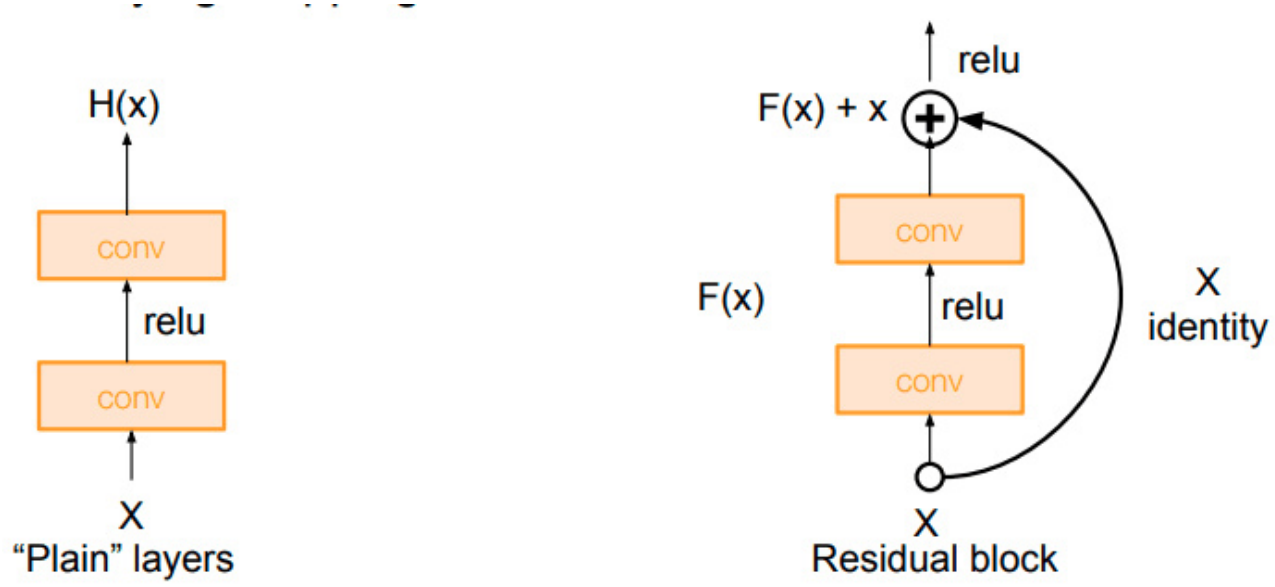
ResNet

ResNet 通过引入了跨层链接解决了梯度回传消失的问题。



这就普通的网络连接跟跨层残差连接的对比图，使用普通的连接，上层的梯度必须要一层一层传回来，而是用残差连接，相当于中间有了一条更短的路，梯度能够从这条更短的路传回来，避免了梯度过小的情况。

假设某层的输入是 x，期望输出是 H(x)， 如果我们直接把输入 x 传到输出作为初始结果，这就是一个更浅层的网络，更容易训练，而这个网络没有学会的部分，我们可以使用更深的网络 F(x) 去训练它，使得训练更加容易，最后希望拟合的结果就是 F(x) = H(x) - x，这就是一个残差的结构

残差网络的结构就是上面这种残差块的堆叠，下面让我们来实现一个 residual block

```
import numpy as np
import torch
from torch import nn
import torch.nn.functional as F
from torch.autograd import Variable
from torchvision.datasets import CIFAR10
```

```
def conv3x3(in_channel, out_channel, stride=1):
    return nn.Conv2d(in_channel, out_channel, 3, stride=stride, padding=1,
bias=False)
```

```
class residual_block(nn.Module):
    def __init__(self, in_channel, out_channel, same_shape=True):
```

```
        super(residual_block, self).__init__()
        self.same_shape = same_shape
        stride=1 if self.same_shape else 2

        self.conv1 = conv3x3(in_channel, out_channel, stride=stride)
        self.bn1 = nn.BatchNorm2d(out_channel)

        self.conv2 = conv3x3(out_channel, out_channel)
        self.bn2 = nn.BatchNorm2d(out_channel)
        if not self.same_shape:
            self.conv3 = nn.Conv2d(in_channel, out_channel, 1, stride=stride)

    def forward(self, x):
        out = self.conv1(x)
        out = F.relu(self.bn1(out), True)
        out = self.conv2(out)
        out = F.relu(self.bn2(out), True)

        if not self.same_shape:
            x = self.conv3(x)
        return F.relu(x+out, True)
```

我们测试一下一个 residual block 的输入和输出

```
# 输入输出形状相同
test_net = residual_block(32, 32)
test_x = Variable(torch.zeros(1, 32, 96, 96))
print('input: {}'.format(test_x.shape))
test_y = test_net(test_x)
print('output: {}'.format(test_y.shape))
```

```
input: torch.Size([1, 32, 96, 96])
output: torch.Size([1, 32, 96, 96])
```

```
# 输入输出形状不同
test_net = residual_block(3, 32, False)
test_x = Variable(torch.zeros(1, 3, 96, 96))
print('input: {}'.format(test_x.shape))
test_y = test_net(test_x)
print('output: {}'.format(test_y.shape))
```

```
input: torch.Size([1, 3, 96, 96])
output: torch.Size([1, 32, 48, 48])
```

下面我们尝试实现一个 ResNet，它就是 residual block 模块的堆叠

```
class resnet(nn.Module):
    def __init__(self, in_channel, num_classes, verbose=False):
        super(resnet, self).__init__()
        self.verbose = verbose

        self.block1 = nn.Conv2d(in_channel, 64, 7, 2)

        self.block2 = nn.Sequential(
            nn.MaxPool2d(3, 2),
            residual_block(64, 64),
            residual_block(64, 64)
        )

        self.block3 = nn.Sequential(
            residual_block(64, 128, False),
            residual_block(128, 128)
        )

        self.block4 = nn.Sequential(
            residual_block(128, 256, False),
            residual_block(256, 256)
        )

        self.block5 = nn.Sequential(
            residual_block(256, 512, False),
            residual_block(512, 512),
            nn.AvgPool2d(3)
        )

        self.classifier = nn.Linear(512, num_classes)

    def forward(self, x):
        x = self.block1(x)
        if self.verbose:
            print('block 1 output: {}'.format(x.shape))
        x = self.block2(x)
        if self.verbose:
            print('block 2 output: {}'.format(x.shape))
        x = self.block3(x)
        if self.verbose:
```

```
            print('block 3 output: {}'.format(x.shape))
        x = self.block4(x)
        if self.verbose:
            print('block 4 output: {}'.format(x.shape))
        x = self.block5(x)
        if self.verbose:
            print('block 5 output: {}'.format(x.shape))
        x = x.view(x.shape[0], -1)
        x = self.classifier(x)
        return x
```

输出一下每个 block 之后的大小

```
test_net = resnet(3, 10, True)
test_x = Variable(torch.zeros(1, 3, 96, 96))
test_y = test_net(test_x)
print('output: {}'.format(test_y.shape))
```

```
block 1 output: torch.Size([1, 64, 45, 45])
block 2 output: torch.Size([1, 64, 22, 22])
block 3 output: torch.Size([1, 128, 11, 11])
block 4 output: torch.Size([1, 256, 6, 6])
block 5 output: torch.Size([1, 512, 1, 1])
output: torch.Size([1, 10])
```

```
from utils import train

def data_tf(x):
    x = x.resize((96, 96), 2) # 将图片放大到 96 x 96
    x = np.array(x, dtype='float32') / 255
    x = (x - 0.5) / 0.5 # 标准化，这个技巧之后会讲到
    x = x.transpose((2, 0, 1)) # 将 channel 放到第一维，只是 pytorch 要求的输入方式
    x = torch.from_numpy(x)
    return x

train_set = CIFAR10('./data', train=True, transform=data_tf)
train_data = torch.utils.data.DataLoader(train_set, batch_size=64, shuffle=True)
test_set = CIFAR10('./data', train=False, transform=data_tf)
test_data = torch.utils.data.DataLoader(test_set, batch_size=128, shuffle=False)

net = resnet(3, 10)
optimizer = torch.optim.SGD(net.parameters(), lr=0.01)
criterion = nn.CrossEntropyLoss()
```

```
train(net, train_data, test_data, 20, optimizer, criterion)
```

```
Epoch 0. Train Loss: 1.437317, Train Acc: 0.476662, Valid Loss: 1.928288, Valid Acc:
0.384691, Time 00:00:44
Epoch 1. Train Loss: 0.992832, Train Acc: 0.648198, Valid Loss: 1.009847, Valid Acc:
0.642405, Time 00:00:48
Epoch 2. Train Loss: 0.767309, Train Acc: 0.732617, Valid Loss: 1.827319, Valid Acc:
0.430380, Time 00:00:47
Epoch 3. Train Loss: 0.606737, Train Acc: 0.788043, Valid Loss: 1.304808, Valid Acc:
0.585245, Time 00:00:46
Epoch 4. Train Loss: 0.484436, Train Acc: 0.834499, Valid Loss: 1.335749, Valid Acc:
0.617089, Time 00:00:47
Epoch 5. Train Loss: 0.374320, Train Acc: 0.872922, Valid Loss: 0.878519, Valid Acc:
0.724288, Time 00:00:47
Epoch 6. Train Loss: 0.280981, Train Acc: 0.904212, Valid Loss: 0.931616, Valid Acc:
0.716871, Time 00:00:48
Epoch 7. Train Loss: 0.210800, Train Acc: 0.929747, Valid Loss: 1.448870, Valid Acc:
0.638548, Time 00:00:48
Epoch 8. Train Loss: 0.147873, Train Acc: 0.951427, Valid Loss: 1.356992, Valid Acc:
0.657536, Time 00:00:47
Epoch 9. Train Loss: 0.112824, Train Acc: 0.963895, Valid Loss: 1.630560, Valid Acc:
0.627769, Time 00:00:47
Epoch 10. Train Loss: 0.082685, Train Acc: 0.973905, Valid Loss: 0.982882, Valid Acc:
0.744264, Time 00:00:44
Epoch 11. Train Loss: 0.065325, Train Acc: 0.979680, Valid Loss: 0.911631, Valid Acc:
0.767009, Time 00:00:47
Epoch 12. Train Loss: 0.041401, Train Acc: 0.987952, Valid Loss: 1.167992, Valid Acc:
0.729826, Time 00:00:48
Epoch 13. Train Loss: 0.037516, Train Acc: 0.989011, Valid Loss: 1.081807, Valid Acc:
0.746737, Time 00:00:47
Epoch 14. Train Loss: 0.030674, Train Acc: 0.991468, Valid Loss: 0.935292, Valid Acc:
0.774031, Time 00:00:45
Epoch 15. Train Loss: 0.021743, Train Acc: 0.994565, Valid Loss: 0.879348, Valid Acc:
0.790150, Time 00:00:47
Epoch 16. Train Loss: 0.014642, Train Acc: 0.996463, Valid Loss: 1.328587, Valid Acc:
0.724387, Time 00:00:47
Epoch 17. Train Loss: 0.011072, Train Acc: 0.997363, Valid Loss: 0.909065, Valid Acc:
0.792919, Time 00:00:47
Epoch 18. Train Loss: 0.006870, Train Acc: 0.998561, Valid Loss: 0.923746, Valid Acc:
0.794403, Time 00:00:46
Epoch 19. Train Loss: 0.004240, Train Acc: 0.999500, Valid Loss: 0.877908, Valid Acc:
0.802314, Time 00:00:46
```

ResNet 使用跨层通道使得训练非常深的卷积神经网络成为可能。同样它使用很简单的卷积层配置，使得其拓展更加简单。

**小练习：
1.尝试一下论文中提出的 bottleneck 的结构
2.尝试改变 conv -> bn -> relu 的顺序为 bn -> relu -> conv，看看精度会不会提高**