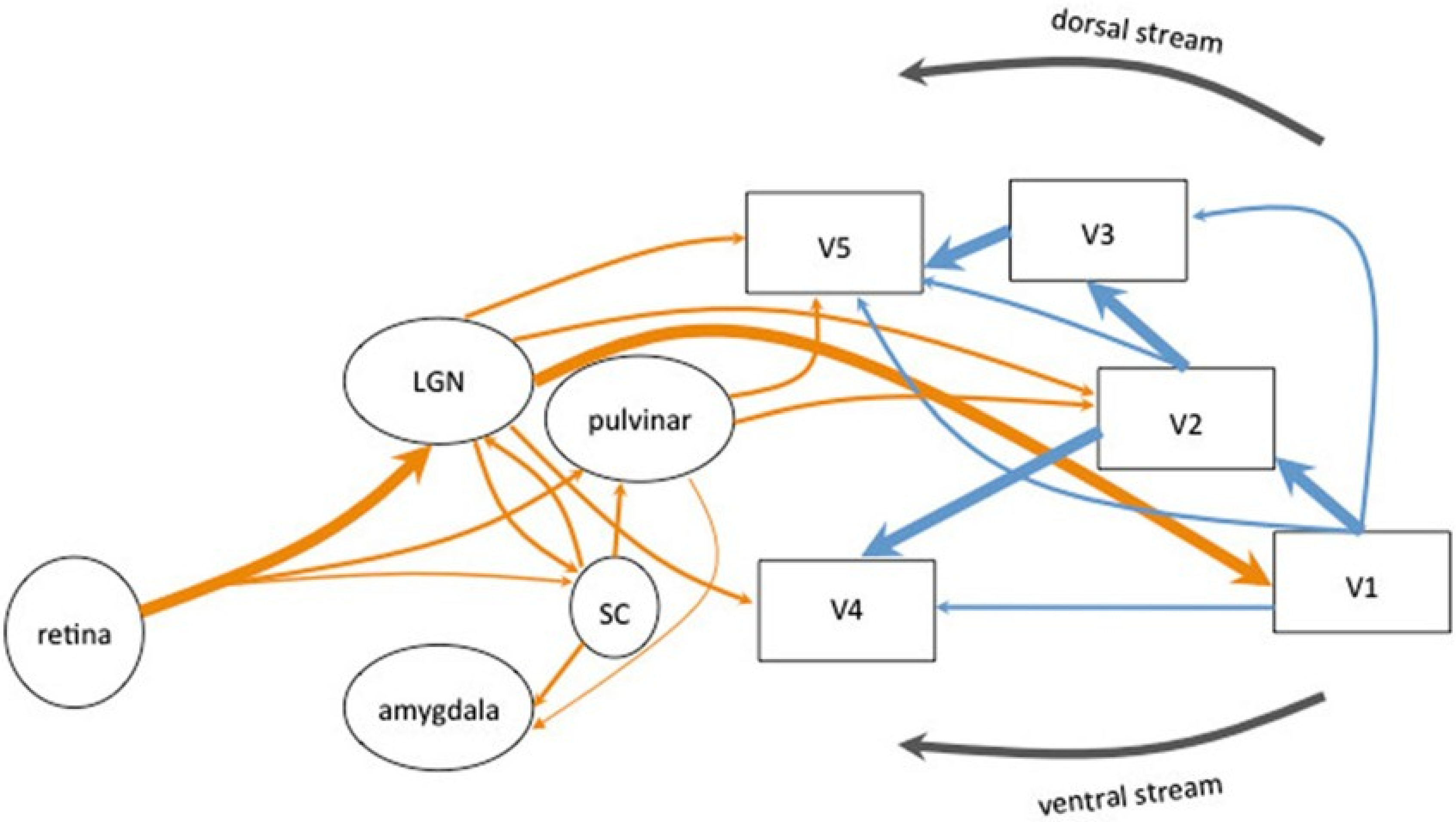
Convolutional Neural Networks

Nathan Sprague

Human Visual System



Urbanski, Marika, Olivier A. Coubard, and Clémence Bourlon. "Visualizing the blind brain: brain imaging of visual field defects from early recovery to rehabilitation techniques." Neurovision: Neural bases of binocular vision and coordination and their implications in visual training programs (2014).

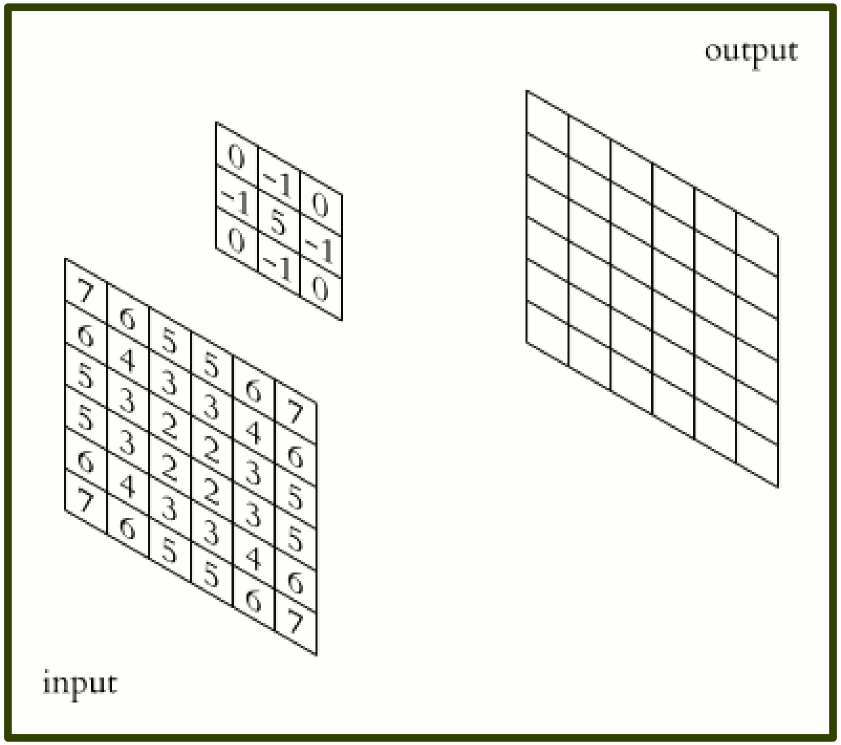
Convolutional Neural Networks

- Convolutional neural networks use the same trick of learning layers of localized features...
- CNN's were actually being used by Yann Lecun at Bell Labs around 1990

Convolutions

Grayscale Image

1 convolutional filter

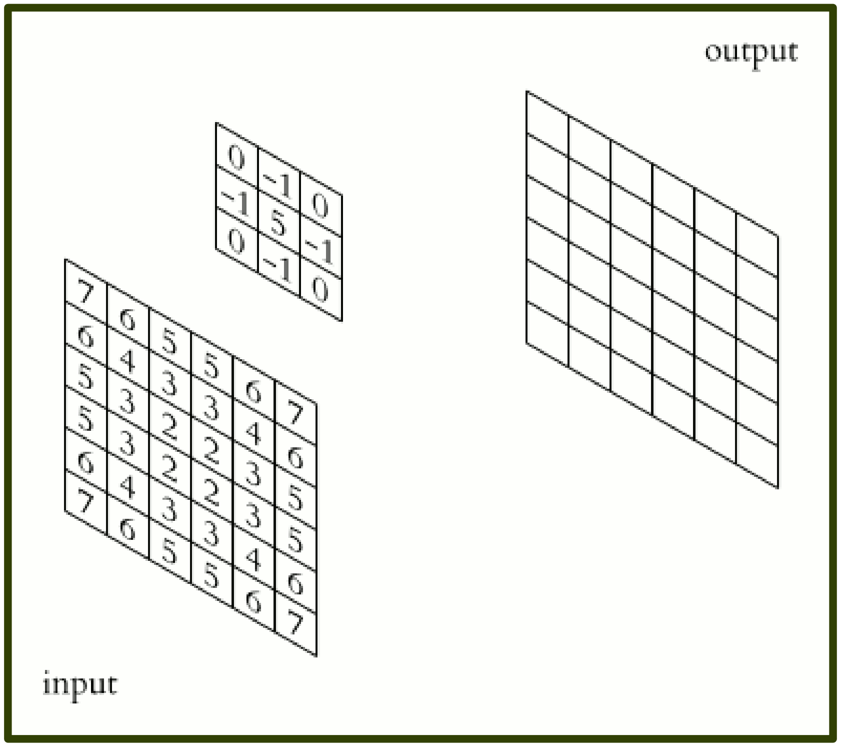


http://upload.wikimedia.org/wikipedia/commons/4/4f/3D_Convolution_Animation.gif

Convolutions

Grayscale Image

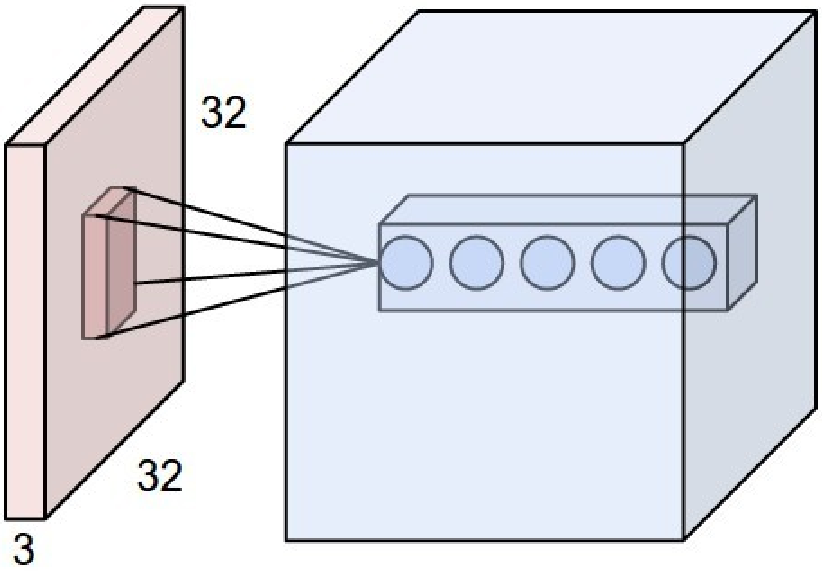
1 convolutional filter



http://upload.wikimedia.org/wikipedia/commons/4/4f/3D_Convolution_Animation.gif

Color Image

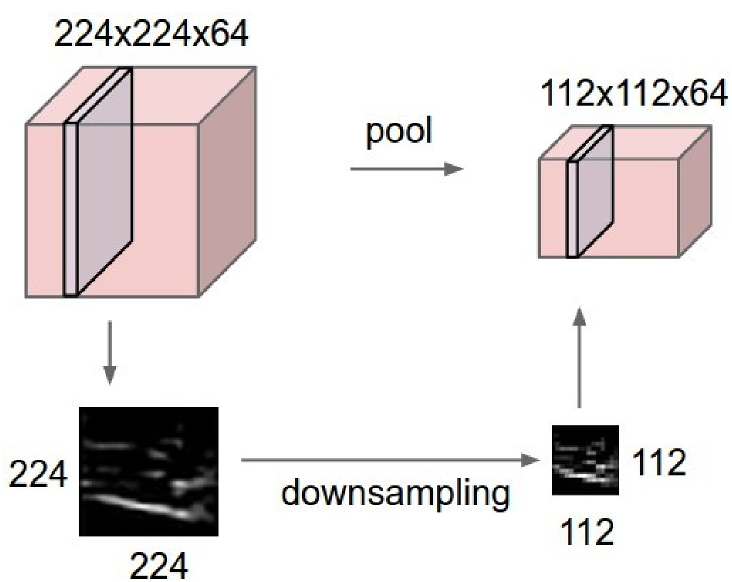
5 convolutional filters

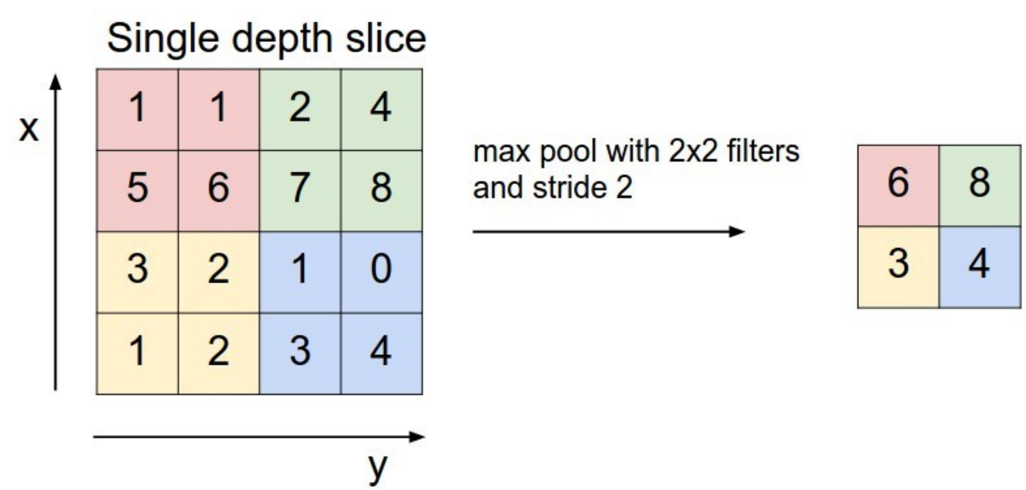


http://cs231n.github.io/convolutional-networks/

Pooling Layers

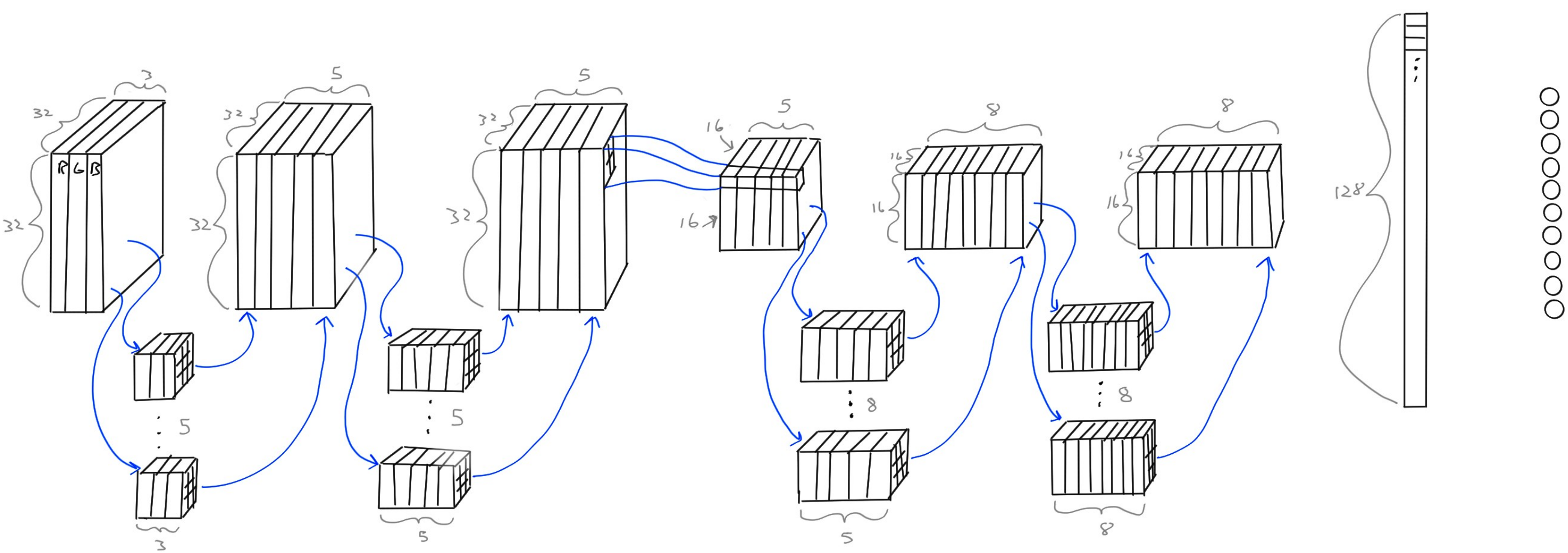
- Pooling layers down-sample the filter outputs to
  - Reduce dimensionality and computational requirements
  - Increase the spatial extent of subsequent filters





Complete Network

- A "traditional" CNN is composed of convolutional layers, each followed by non-linearities, followed by pooling layers, with one or more dense (non-convolutional) layer at the end:



Complete Network (in PyTorch)

Channels in Channels out Convolution size

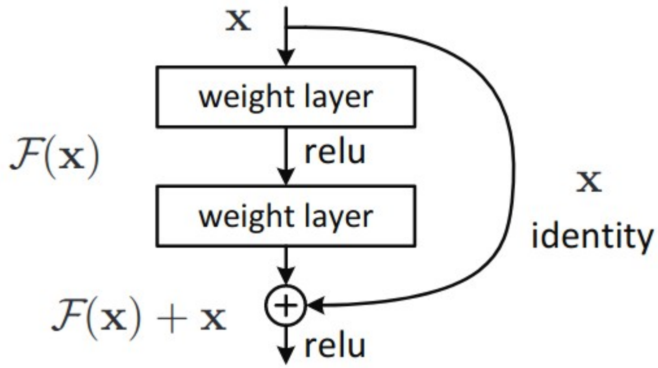
```
model = nn.Sequential(

    nn.Conv2d(3, 5, 3, padding='same'),
    nn.ReLU(),

    nn.Conv2d(5, 5, 3, padding='same'),
    nn.ReLU(),

    nn.MaxPool2d(2, 2),

    nn.Conv2d(5, 8, 3, padding='same'),
    nn.ReLU(),

    nn.Conv2d(8, 8, 3, padding='same'),
    nn.ReLU(),

    nn.Flatten(),
    nn.Linear(16 * 16 * 8, 128),
    nn.ReLU(),

    nn.Linear(128, 10)
)
```

Complete Network (alternate version)

```
class ConvNet(nn.Module):

    def __init__(self):
        super().__init__()
        self.relu = nn.ReLU()
        self.conv1 = nn.Conv2d(3, 5, 3, padding='same')
        self.conv2 = nn.Conv2d(5, 5, 3, padding='same')
        self.pool = nn.MaxPool2d(2, 2)
        self.conv3 = nn.Conv2d(5, 8, 3, padding='same')
        self.conv4 = nn.Conv2d(8, 8, 3, padding='same')
        self.flatten = nn.Flatten()
        self.fc = nn.Linear(16 * 16 * 8, 128)
        self.out = nn.Linear(128, 10)

    def forward(self, x):
        x = self.relu(self.conv1(x))
        x = self.relu(self.conv2(x))
        x = self.pool(x)
        x = self.relu(self.conv3(x))
        x = self.relu(self.conv4(x))
        x = self.flatten(x)
        x = self.relu(self.fc(x))
        x = self.out(x)
        return x

model = ConvNet()
```

Residual Networks

- How deep can we make these networks? Simply stacking more convolutional layers eventually degrades performance.
- One solution is to introduce "skip connections":



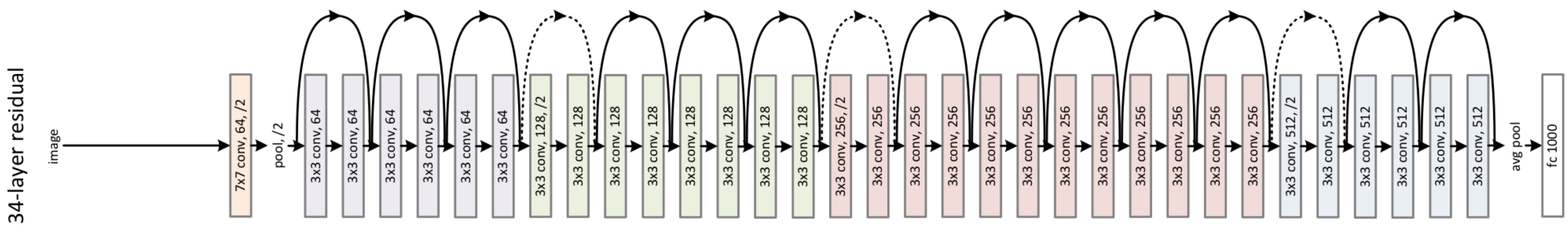
- "Residual learning"

He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

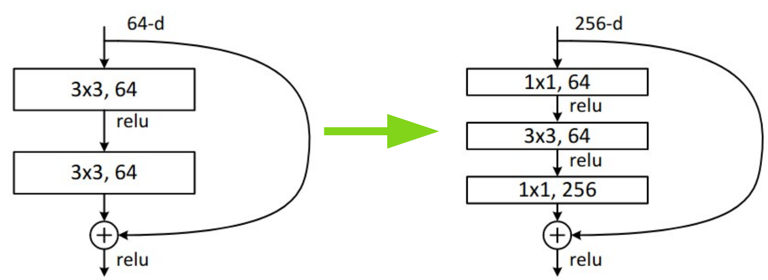
> 150,000 citations!

Residual Networks

- ResNet-34:



- Get ResNet-50 by introducing "bottleneck" blocks:



- The 1x1 convolutions can be used to increase or decrease the number of channels