

- Why Deep Learning Libraries and Why PyTorch ?
- **A Brief Introduction to PyTorch**
- PyTorch in action

# Installing **PYTORCH**

OS	<input checked="" type="radio"/> Linux	<input type="radio"/> OSX		
Package Manager	<input type="radio"/> conda	<input checked="" type="radio"/> pip	<input type="radio"/> Source	
Python	<input type="radio"/> 2.7	<input type="radio"/> 3.5	<input checked="" type="radio"/> 3.6	
CUDA	<input type="radio"/> 8	<input type="radio"/> 9.0	<input checked="" type="radio"/> 9.1	<input type="radio"/> None

**Run this command:**

```
pip3 install http://download.pytorch.org/whl/cu91/torch-0.3.1-cp36-cp36m-linux_x86_64.whl  
pip3 install torchvision
```

# Three Levels of Abstraction

- **Tensor:** Imperative ndarray
- **Variable:** Node in a computational graph (data,grad)
- **Module:** A neural network layer

```
In [1]: import torch
x = torch.FloatTensor([[1.0,2.0],[3.0,4.0]])
y = torch.FloatTensor(torch.randn(2,2))
z = torch.randn(2,2).type(torch.FloatTensor)
```

```
In [2]: var = torch.autograd.Variable(x)
```

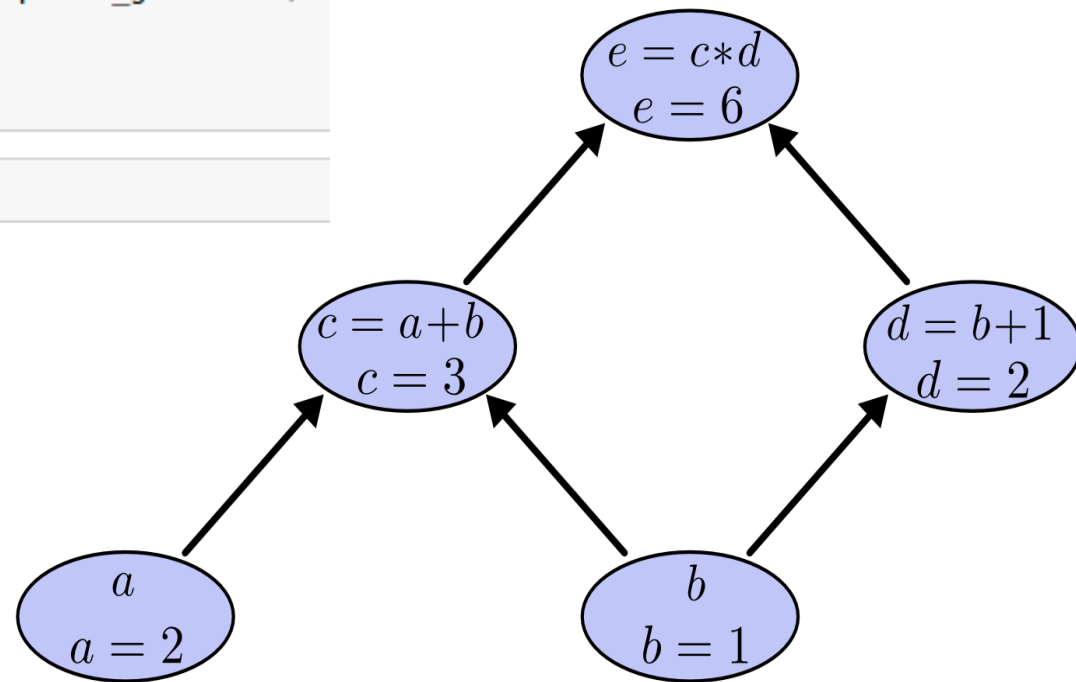
```
In [3]: fc = torch.nn.Linear(2,2)
```

# A Toy Neural Network

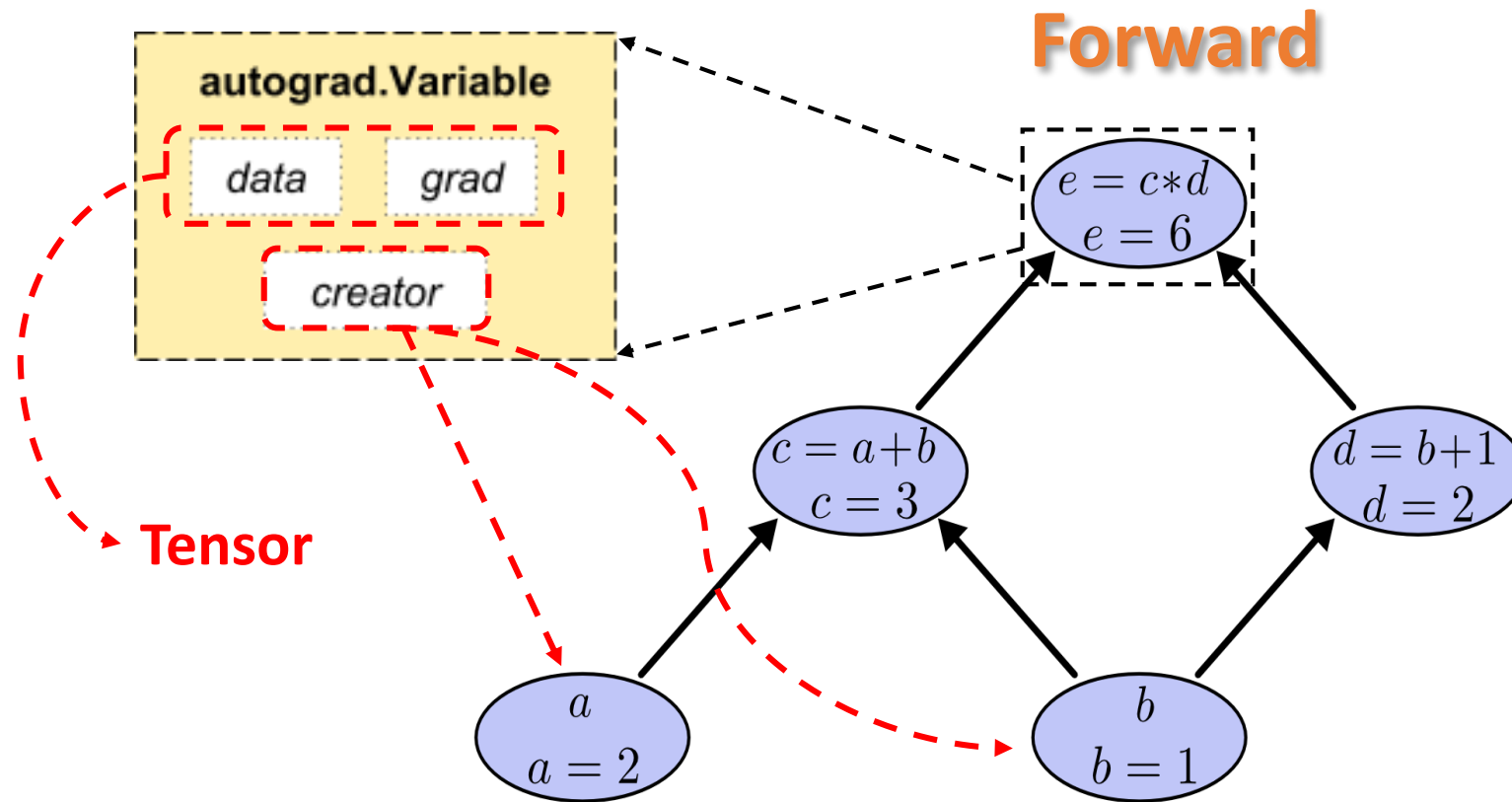
```
In [1]: import torch  
        from torch.autograd import Variable
```

```
In [2]: a = Variable(torch.LongTensor([2]),requires_grad=True)  
        b = Variable(torch.LongTensor([1]),requires_grad=True)  
        c = a + b  
        d = b + 1  
        e = c * d
```

```
In [3]: print a,b,c,d,e
```



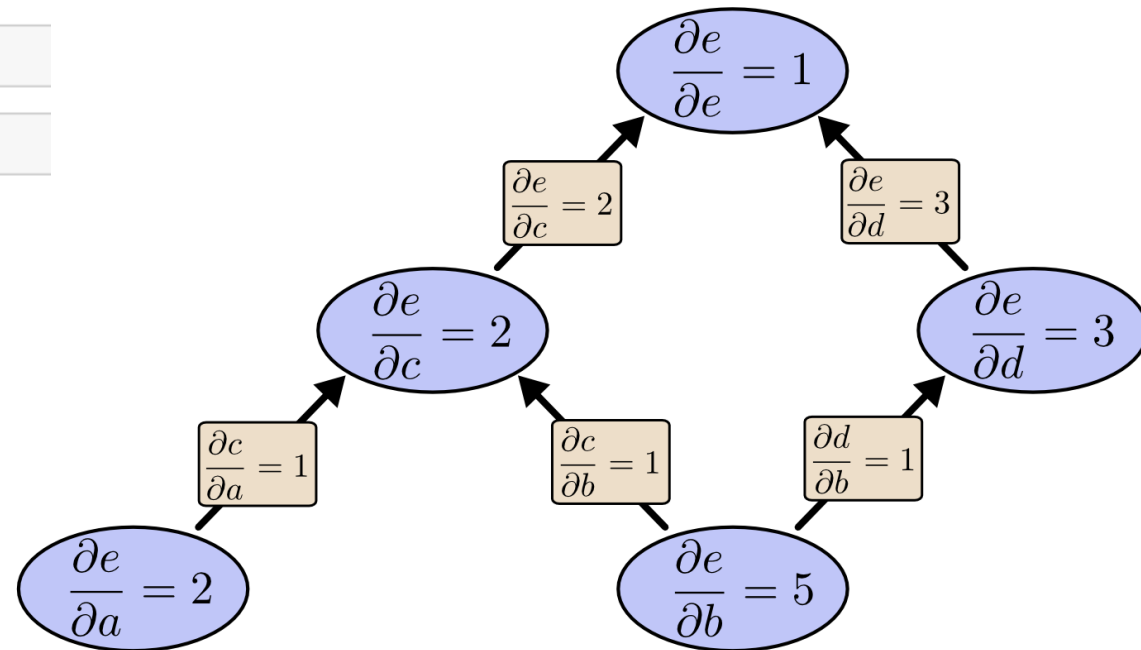
# A Toy Neural Network



# A Toy Neural Network

```
In [4]: e.backward()
```

```
In [5]: print a.grad,b.grad
```



# A Toy Neural Network



```
In [1]: import tensorflow as tf

a = tf.placeholder(tf.float32)
b = tf.placeholder(tf.float32)

c = a + b
d = b + 1
e = c * d

grad_a, grad_b = tf.gradients(e, [a, b])

with tf.Session() as sess:
    grad_a, grad_b = sess.run([grad_a, grad_b], feed_dict={a: 2, b: 1})
```



```
In [1]: import torch
        from torch.autograd import Variable

a = Variable(torch.LongTensor([2]), requires_grad=True)
b = Variable(torch.LongTensor([1]), requires_grad=True)
c = a + b
d = b + 1
e = c * d

e.backward()

print a.grad.data, b.grad.data
```

# Major Components of PyTorch

Package	Description
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.utils	DataLoader, Dataset and other utility functions for convenience



# Torch Module: PyTorch as A Tensor Library

- Tensor operations: slicing, indexing, math operations, linear algebra, reductions
  - CPU & GPU
  - Fast! (comparison on speed of **matrix multiplication**)

$$\mathbf{M} * \mathbf{M} * \mathbf{M} \quad \mathbf{M} \in \mathbb{R}^{1000 \times 1000}$$

**Numpy**

```
In [2]: M = numpy.random.randn(1000,1000)

In [3]: timeit -n 500 M.dot(M).dot(M)
500 loops, best of 3: 30.7 ms per loop
```

---

**PyTorch**

```
In [4]: N = torch.randn(1000,1000).cuda()

In [5]: timeit -n 500 N.mm(N).mm(N)
500 loops, best of 3: 474 µs per loop
```

# Torch.nn : a neural networks library

<b>Containers</b>	Module, Sequential,ModuleList,ParameterList
<b>Convolution Layers</b>	Conv1d,Conv2d,Conv3d...
<b>Recurrent Layers</b>	RNN,LSTM,GRU,RNNCell...
<b>Linear Layers</b>	Linear, Bilinear
<b>Non-linear Activations</b>	ReLU,Sigmoid,Tanh,LeakyReLU...
<b>Loss Functions</b>	NLLLoss,BCELoss,CrossEntropyLoss...

# Torch.nn.functional

## Torch.nn

```
In [1]: import torch
import torch.nn as nn
from torch.autograd import Variable

relu = nn.ReLU(inplace=True)

x = Variable(torch.randn(10,128))
x = relu(x)
```

---

## Torch.nn.functional

```
In [1]: import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.autograd import Variable

x = Variable(torch.randn(10,128))
x = F.relu(x)
```

# How to load dataset?

```
In [7]: class MyData(Dataset):
        def __init__(self):
            super(MyData,self).__init__()
            ex1 = {'sent':'Nice to meet you','label':1}
            ex2 = {'sent':'I hate you','label':0}
            self.examples = [ex1,ex2]
        def __len__(self):
            return len(self.examples)
        def __getitem__(self,index):
            return self.examples[index]
```

```
In [8]: dataset = MyData()
        data_iter = DataLoader(dataset=dataset,batch_size=2,shuffle=True)
        for batch in data_iter:
            print batch
```

```
{'sent': ['I hate you', 'Nice to meet you'], 'label':
 0
 1
[torch.LongTensor of size 2]
}
```

# How to build a model?

```
In [9]: import torch
import torch.nn as nn
```

```
In [10]: class Net(nn.Module):
def __init__(self):
    super(Net,self).__init__()
    self.fc = nn.Linear(10,2)
def forward(self,x):
    return self.fc(x)
```

```
In [11]: net = Net()
x = torch.autograd.Variable(torch.randn(2,10))
print net(x)
```

```
Variable containing:
-0.4123 -0.6326
 0.7484 -0.2521
[torch.FloatTensor of size 2x2]
```

# How to train a model?

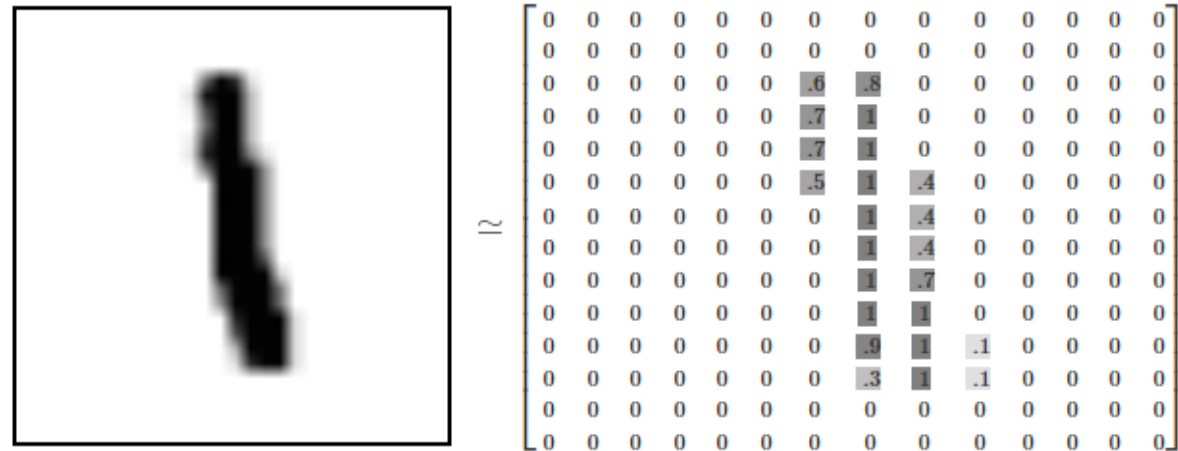
```
In [12]: net = Net()
         criterion = nn.CrossEntropyLoss()
         optimizer = torch.optim.Adam(net.parameters(), lr=1e-3)

         for epoch in range(10):
             ...
             for x,y in data_loader:
                 x,y = Variable(x),Variable(y)
                 x = net(x)
                 loss = criterion(x,y)
                 optimizer.zero_grad()
                 loss.backward()
                 optimizer.step()
             ...
         ...
```

# Outline

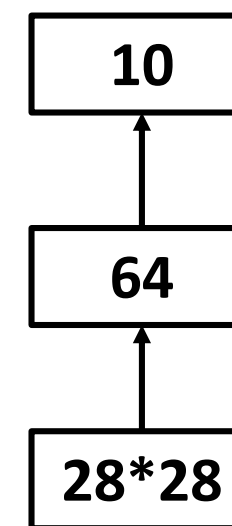
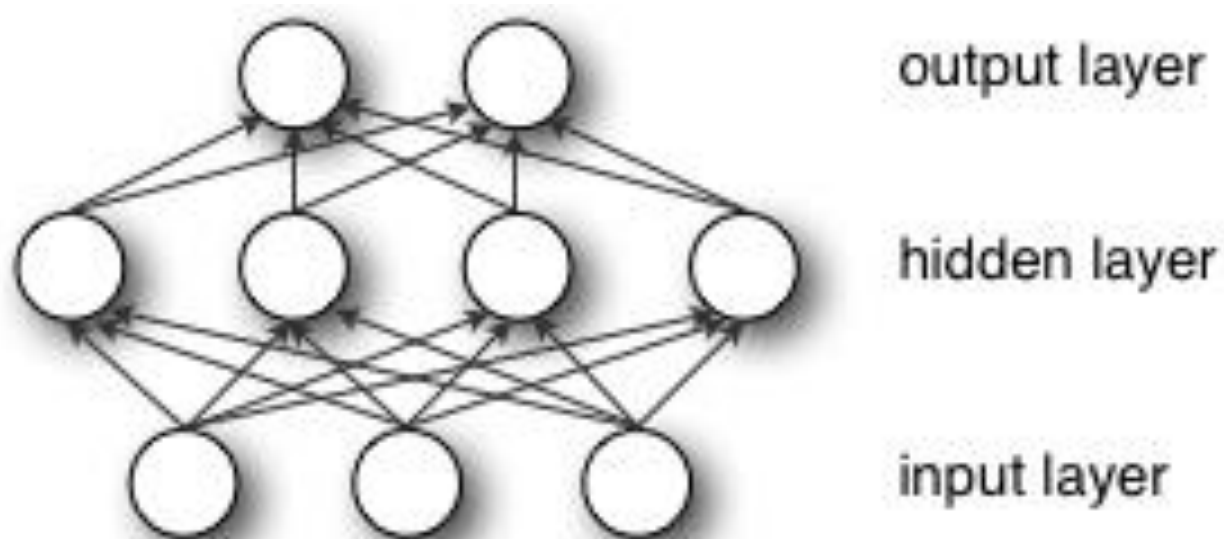
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# MNIST Dataset





# MLP for MNIST (0-d features)



# MLP for MNIST

In [3]:

```
class MLP(nn.Module):
    def __init__(self, n_class=10):
        super(MLP, self).__init__()

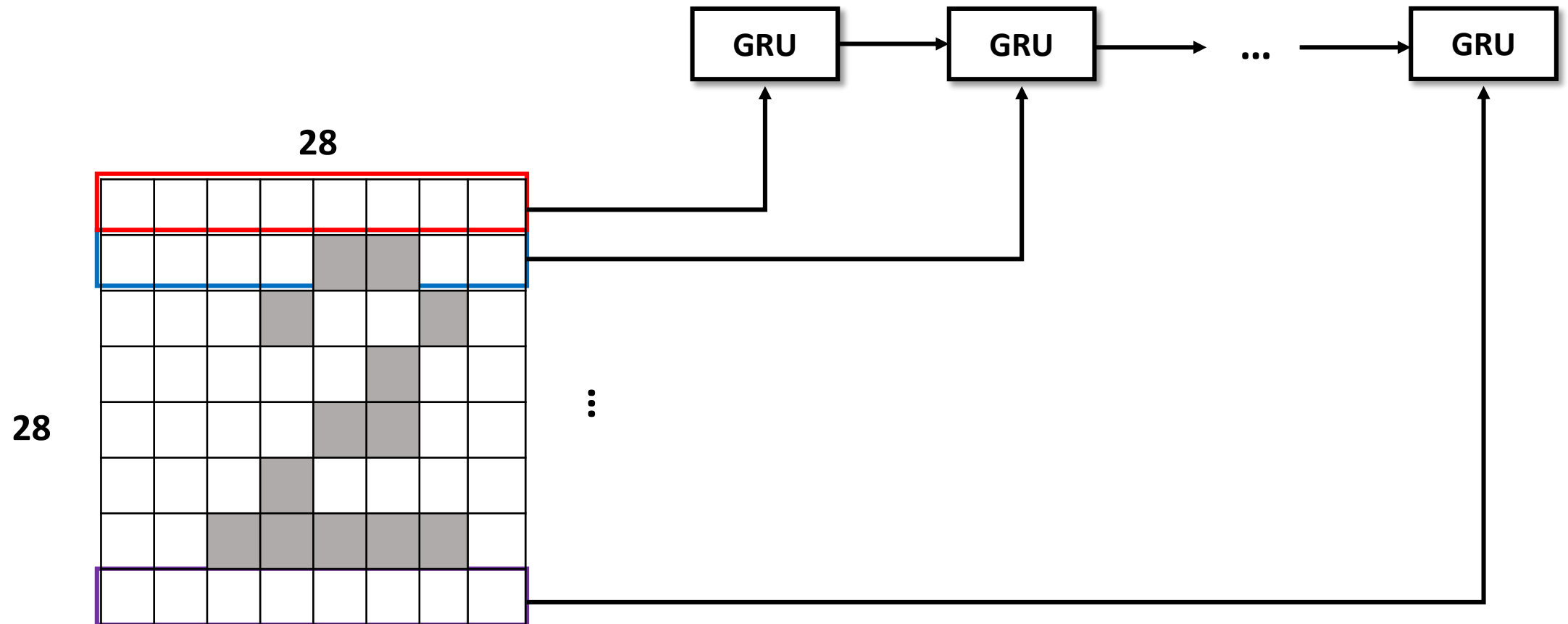
        self.fc = nn.Sequential(
            nn.Linear(28*28, 64),
            nn.ReLU(inplace=True),
            nn.Linear(64, n_class)
        )

        """
        self.fc1 = nn.Linear(28*28, 64)
        self.relu = nn.ReLU(inplace=True)
        self.fc2 = nn.Linear(64, n_class)
        """

    def forward(self, x):
        x = x.view(-1, 28*28)      # x: (batch_size, 1, 28, 28) => x: (batch_size, 28*28)
        logits = self.fc(x)
        return logits
```

Last Test Acc: 95.8%

# RNN for MNIST (1-d features)



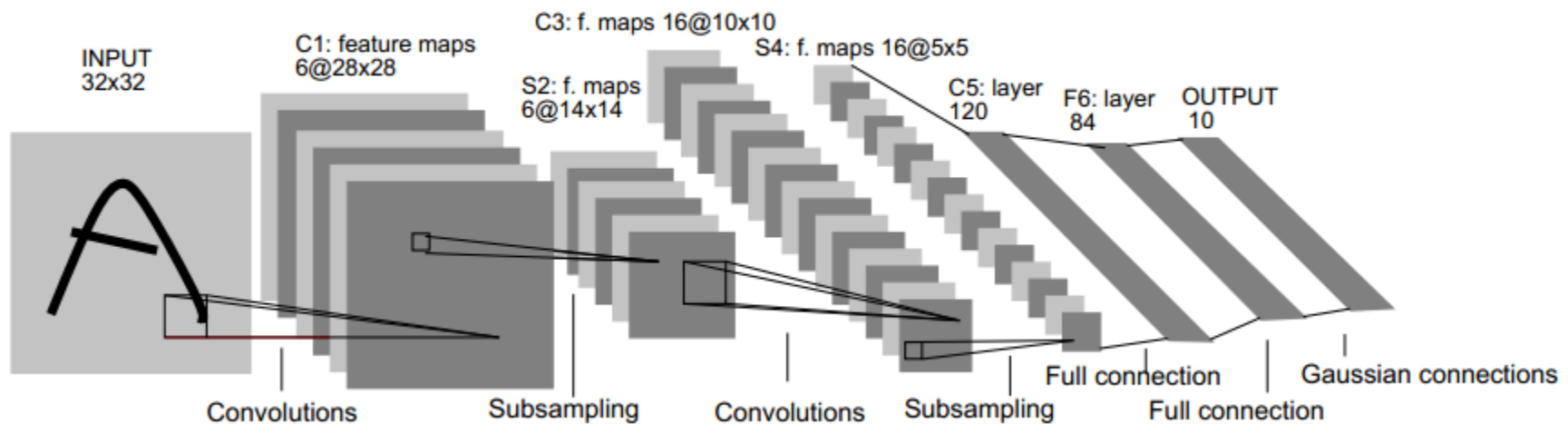
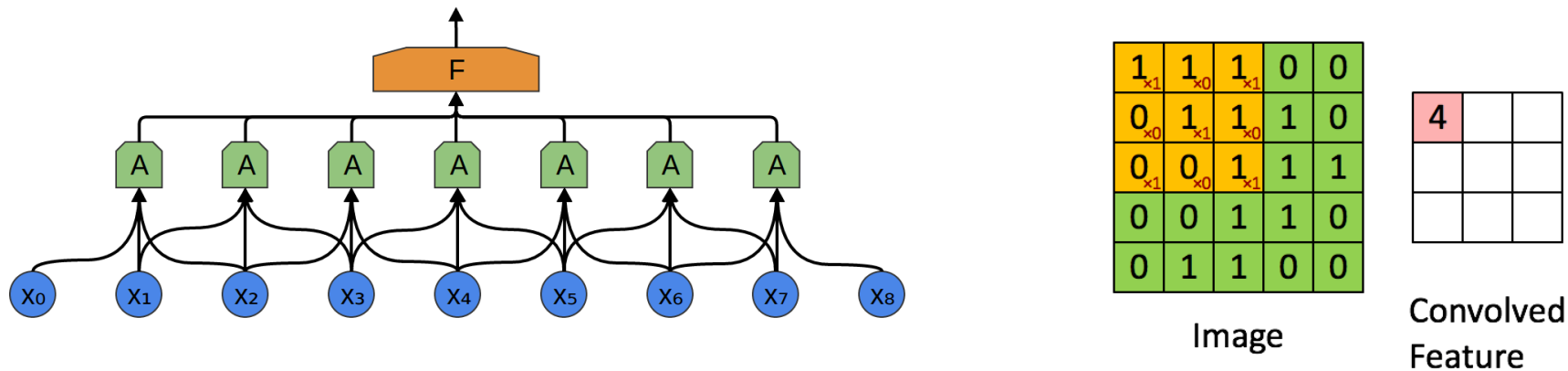
# RNN for MNIST

```
class RNN(nn.Module):
    def __init__(self, input_size=28, hidden_size=64, n_class=10):
        super(RNN, self).__init__()
        self.RNN = nn.GRU(
            input_size = input_size,
            hidden_size = hidden_size,
            batch_first = True
        )
        self.fc = nn.Linear(hidden_size, 10)

    def forward(self, x):
        x = x.squeeze()      # x:(batch_size,1,28,28) => x:(batch_size,28,28)
        out, _ = self.RNN(x) # x:(batch_size,28,28) => out:(batch_size,28,hidden_size)
        # get last hidden
        out = out[:, -1, :]  # out:(batch_size,hidden_size)
        logits = self.fc(out)
        return logits
```

Last Test Acc: 97.7%

# CNN for MNIST (2-d features)



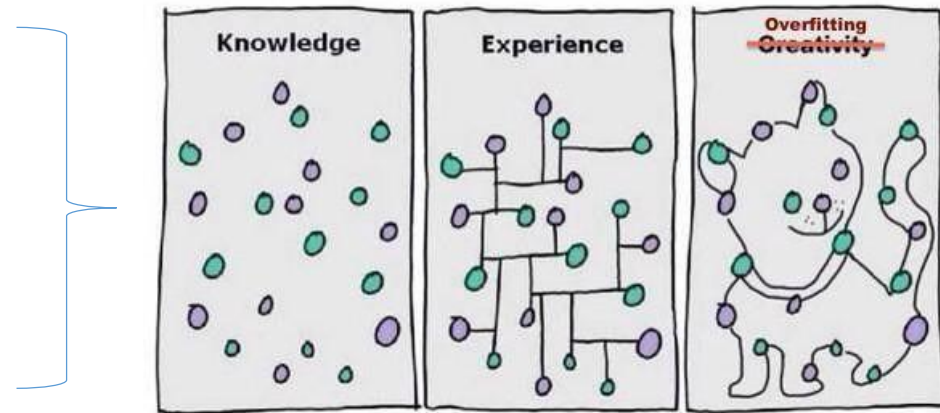
# CNN for MNIST

```
class LeNet(nn.Module):
    def __init__(self, n_class=10):
        super(LeNet, self).__init__()
        self.conv1 = nn.Conv2d(
            in_channels = 1,
            out_channels = 20,
            kernel_size = 5
        )
        self.conv2 = nn.Conv2d(
            in_channels = 20,
            out_channels = 50,
            kernel_size = 5
        )
        self.fc1 = nn.Linear(4*4*50, 500)
        self.fc2 = nn.Linear(500, n_class)
    def forward(self, x):
        x = F.relu(self.conv1(x))      # x:[batch_size,1,28,28] => x:[batch_size,20, 24, 24]
        x = F.max_pool2d(x, 2, 2)      # x:[batch_size,20,24,24] => x:[batch_size,20, 12, 12]
        x = F.relu(self.conv2(x))      # x:[batch_size,20,12,12] => x:[batch_size,50, 8, 8]
        x = F.max_pool2d(x, 2, 2)      # x:[batch_size,50,8,8] => x:[batch_size,50, 4, 4]
        x = x.view(-1, 4*4*50)         # x:[batch_size,50,4,4] => x:[batch_size,50*4*4]
        x = F.relu(self.fc1(x))        # x:[batch_size,50*4*4] => x:[batch_size,500]
        x = self.fc2(x)               # x:[batch_size,500] => x:[batch_size,10]
        return x
```

Last Test Acc: 99.2%

# Assignments

1. Try more models (Bi-LSTM, ResNet...)
2. L2 Regularization
3. Dropout
4. Data Argumentation
5. Batch Normalization
6. Try other optimization algorithms(SGD...)
7. Try more activation function(Tanh, Sigmoid...)



# Resources

- Official resources
  - Documentation <http://pytorch.org/docs/master/>
  - Tutorials <http://pytorch.org/tutorials/index.html>
  - Example projects <https://github.com/pytorch/examples>
- Github code
  - fairseq-py
  - OpenNMT-py
- Open courses and blogs
  - **Stanford CS231N 2017**, Lecture 8 “Deep Learning Software”