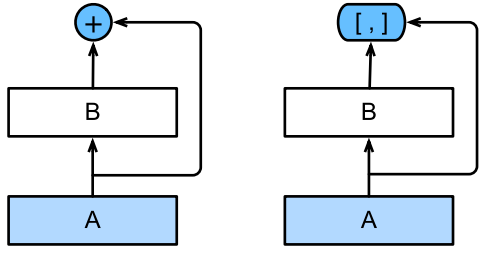
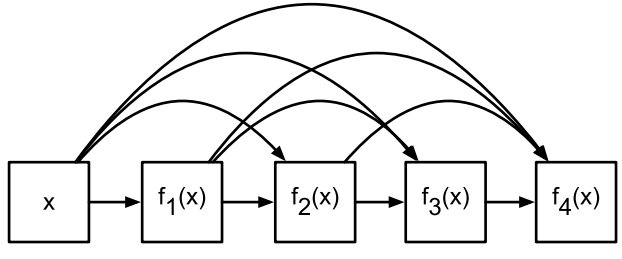
Densely Connected Networks (DenseNet)



$$\mathbf{x} \to [\mathbf{x}, f_1(\mathbf{x}), f_2(\mathbf{x}, f_1(\mathbf{x})), f_3(\mathbf{x}, f_1(\mathbf{x}), f_2(\mathbf{x}, f_1(\mathbf{x})), \ldots]$$



Dense Blocks

In [1]:

```
import d2l
from mxnet import gluon, init, nd
from mxnet.gluon import nn

def conv_block(num_channels):
    blk = nn.Sequential()
    blk.add(nn.BatchNorm(),
            nn.Activation('relu'),
            nn.Conv2D(num_channels, kernel_size=3, padding=1))
    return blk
```

A dense block consists of multiple `conv_block` units, each using the same number of output channels. In the forward computation, however, we concatenate the input and output of each block on the channel dimension.

In [2]:
```
class DenseBlock(nn.Block):
    def __init__(self, num_convs, num_channels, **kwargs):
        super(DenseBlock, self).__init__(**kwargs)
        self.net = nn.Sequential()
        for _ in range(num_convs):
            self.net.add(conv_block(num_channels))

    def forward(self, X):
        for blk in self.net:
            Y = blk(X)
            X = nd.concat(X, Y, dim=1)  # Concatenate the input and output of each
block on the channel dimension.
        return X
```

Testing it with data.

In [3]:
```
blk = DenseBlock(2, 10)
blk.initialize()
X = nd.random.uniform(shape=(4, 3, 8, 8))
Y = blk(X)
Y.shape
```

Out[3]:
```
(4, 23, 8, 8)
```

Transition Layers to reduce dimensionality

In [4]:
```
def transition_block(num_channels):
    blk = nn.Sequential()
    blk.add(nn.BatchNorm(), nn.Activation('relu'),
            nn.Conv2D(num_channels, kernel_size=1),
            nn.AvgPool2D(pool_size=2, strides=2))
    return blk
```

In [5]:
```
blk = transition_block(10)
blk.initialize()
print(Y.shape)
print(blk(Y).shape)
```

```
(4, 23, 8, 8)
(4, 10, 4, 4)
```

DenseNet Model

In [6]:
```
net = nn.Sequential()
net.add(nn.Conv2D(64, kernel_size=7, strides=2, padding=3),
        nn.BatchNorm(), nn.Activation('relu'),
        nn.MaxPool2D(pool_size=3, strides=2, padding=1))
```

4 dense blocks with a transition layer in between.

In [7]:
```
num_channels, growth_rate = 64, 32  # Num_channels: the current number of channel
s.
num_convs_in_dense_blocks = [4, 4, 4, 4]

for i, num_convs in enumerate(num_convs_in_dense_blocks):
    net.add(DenseBlock(num_convs, growth_rate))
    # This is the number of output channels in the previous dense block.
    num_channels += num_convs * growth_rate
    # A transition layer that haves the number of channels is added between the de
nse blocks.
    if i != len(num_convs_in_dense_blocks) - 1:
        net.add(transition_block(num_channels // 2))
```

Last stage

Similar to ResNet, a global pooling layer and fully connected layer are connected at the end to produce the output.

In [8]:
```
net.add(nn.BatchNorm(),
        nn.Activation('relu'),
        nn.GlobalAvgPool2D(),
        nn.Dense(10))
```

Data Acquisition and Training

Since we are using a deeper network here we only use 96x96 images for speed.

In [9]:
```
lr, num_epochs, batch_size, ctx = 0.1, 5, 256, d2l.try_gpu()
net.initialize(ctx=ctx, init=init.Xavier())
trainer = gluon.Trainer(net.collect_params(), 'sgd', {'learning_rate': lr})
train_iter, test_iter = d2l.load_data_fashion_mnist(batch_size, resize=96)
d2l.train_ch5(net, train_iter, test_iter, batch_size, trainer, ctx, num_epochs)
```

```
training on gpu(0)
epoch 1, loss 0.5356, train acc 0.811, test acc 0.866, time 15.0 sec
epoch 2, loss 0.3142, train acc 0.886, test acc 0.829, time 13.2 sec
epoch 3, loss 0.2647, train acc 0.904, test acc 0.904, time 13.2 sec
epoch 4, loss 0.2304, train acc 0.917, test acc 0.909, time 13.2 sec
epoch 5, loss 0.2105, train acc 0.923, test acc 0.915, time 13.2 sec
```