

*Postgraduate course*

*Universitat de Valencia 2020*

# Introduction to Machine Learning for physicists

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## LECTURE 4 SHORT Intro SUSY



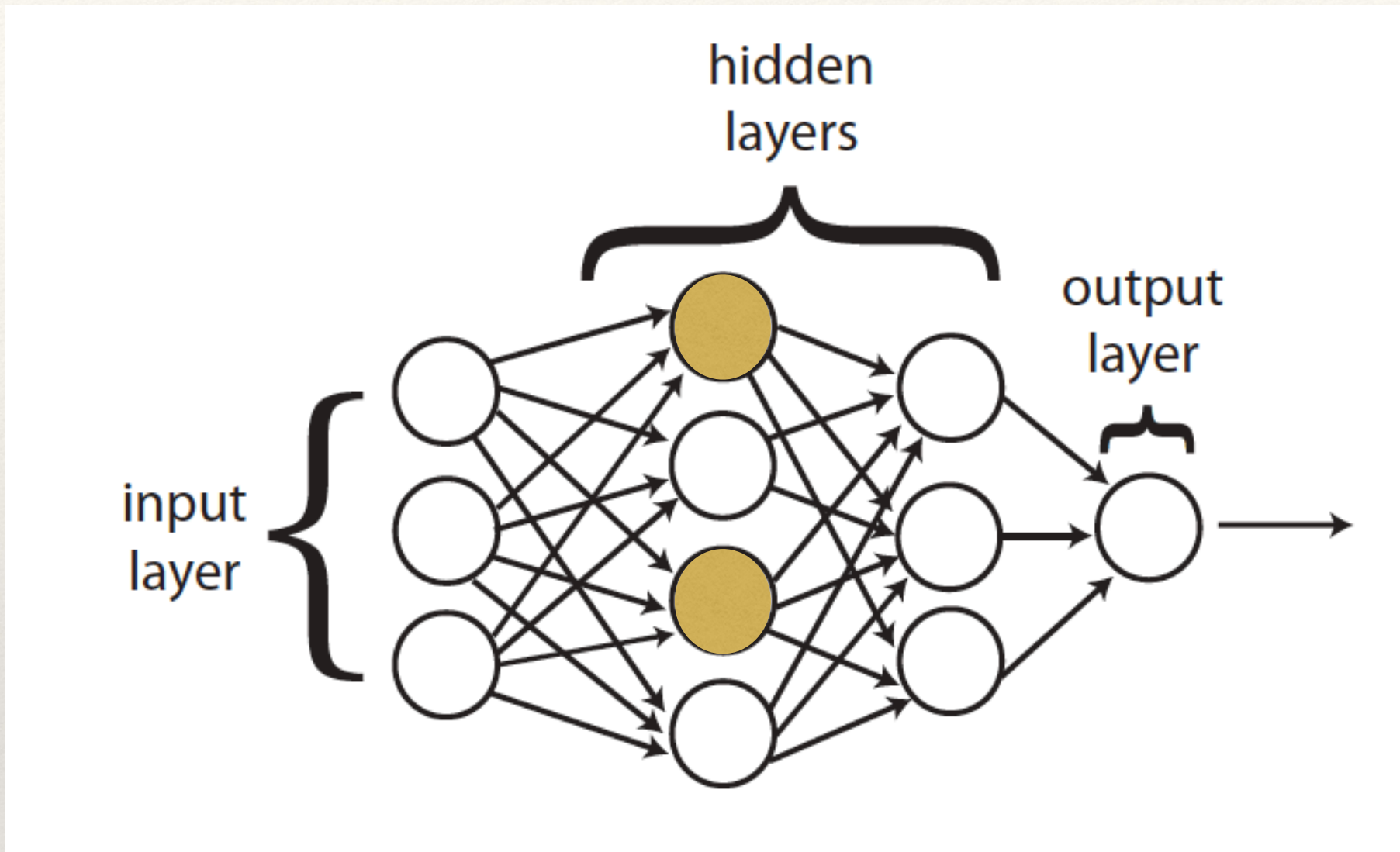


# Today

You'll be going over the CNN notebook, learning the syntax of keras,  
the different parameters in Sequential etc  
but some of you may finish early  
additional task: Supersymmetry search  
using LogReg, Trees, and DNNs



# Why are we doing this?



Neural Networks can model **complexity**

They have a high degree of expressivity

/ exhibit high representational power

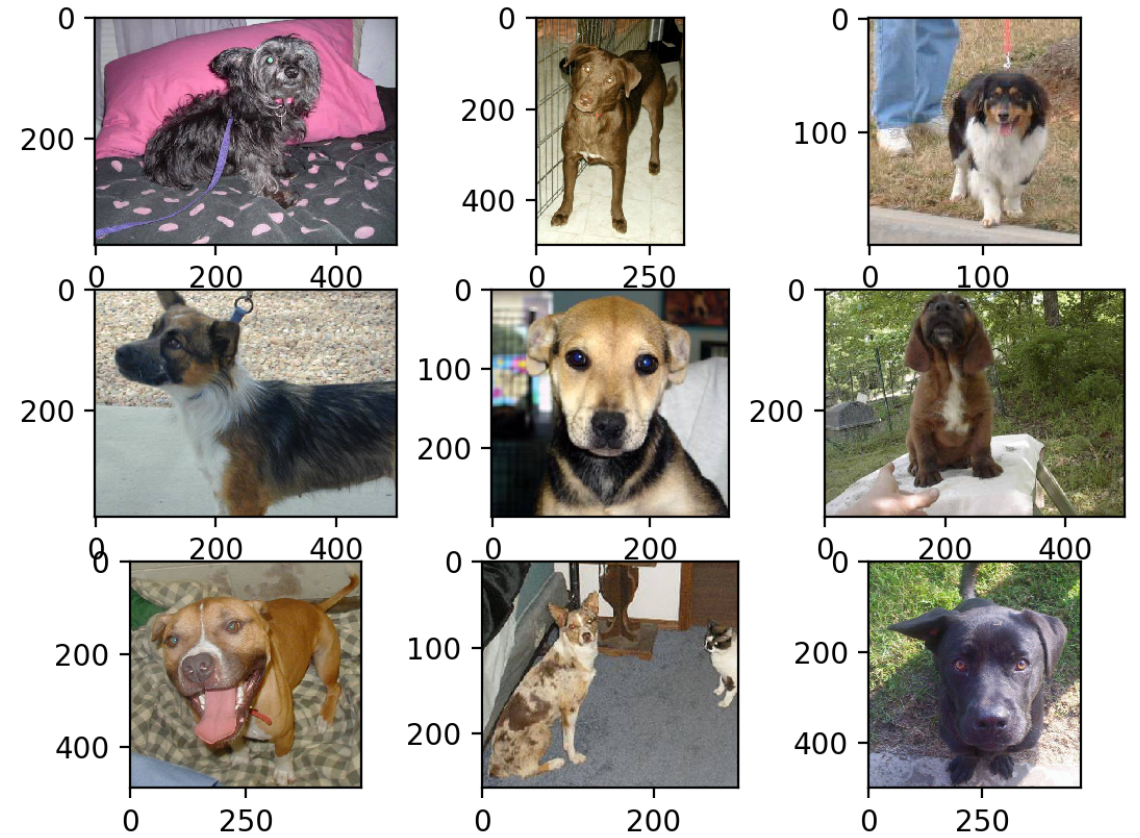
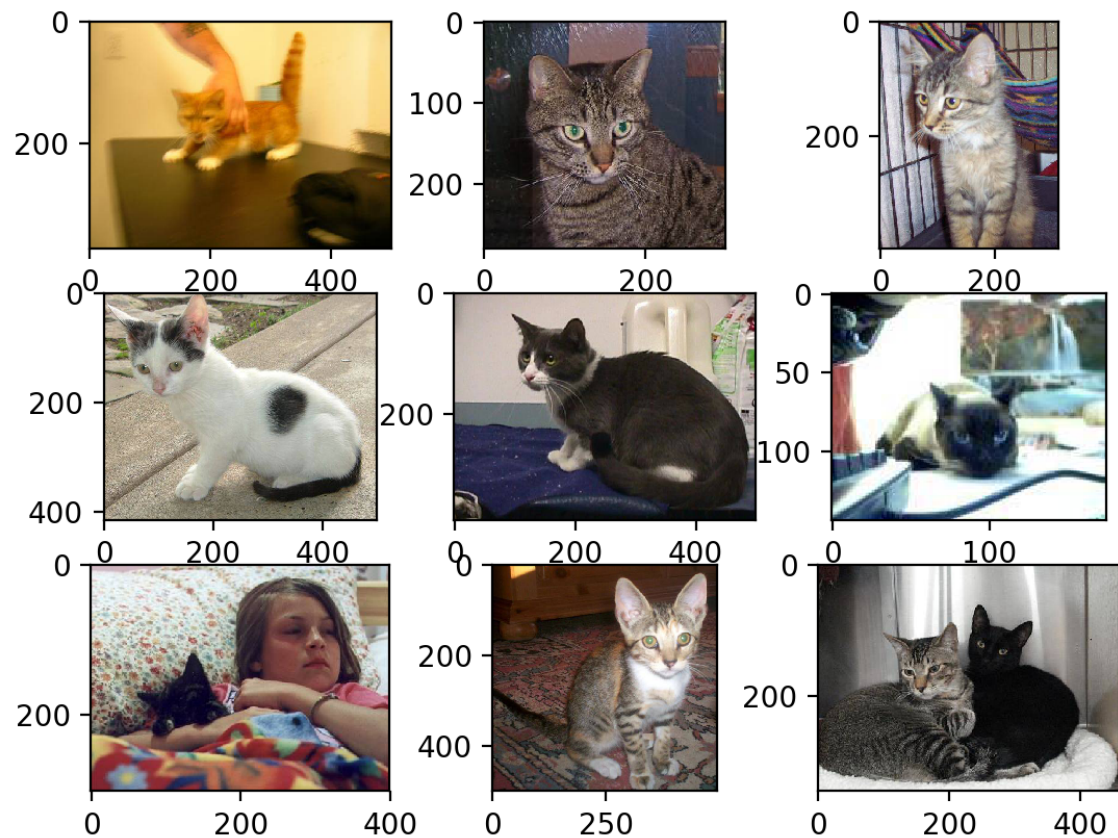
More hidden layers=> more complex features

Deep learning, deep NN



# Complex features

images, speech : are complex  
For example: cats / dogs



you can distinguish these cats and dogs, right? but how?  
would you be able to write a code which classifies them with  $\sim 100\%$   
accuracy? well, a NN can learn to do this!

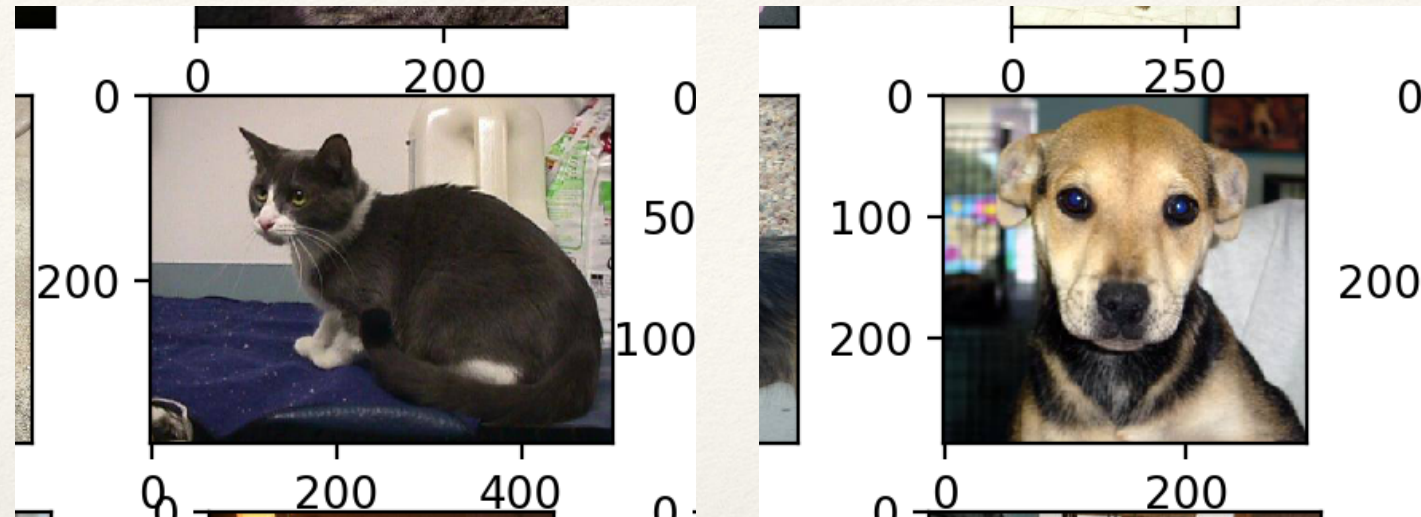


# Convolutional Neural Networks

CNNs



# Complex features are often *local*



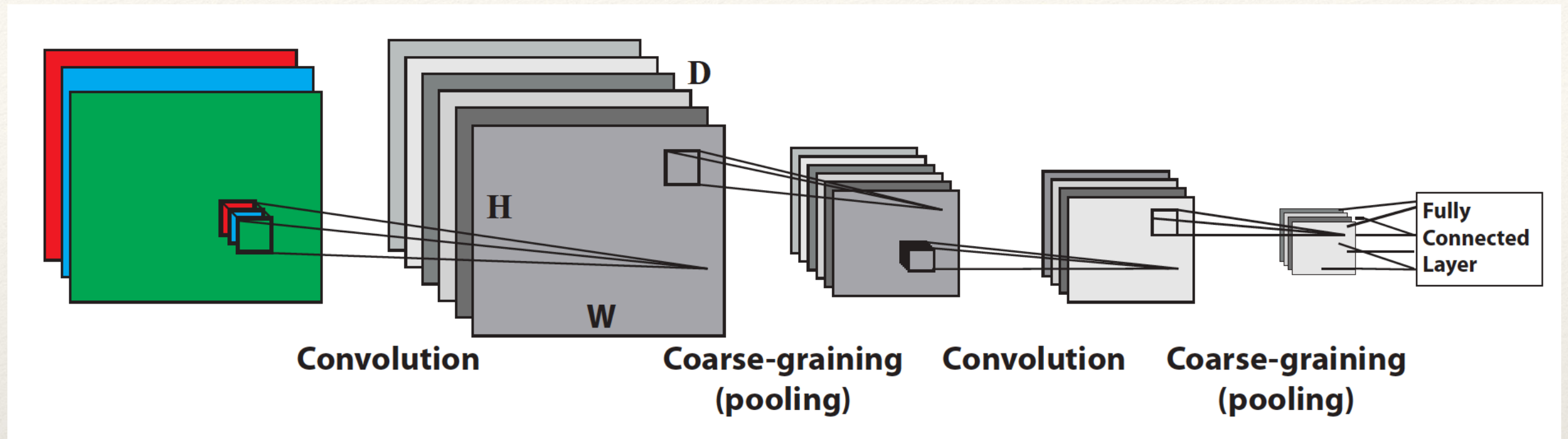
Apart from shape and color,  
we know a cat is a cat because there are relations  
among their features, e.g. the position of the eyes/  
ears respect to the head centre, independently of  
where in the image the cat is

**Locality** and **translational invariance** must end up  
playing a role in the identification task

Convolutional Neural Network (CNN)  
a type of NN architecture designed to exploit  
these two characteristics



# CNNs



Two types of basic layers

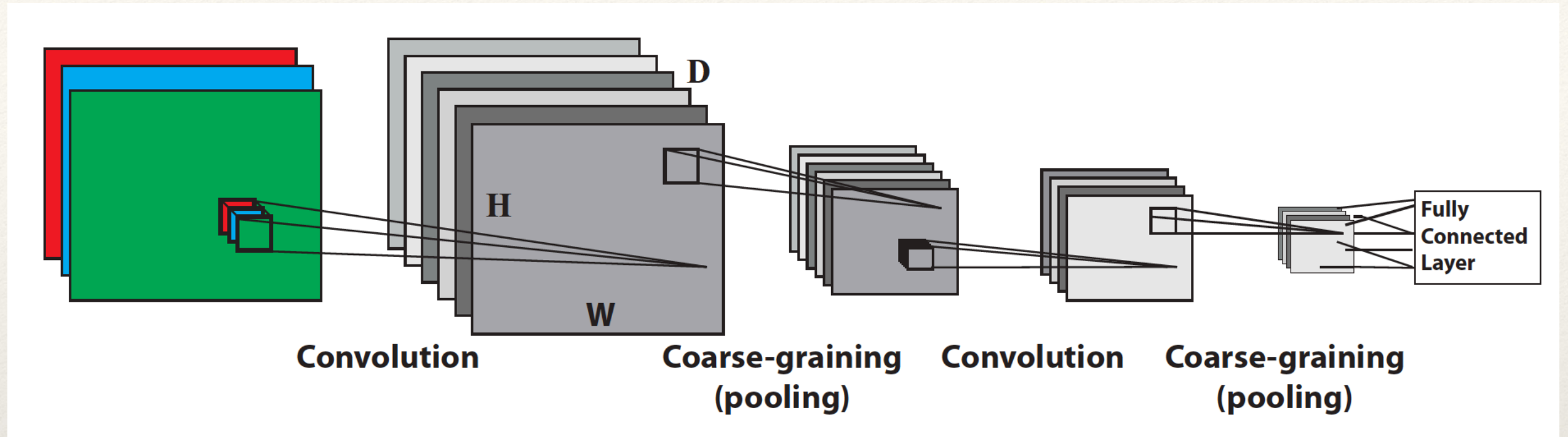
**Convolution layer:** Height, Width and Depth (e.g. RGB channels)

*Convolution* = operation to reduce information while maintaining spatial relations (locality and translation properties)

**Pooling:** Take areas of the image and reduce them. Example, max-pooling would take 2X2 neurons and replace by a single neuron with input the max of the 4



# CNNs



Why do we do this?

**Too much superfluous information in an image**

Need to transform the image and capture the essentials  
while maintaining spatial relations

**As we advance in the layers, the CNN is transforming the original  
image into something more and more abstract**

In physics, translationally invariant systems can be parametrised by  
wave number and functional form (sin, cos)  
whereas an arbitrary system would be *much more complex*

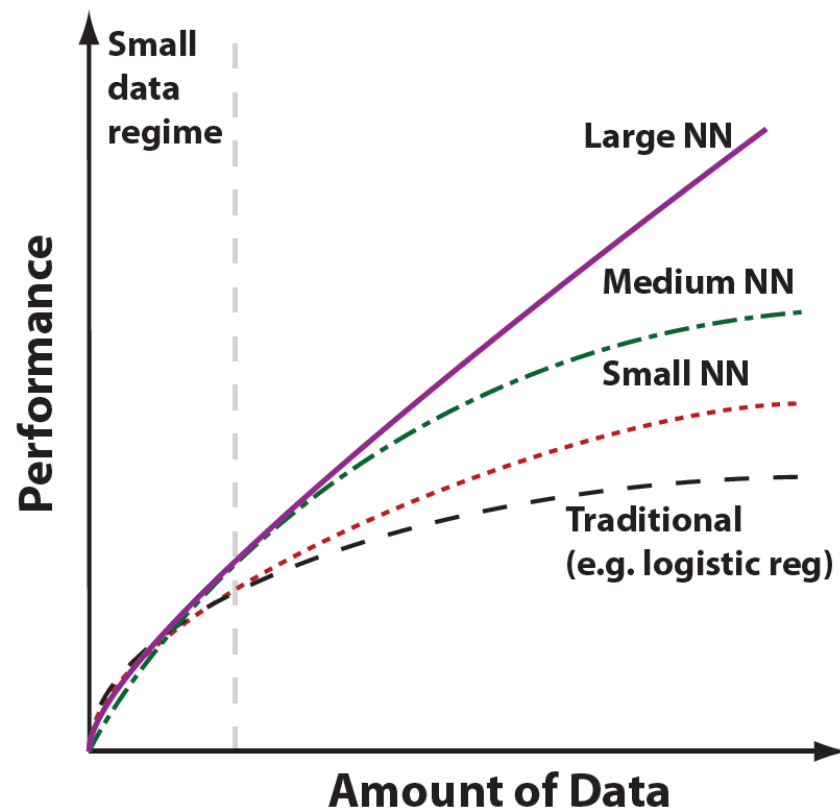


# Why are NNs so good at learning?

**Good at learning: ability to learn with little *domain knowledge***

That's something physicists (as humans) are good at  
(Physics -> other things)

DNNs are good at this too, they are able to take large streams of data and learn features with little guidance, work like *black boxes*



**Good at handling large amounts of data:  
needle in a haystack**

The NN structure (layers, 0/1 gates) allows a high representation power with moderate computational demands, e.g. allows parallelisation, use of GPUs...

It scales better than other learning methods (like SVMs)



# Today: NNs and CNNs

We will take a standard dataset, MNIST



Build and train a NN  
to become better at recognising hand-  
written numbers

This is a *supervised* ML problem  
(we know the true labels)

we train on a large sample (60K) images

We will build a **fully connected NN**,  
a **Convolutional Neural Network**,  
and use **Data Augmentation**

Our precision will go from 96% till 99%

[Link to Google Colab notebook on Neural Networks](#)

**TOMORROW:** *Unsupervised*