



# MODERN COMPUTER VISION

BY RAJEEV RATAN

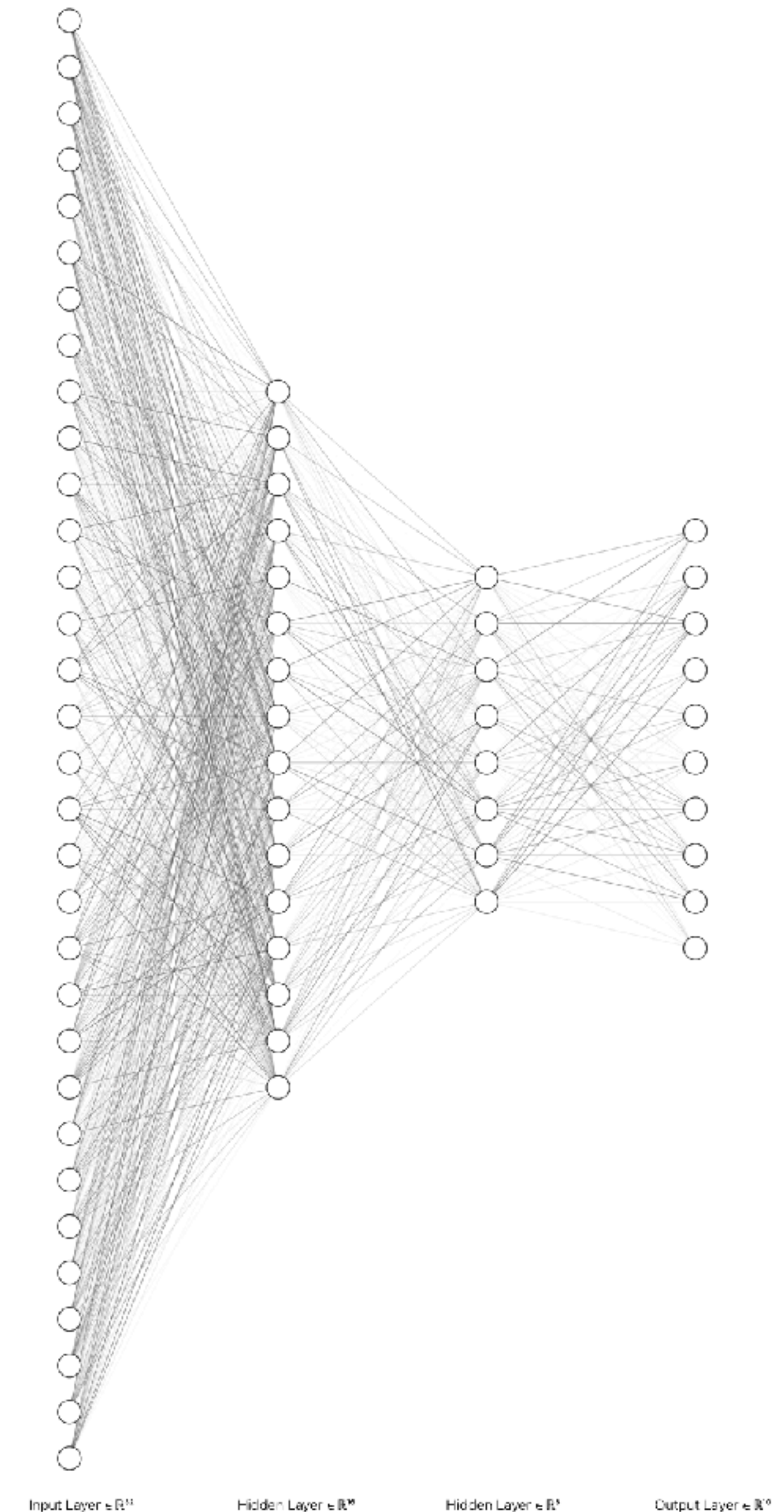
## Why CNNs Work So Well For Images

We explore design choices in CNNs and how it relates to their performance in the real world

# Standard Neural Networks

## A thought experiment...

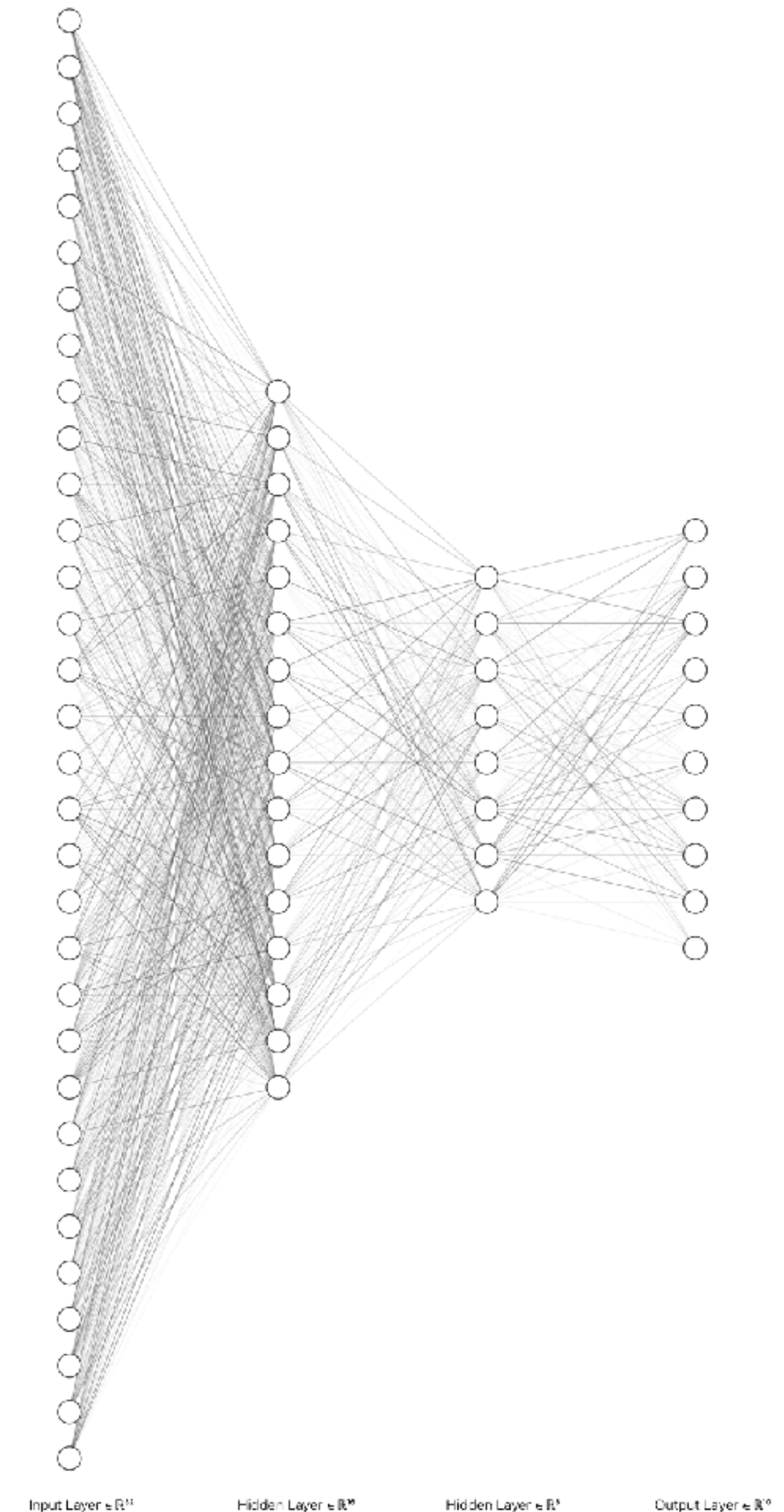
- Standard Neural Networks don't have Convolution Filter Inputs
- For Images every pixel will be it's own input
- Therefore, a small image that's 28 x 28 would have 784 input nodes for our first layer



# Standard Neural Networks

## A thought experiment...

- Our second layer, if we breakdown our previous CNN model would be:
  - 32 Filters for 26 x 26 Feature Maps
  - 13,312
- If they were fully connected, our weight matrix would be:
  - $784 \times 13,312 = \mathbf{10,436,608}$
- For just one hidden layer!

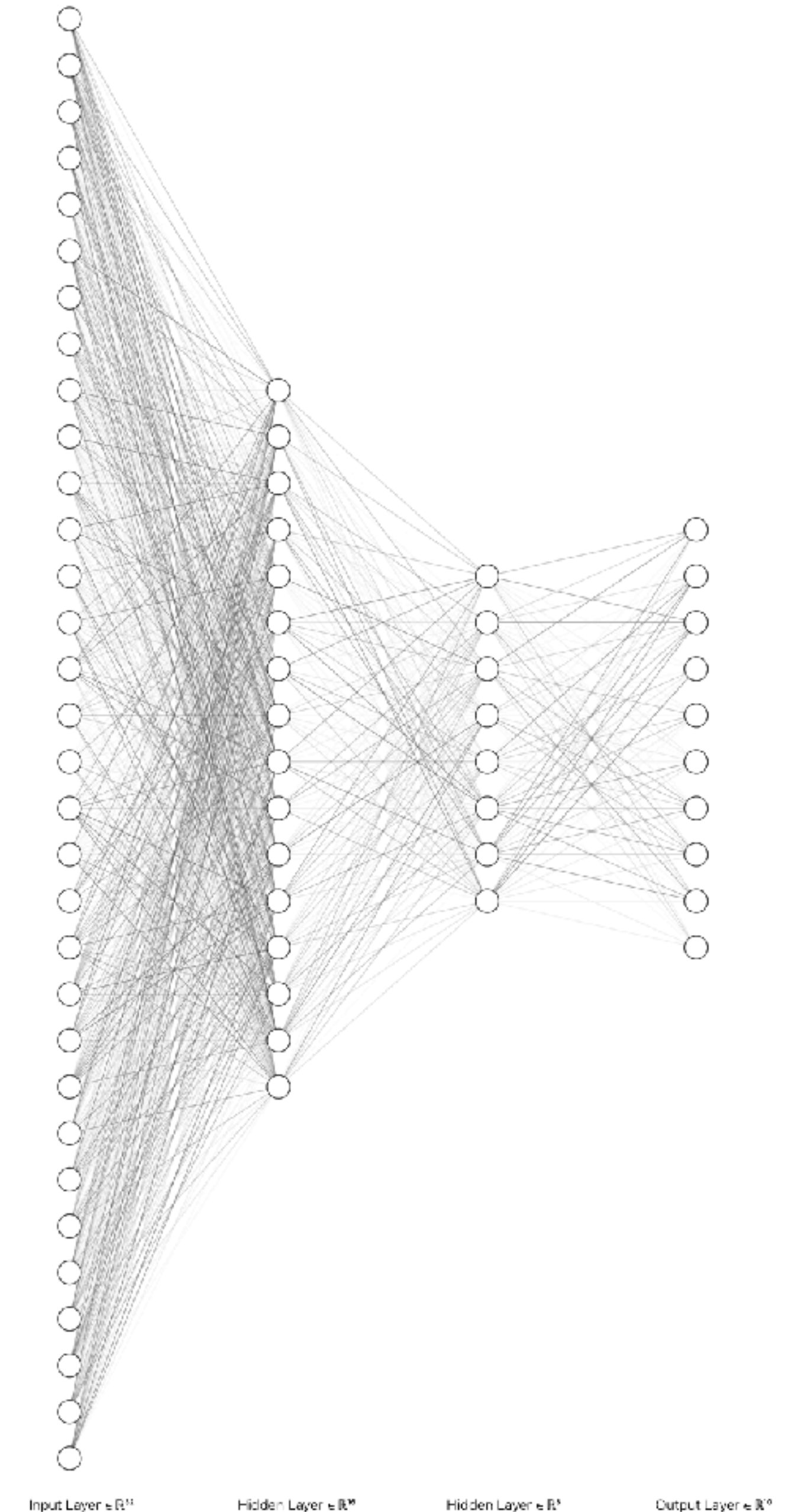




# Standard Neural Networks

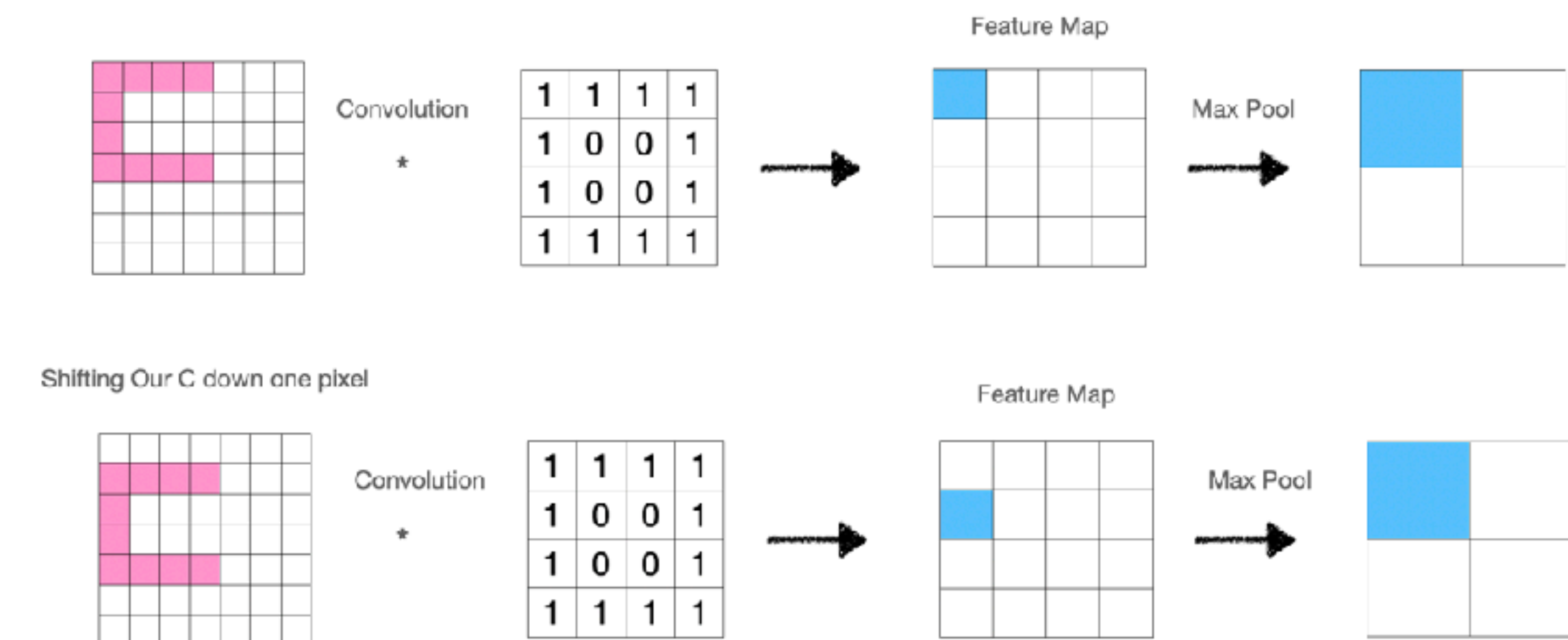
## Not Feasible for Image Classification!

- Not scalable to large data inputs
- Overfitting



# Advantages of Convolution Neural Networks

- **Parameter sharing** - where a single filter can be used all parts of an image
- **Sparsity of connections** - As we saw, fully connected layers in a typical Neural Network result in a weight matrix with large number of parameters.
- **Invariance** - Remember our Max Pool Example

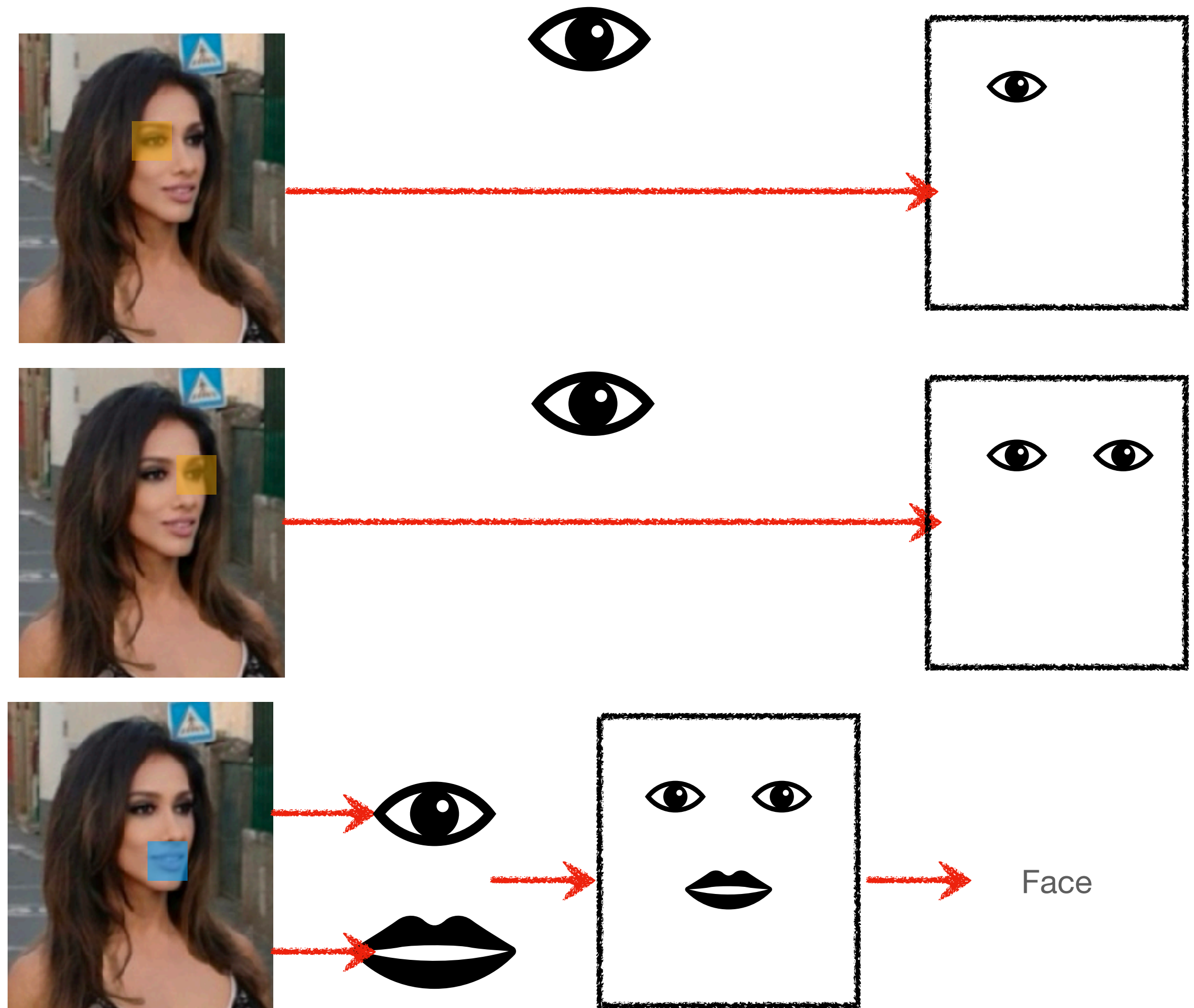


$$\begin{bmatrix} 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 \end{bmatrix} * \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix}$$



# Convolution Neural Networks Assumptions

- Low-level features are local
- Features are translational invariant
- High-level features are made up of low-level features





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# Next...

How to Train a CNN