

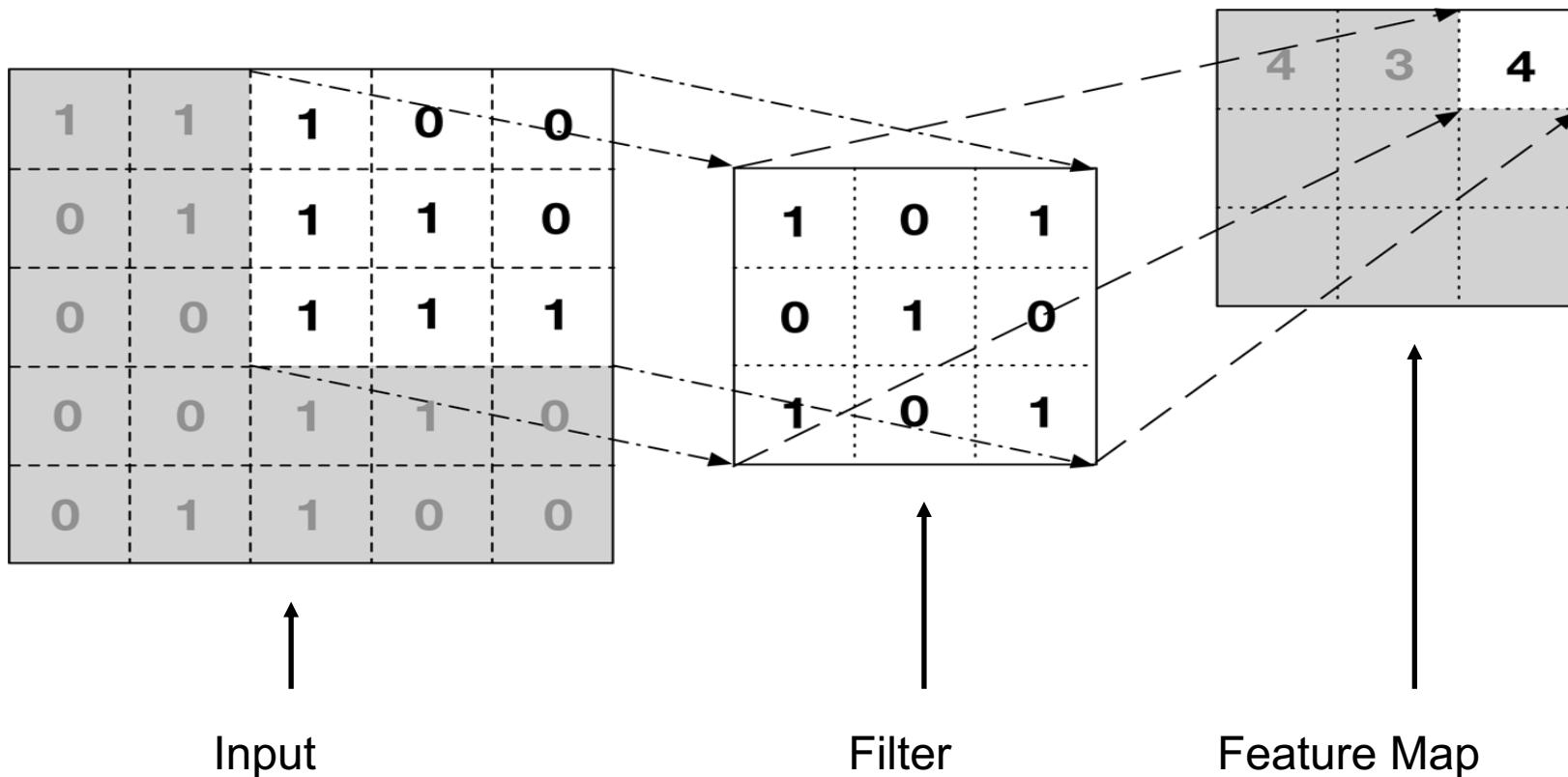
# CONVOLUTIONAL NEURAL NETWORKS

---

# Convolutional Neural Networks (CNNs)

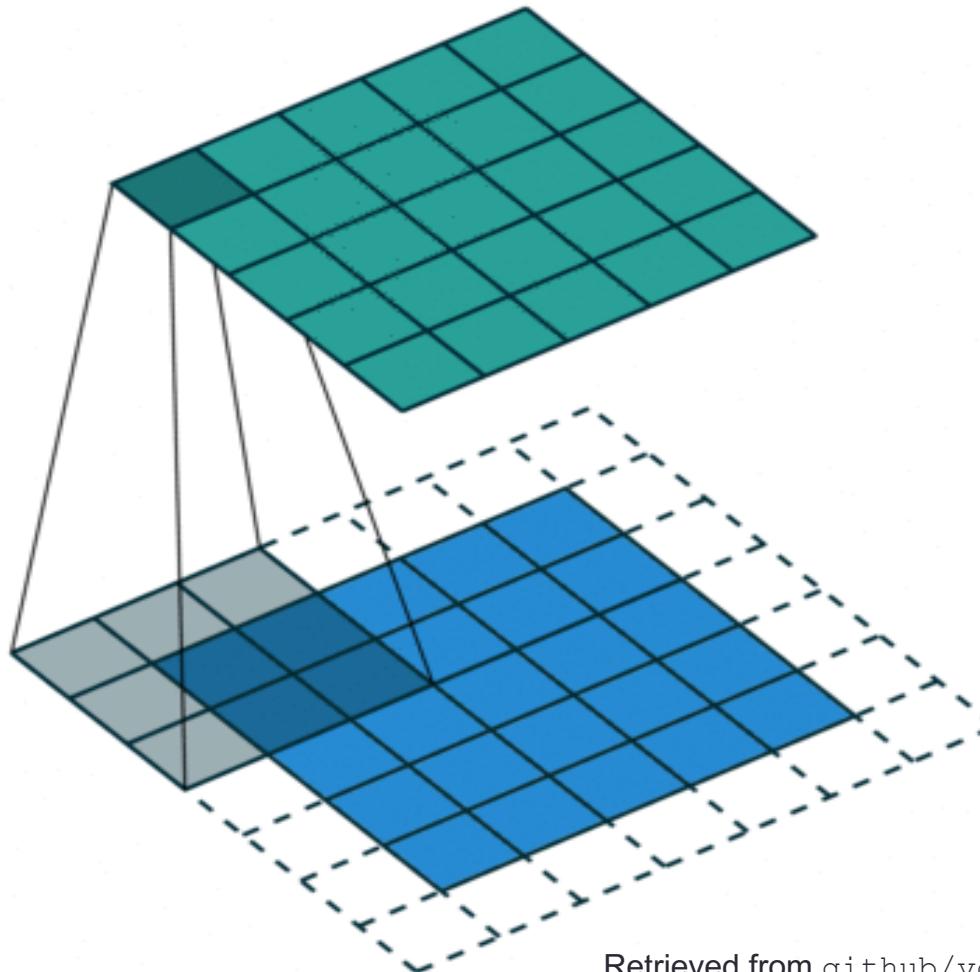
- Biggest driver of much recent excitement in machine learning
- Specialized architecture for grid-like data
  - Images
  - Sound
- Key operation: *discrete convolution*

# Discrete Convolution



$$\begin{array}{r} 1 * 1 = 1 \\ 0 * 0 = 0 \\ 0 * 1 = 0 \\ 1 * 0 = 0 \\ 1 * 1 = 1 \\ 0 * 0 = 0 \\ 1 * 1 = 1 \\ 1 * 0 = 0 \\ + 1 * 1 = 1 \\ \hline 4 \end{array}$$

# Discrete Convolution



# Applications of Convolutions



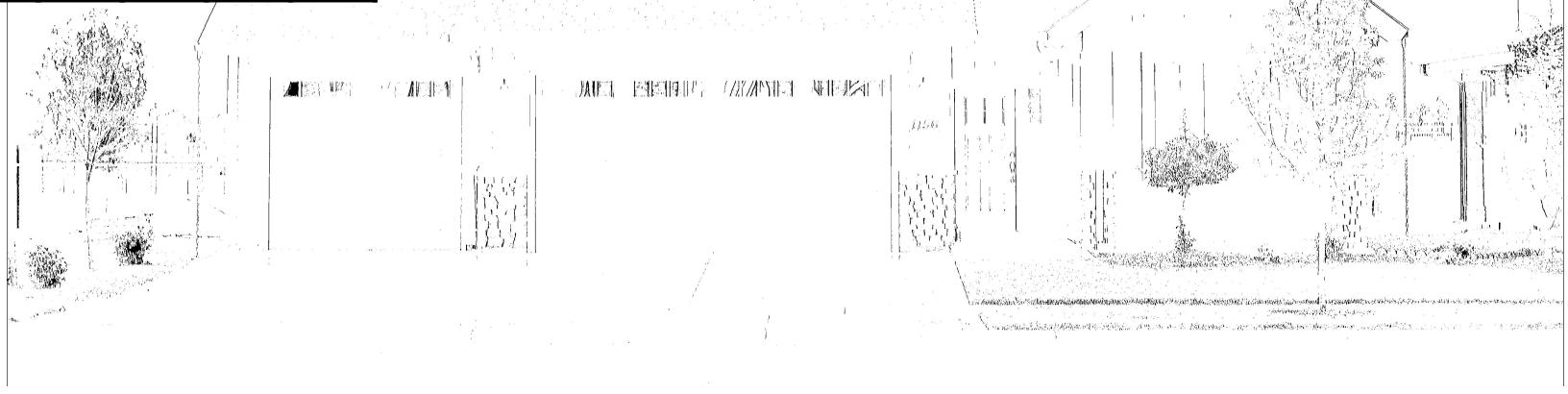
# Applications of Convolutions

-	-	-	-	-
1	1	1	1	1
-	-	-	-	-
1	1	1	1	1
5	5	5	5	5
-	-	-	-	-
1	1	1	1	1
-	-	-	-	-
1	1	1	1	1



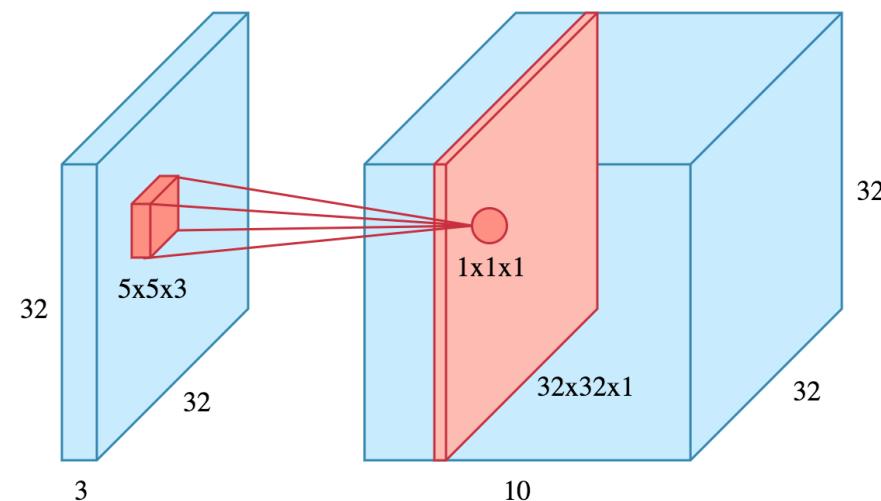
# Applications of Convolutions

-	-	5	-	-
1	1	5	1	1
-	-	5	-	-
1	1	5	1	1
-	-	5	-	-
1	1	5	1	1
-	-	5	-	-
1	1	5	1	1



# A Convolutional Layer

- Maps an input volume to an output volume
- Comprised of many convolutional filters
  - Let's say input volume is  $h \times w \times d$
  - We have  $s$  filters that are  $m \times n$
  - Output volume is  $h \times w \times s$
- Each filter is highly localized
  - “Receptive field”
  - Weight sharing
- **Kernel weights are learned**



# Pooling Layer

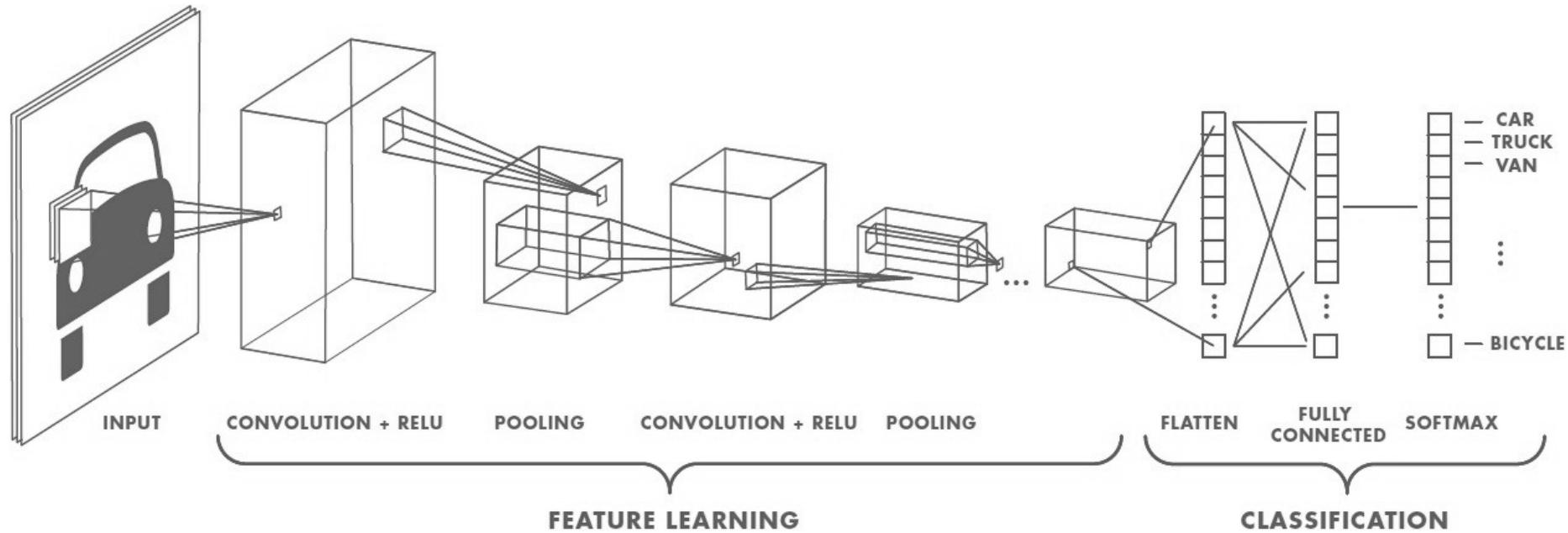
1	1	2	4
5	6	9	3
3	2	4	4
1	2	0	7

Max pool with  $2 \times 2$  filters and stride 2

The diagram illustrates a max pooling operation. A horizontal arrow points from the input matrix on the left to the output matrix on the right. The input matrix is a 4x4 grid of numbers. The output matrix is a 2x2 grid where each cell contains the maximum value from a 2x2 receptive field in the input. Specifically, the output cells are: top-left (6), top-right (9), bottom-left (3), and bottom-right (7). The input cells corresponding to the maximum values are highlighted in different colors: 6 (tan), 9 (blue-gray), 3 (red-orange), and 7 (light green).

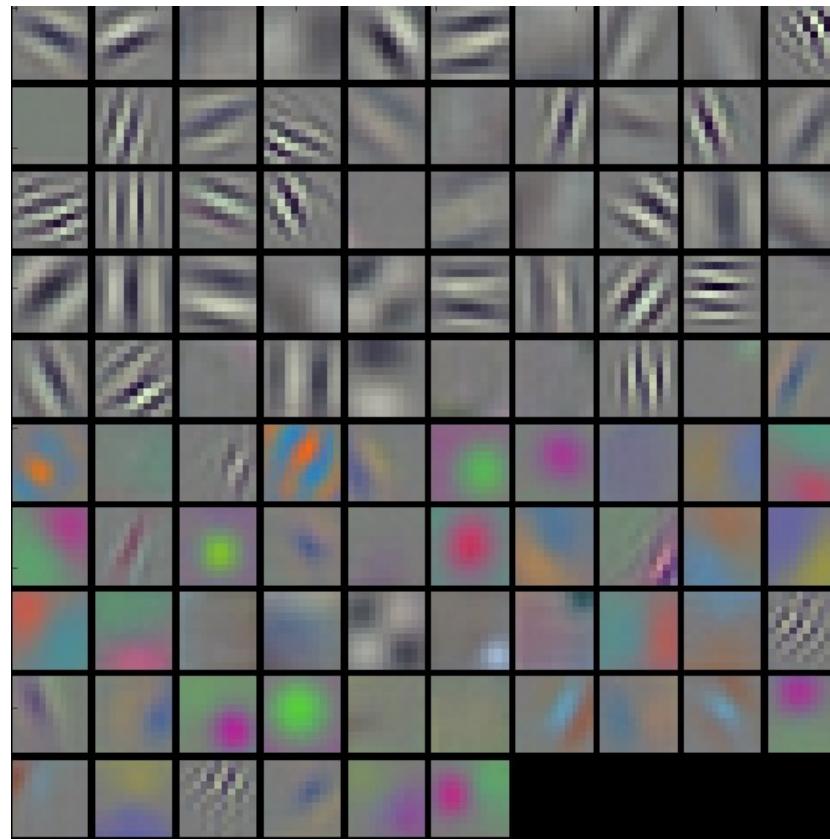
6	9
3	7

# A Typical CNN Architecture



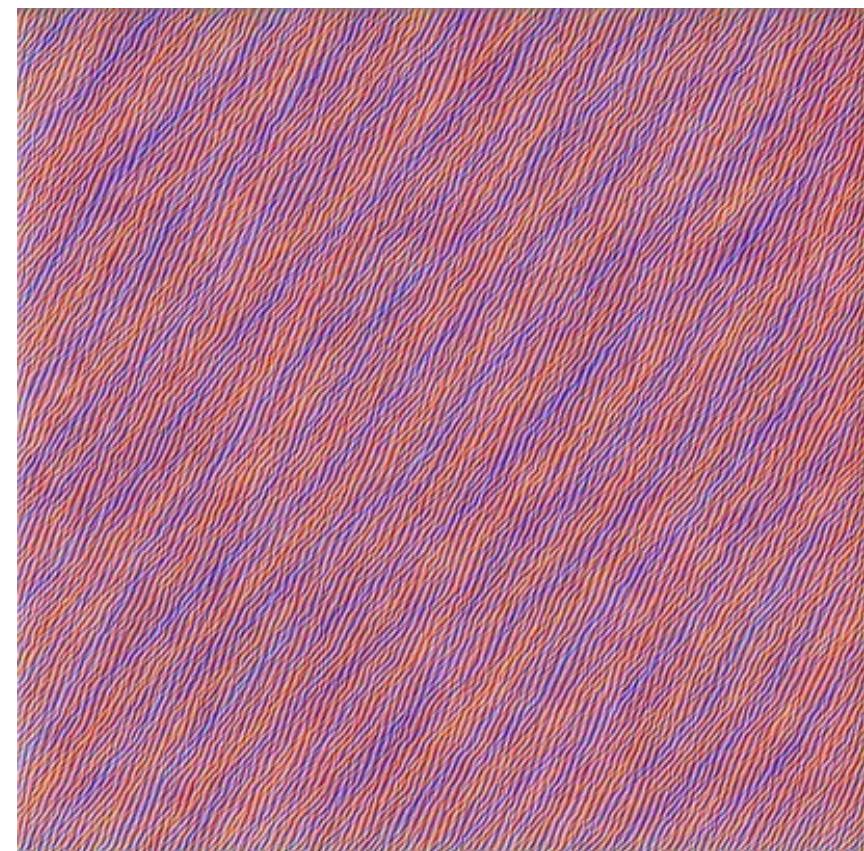
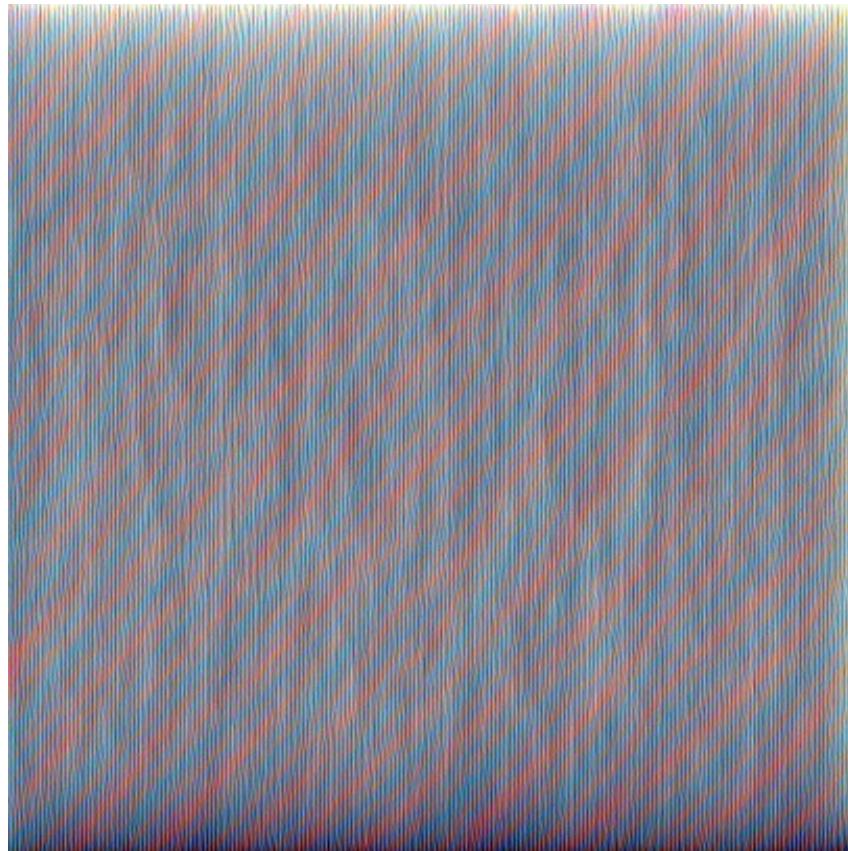
# What We Know About Learning in CNNs

- Early filters are more abstract, later filters less so



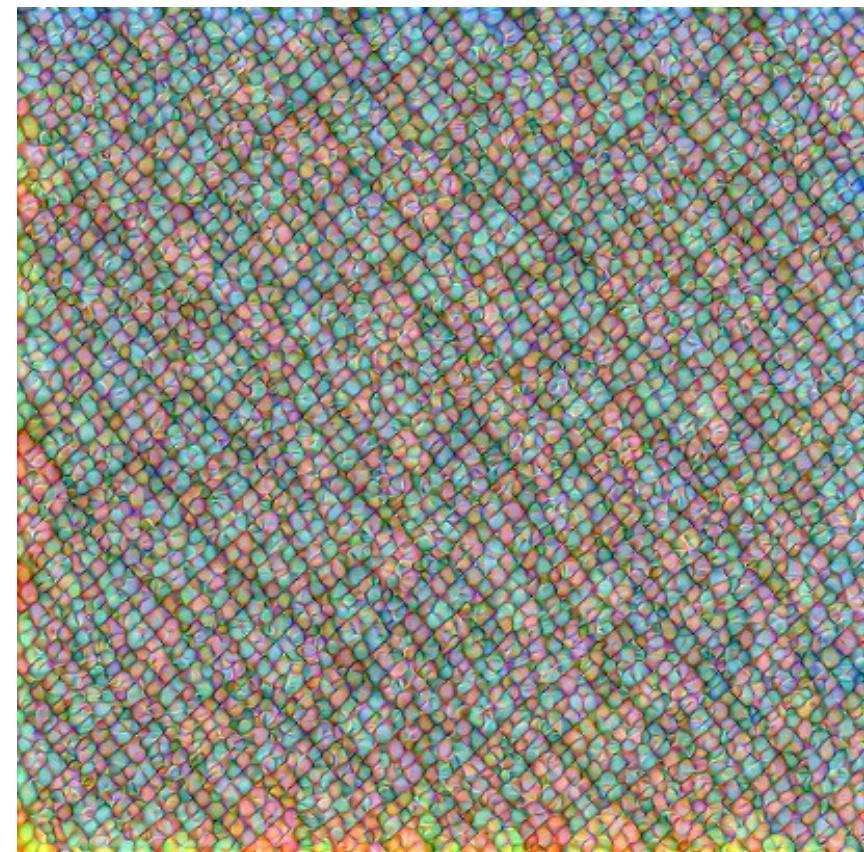
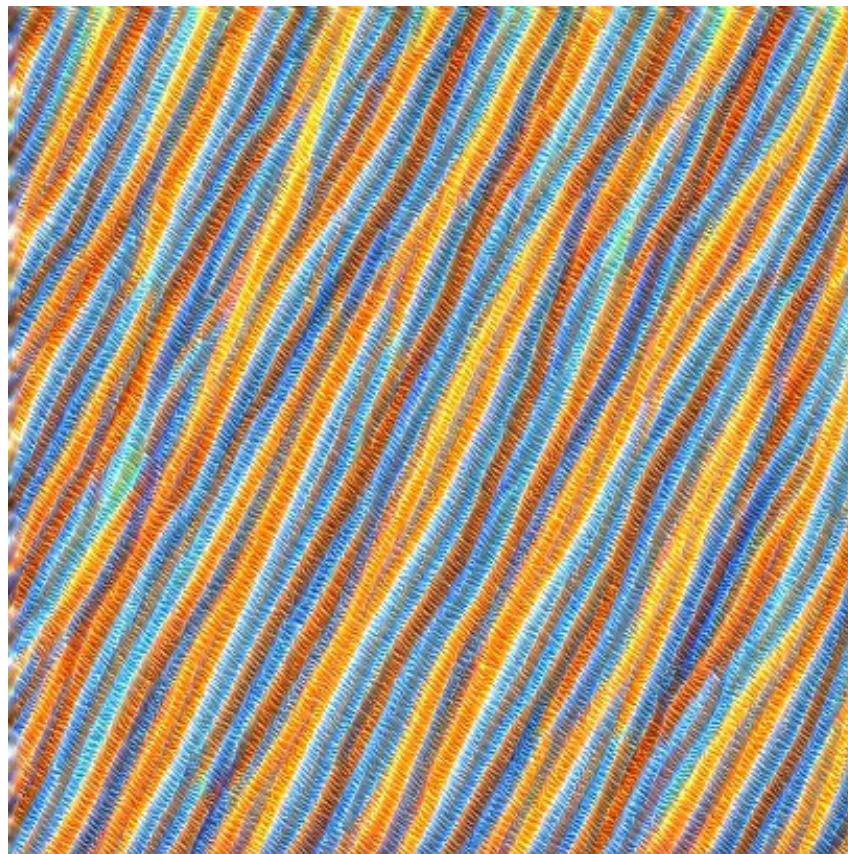
# What We Know About Learning in CNNs

- Early filters are more abstract, later filters less so



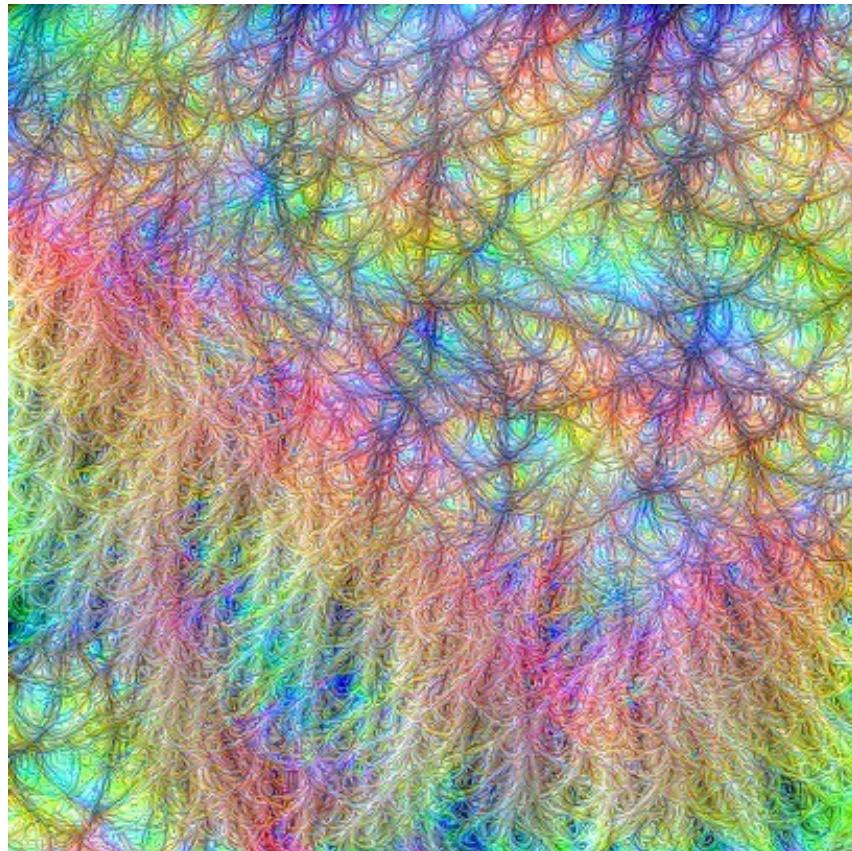
# What We Know About Learning in CNNs

- Early filters are more abstract, later filters less so



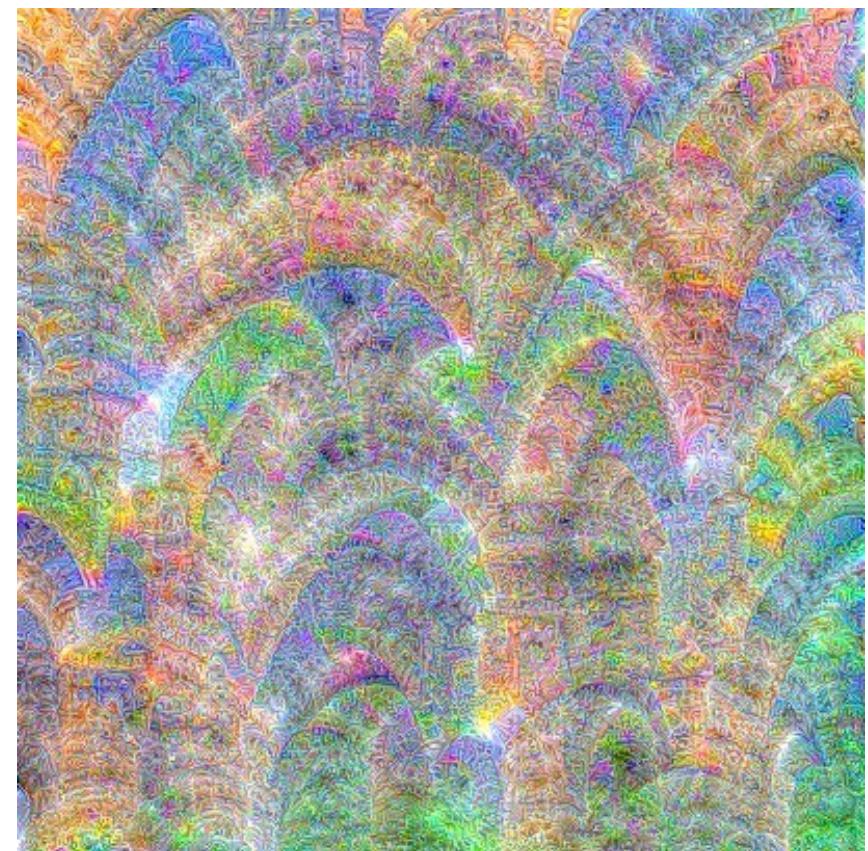
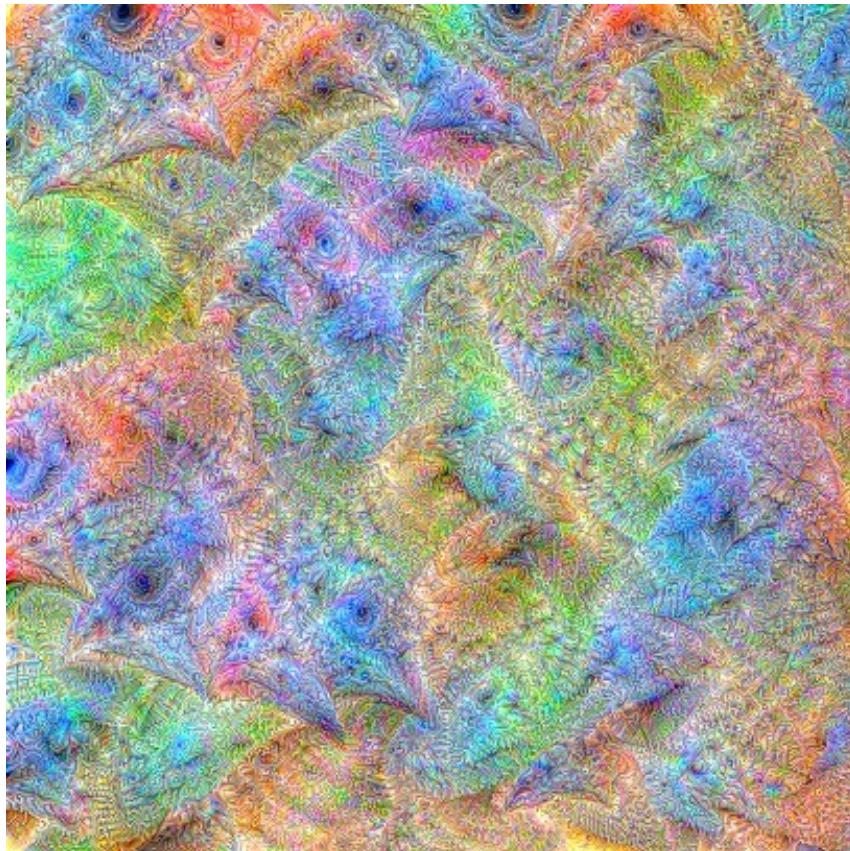
# What We Know About Learning in CNNs

- Early filters are more abstract, later filters less so



# What We Know About Learning in CNNs

- Early filters are more abstract, later filters less so



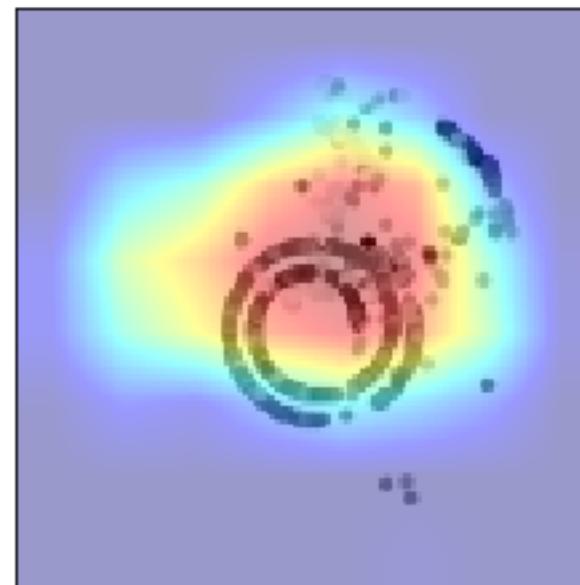
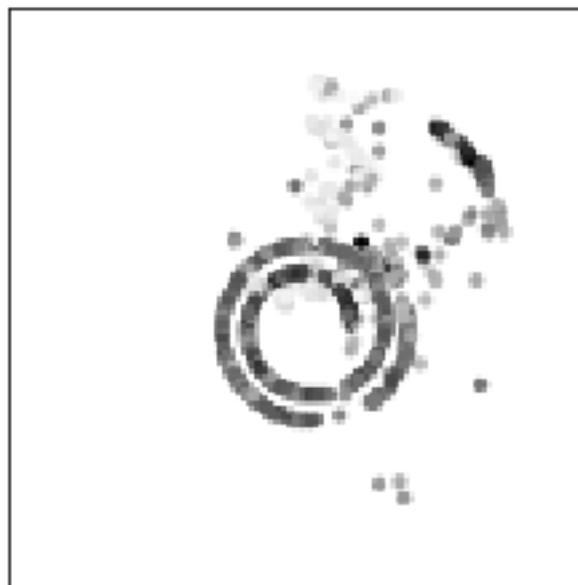
# What We Know About Learning in CNNs

- Early filters are more abstract, later filters less so
- Deeper networks are better, but harder to train
  - “Vanishing gradient” problem
- “Skip connections” help
  - Most significant advance since AlexNet (2012)
  - Main enhancement in ResNet, also used by Google’s Inception
- Lessons from earlier:
  - Use ReLU, Adam, careful initialization, batch normalization

# Getting Started with CNNs

- Many popular architectures are available in Tensorflow/Keras
- Have a lot of labeled data?
  - If you also have a lot of patience, you can train a CNN from scratch
  - Creative augmentation can help
- Have a lot of cheap, lower-fidelity data?
  - For example, simulations
  - Can train from scratch on simulated data, fine-tune on “real” data
- Not much data?
  - Use pre-trained model
  - Can be a feature extractor
  - Can be starting point for further tuning

# Interpreting Predictions



# Interpreting Predictions

