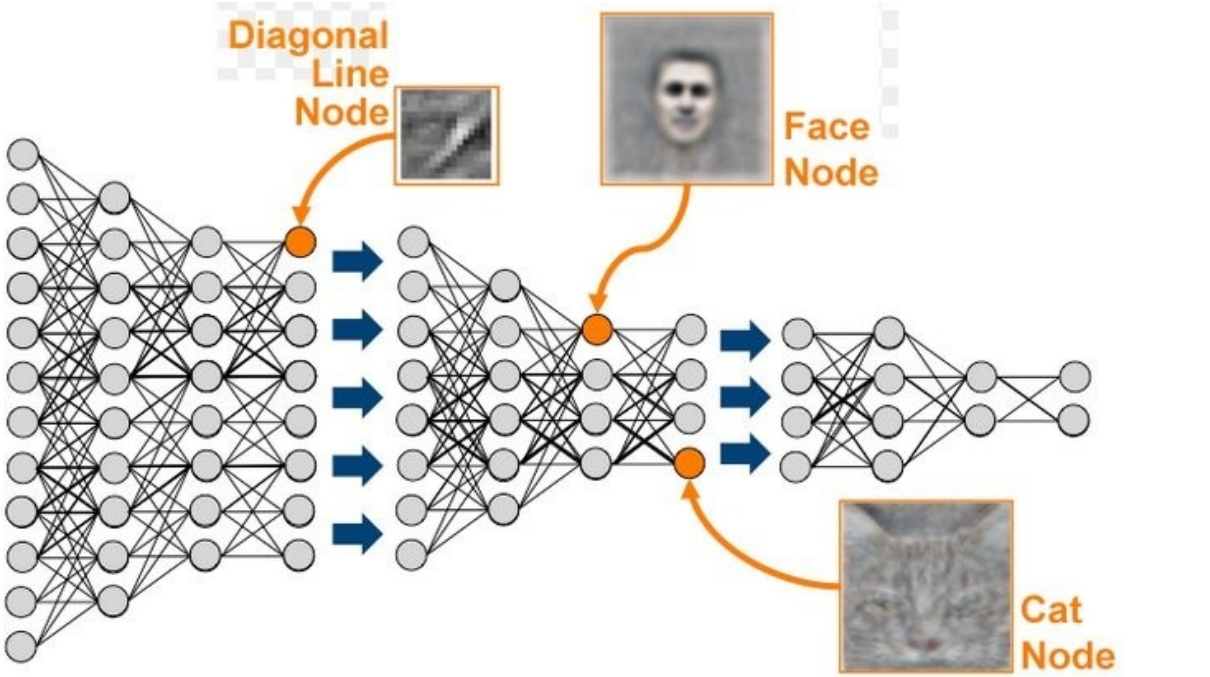
Universal approximation theorem

The “universal approximation theorem” (Cybenko, 1989, Hornik, 1991) proves, that already with a single hidden layer, we can essentially learn every continuous function (with a few mild assumptions).

So why introduce more than one hidden layer?

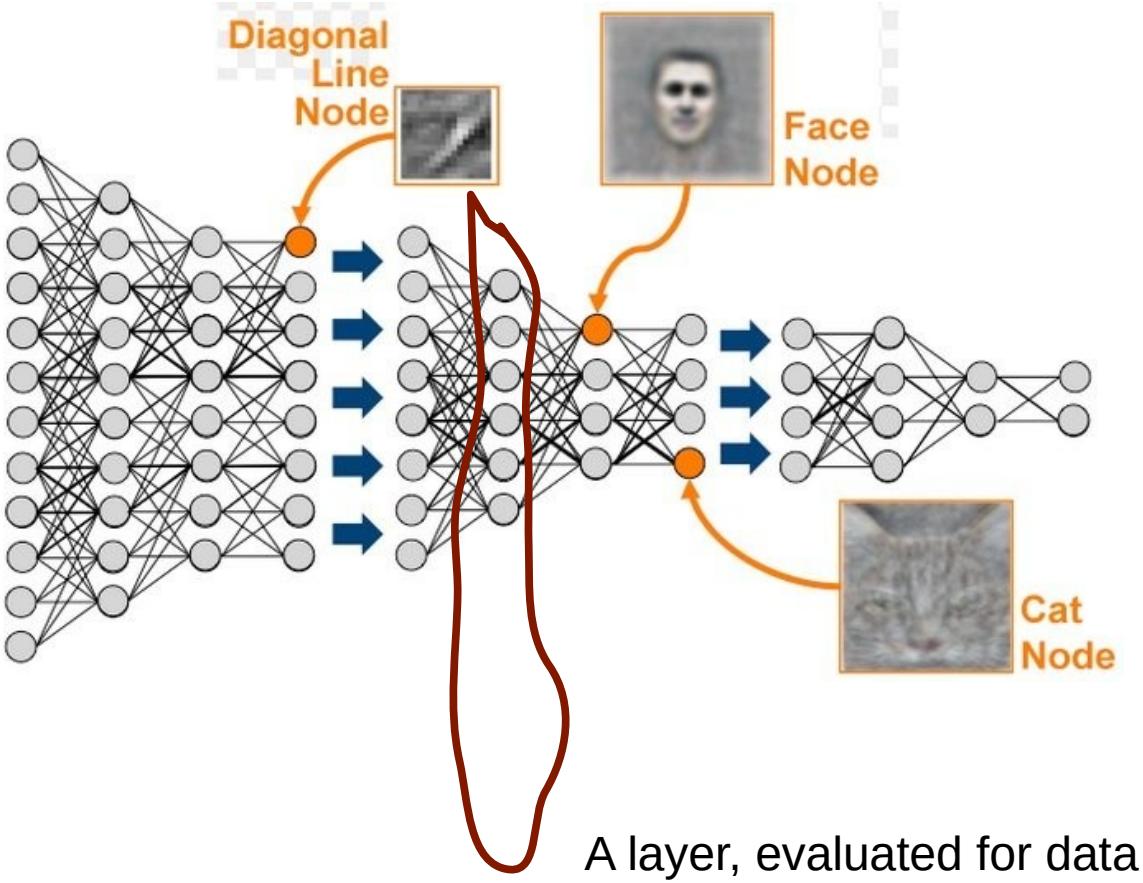
Deep learning = learning abstractions

Because when done right, a deep network can learn “abstract features” of the input data:



Deep learning = hierarchical representation learning

Because when done right, a deep network can learn “abstract features” of the input data:

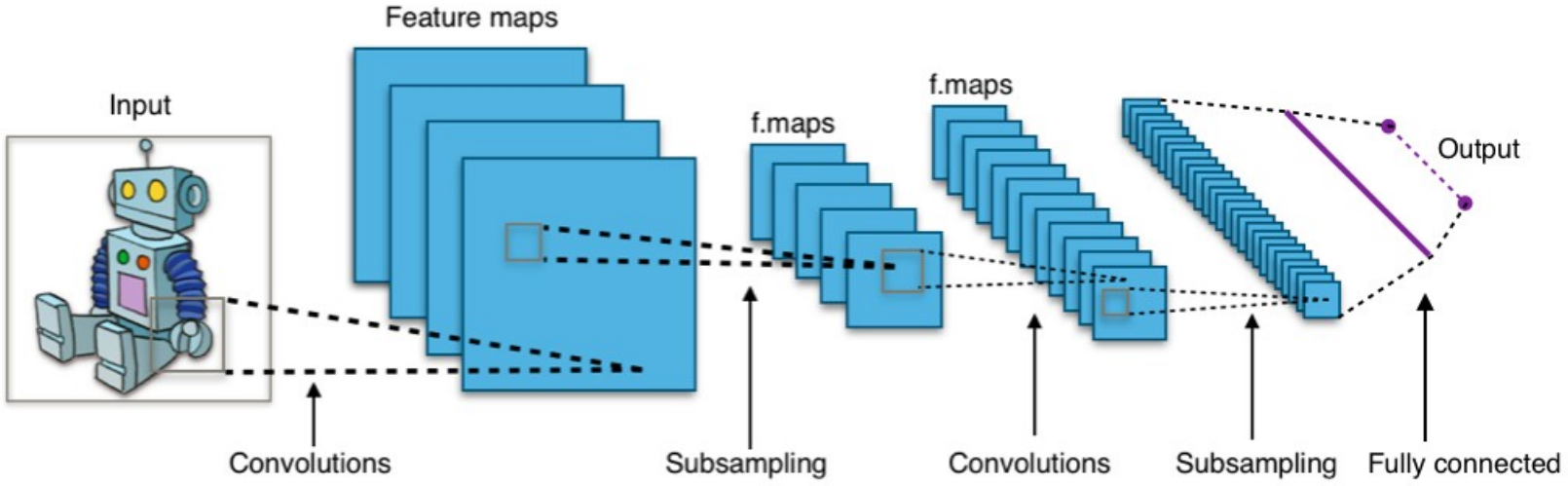


A layer, evaluated for data = a “representation” of the data

Convolutional layers

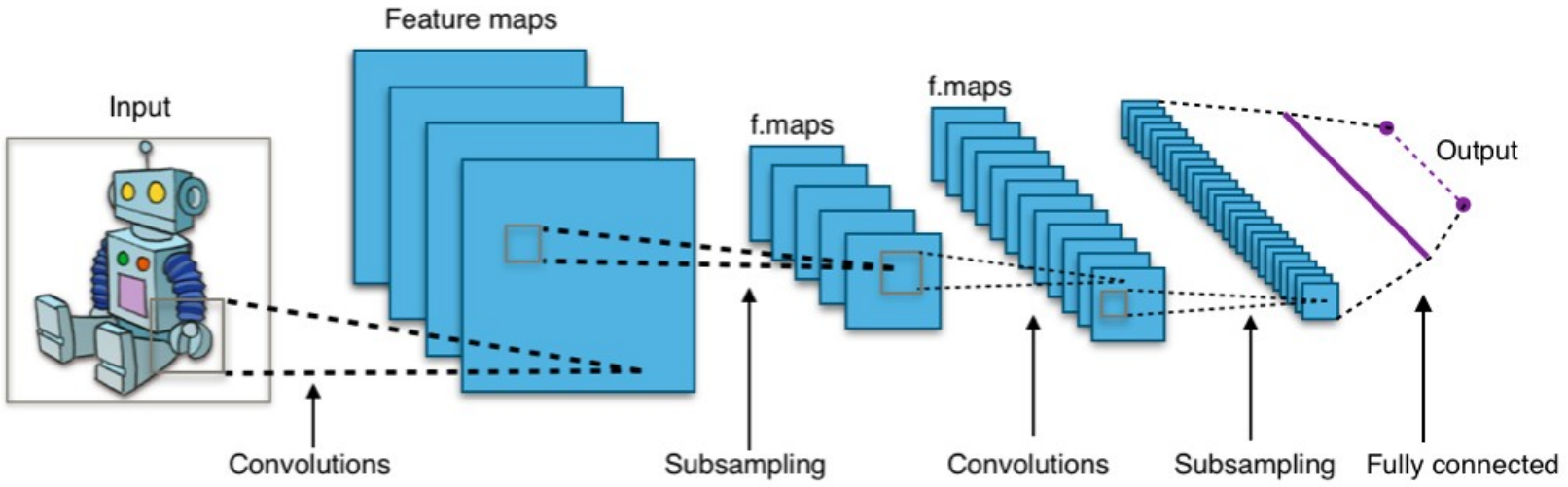
Think computer vision: we want to detect a cat,

independent of where she is in the photo: translation invariance!
Answer: convolutional layers: many several small convolution matrices (“filters”, “maps”, “kernels”)



Convolutional layers

Answer: convolutional layers: many several small convolution matrices (“kernels”) that “scan” over the input image, “sharing” the learned weights and thus detect features independent of their position



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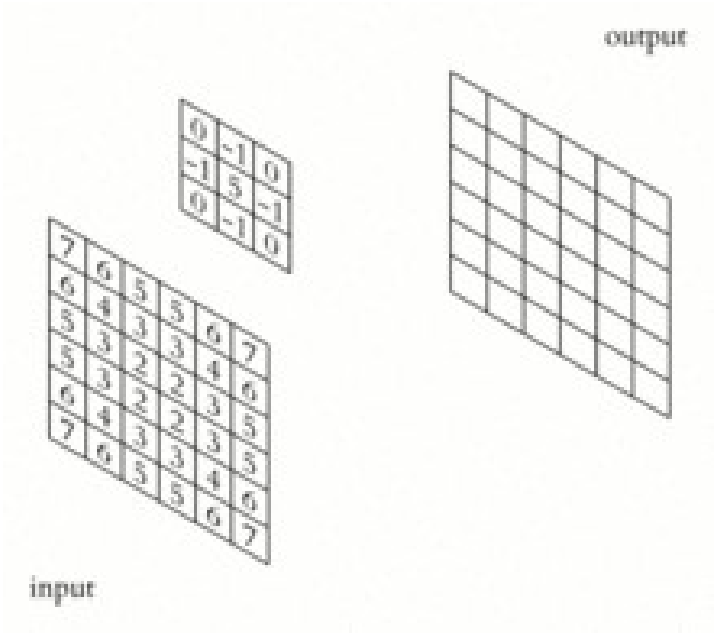
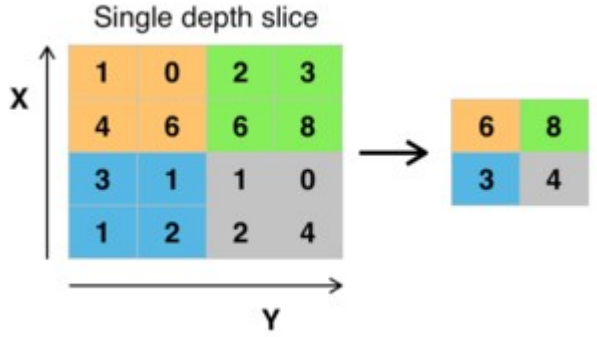


Convolutions



Max Pooling (subsampling)

Inspired by the “receptive field” in biology