Introduction to Deep Learning

(Ensuring Full Literacy Training Workshop)

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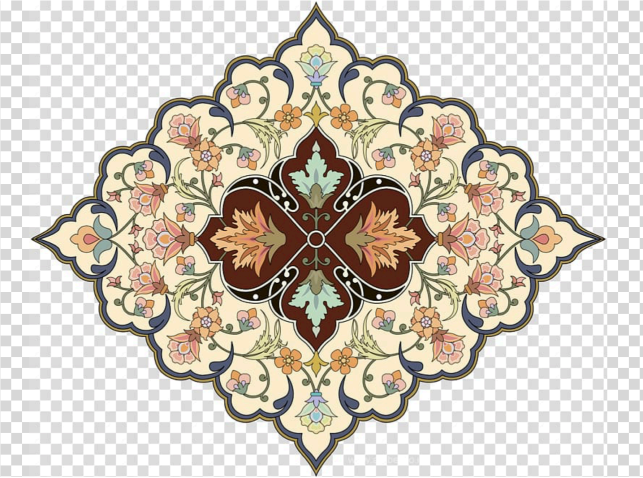
Agenda

1. Overview of AI
2. Deep Learning Inspiration & Architectures
   - Biological Inspiration
   - Recurrent Neural Networks
   - Convolutional Neural Networks

What is Artificial Intelligence?

Figure: Legendary inventors in Greek mythology. Pygmalion and the Statue [Wikimedia commons].

Art *Contd.*

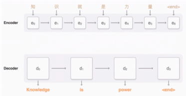


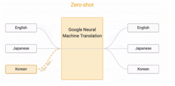
Can **programmable machines** become ***intelligent?***

Figure: **Ada Lovelace. 1842** [Wikipedia]

Deep Learning & Its Impact

Machine Translation

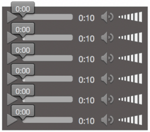


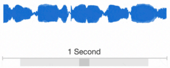


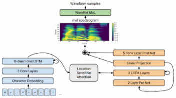
https://research.googleblog.com/

https://translator.microsoft.com/help/articles/neural/

Speech

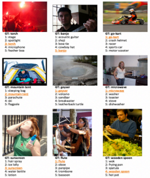






https://research.googleblog.com/

Image (Captioning)



[Microsoft Research: He et al., 2015]

https://research.googleblog.com/

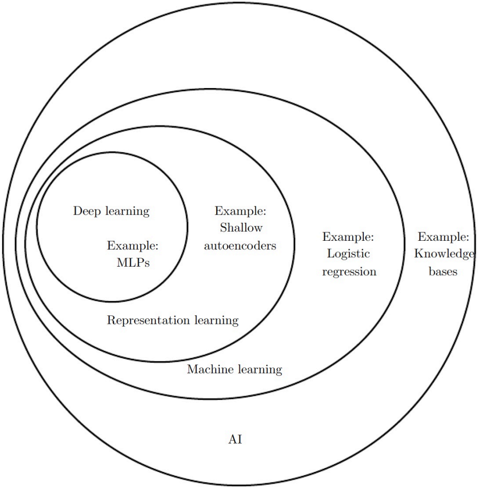


Figure: A Venn diagram situating DL within AI [Goodfellow et al., 2016].

Biological Inspiration

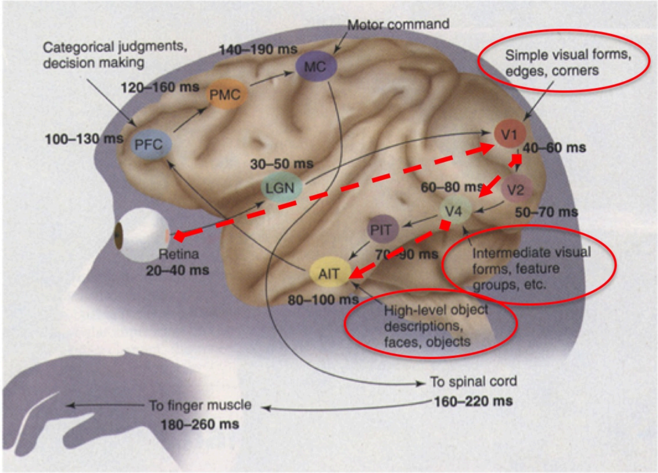


Figure: Visual cortex. [Modified from Simon Thorpe].

Networks with Multiple Layers

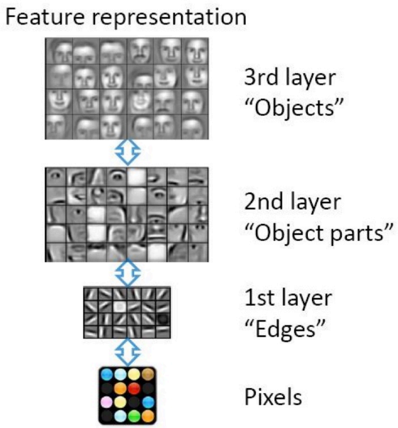


Figure: Leaerning in stages

Information processing in a neuron

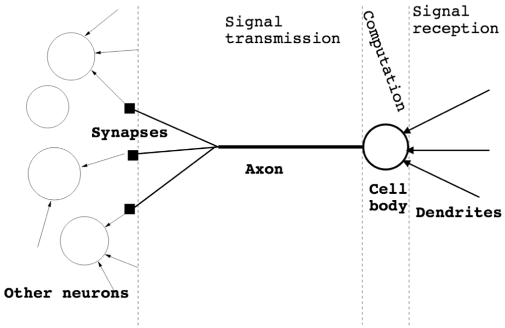


Figure: Information processing in a neuron. [Hyvarinen, Hurri, & Hoyer, 2009]

Neuron With Input

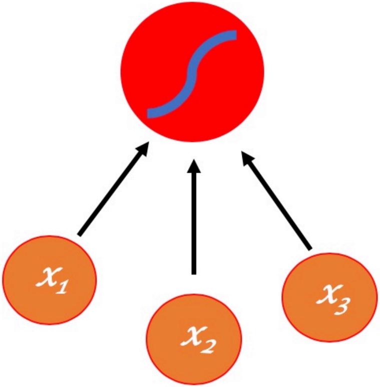


Figure: Input is a vector of $\mathbf{x}$ with three units, each taking an index j

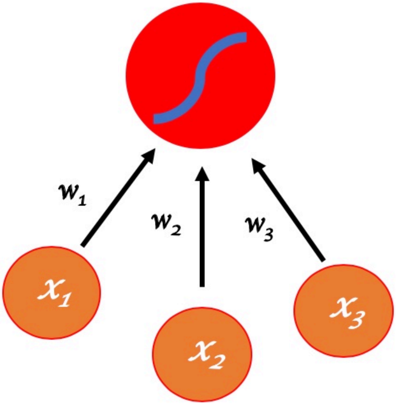


Figure: A vector of free parameters **w** with several items, each taking an index *i*

A Bias Unit

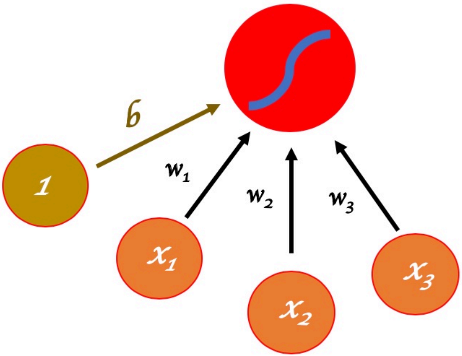


Figure: A bias unit b, equal to 1

A Deep Neural Network

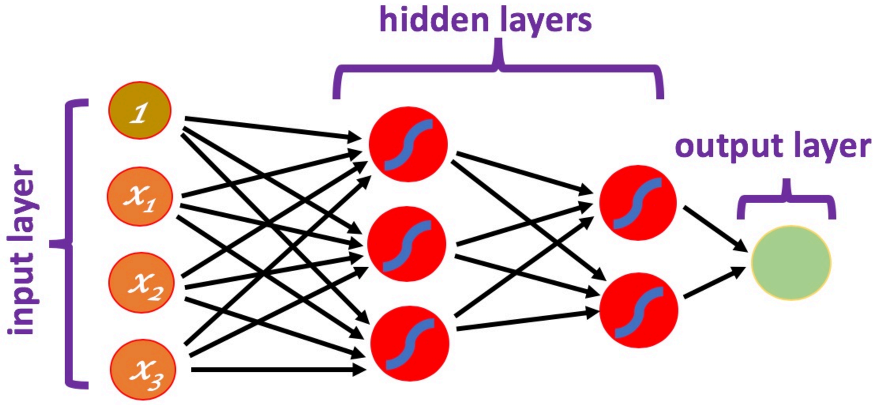


Figure: A **deep neural network**. The network has **2 hidden layers**.

RNN With Output

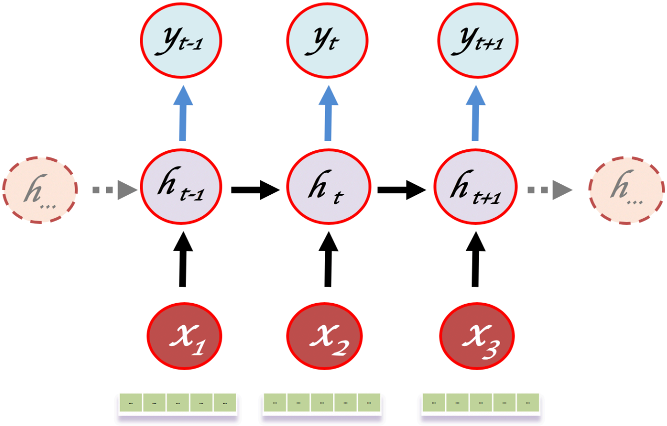


Figure: RNN is a generative model (can output a y at each time step).

Bidirectional RNNs

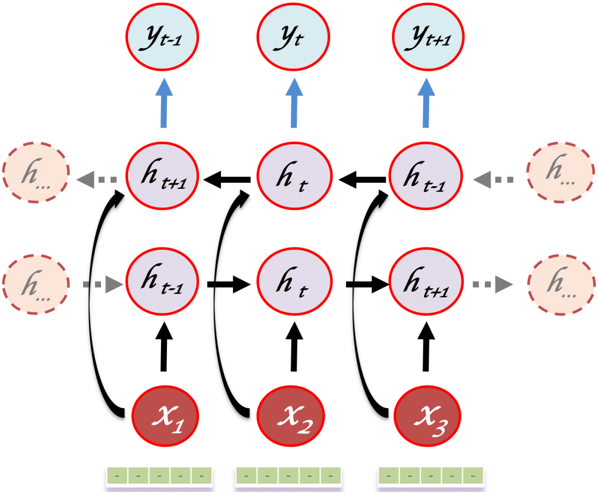


Figure: A bidirectional RNN (BiRNN).

Seq2Seq Models

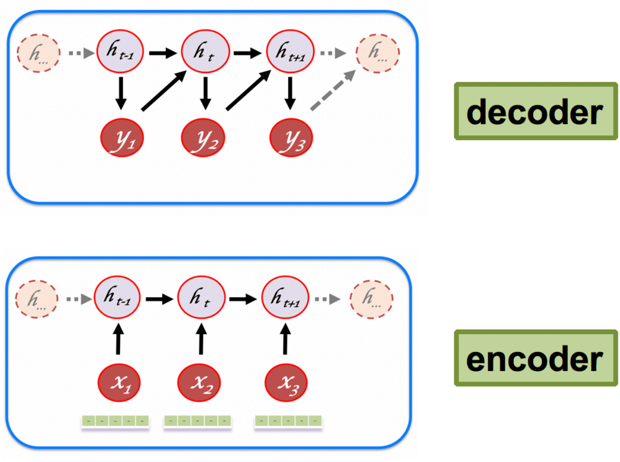


Figure: An Encoder and decoder.

Seq2Seq Models has Encoder Context

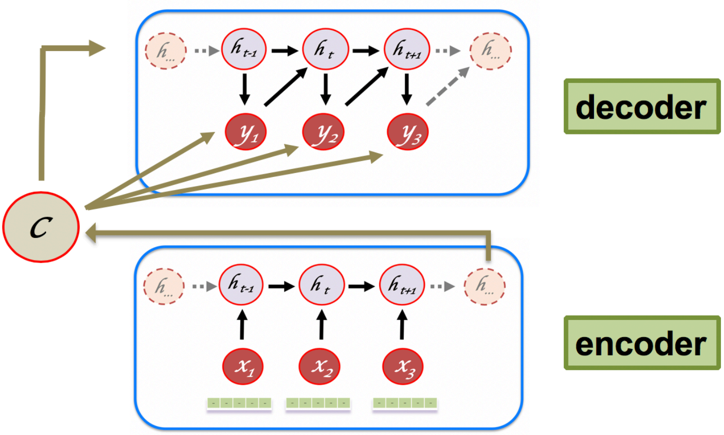
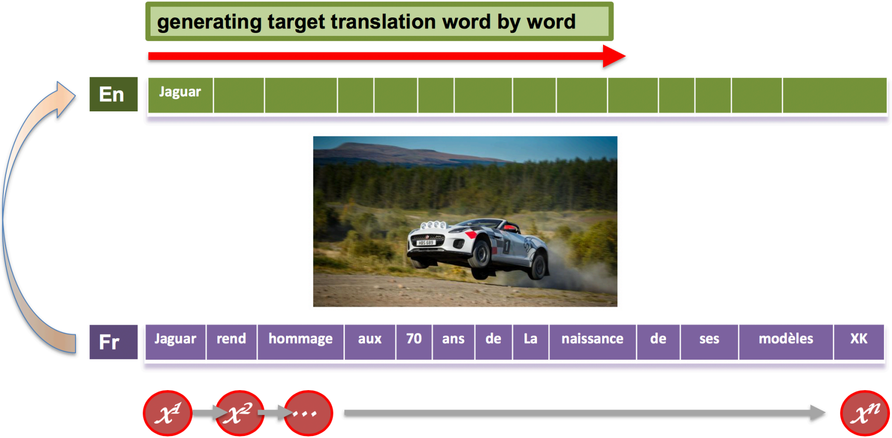
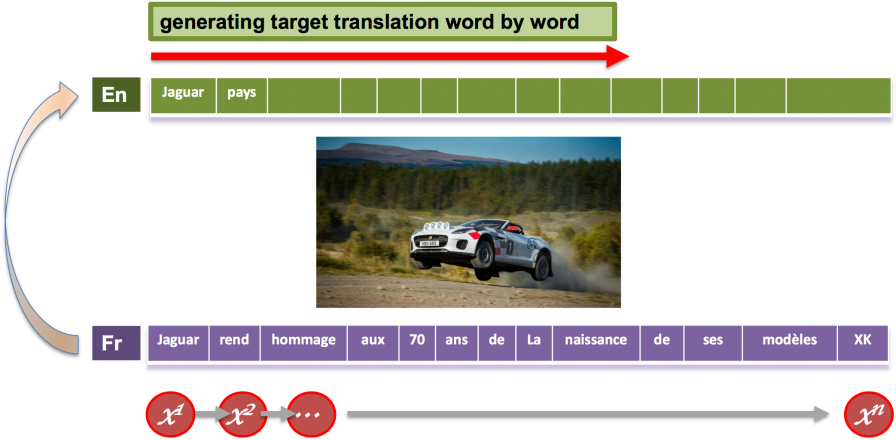


Figure: An Encoder and decoder connected via a context vector C.

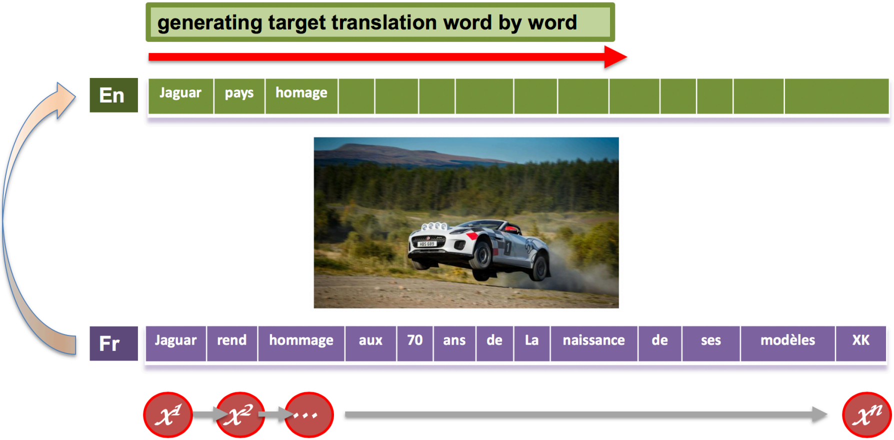
Generating Target (En) One Word at a Time



Generating Target (En) One Word at a Time *Contd. I*



Generating Target (En) One Word at a Time *Contd. II*



Generating Target (En) One Word at a Time *Contd. III*

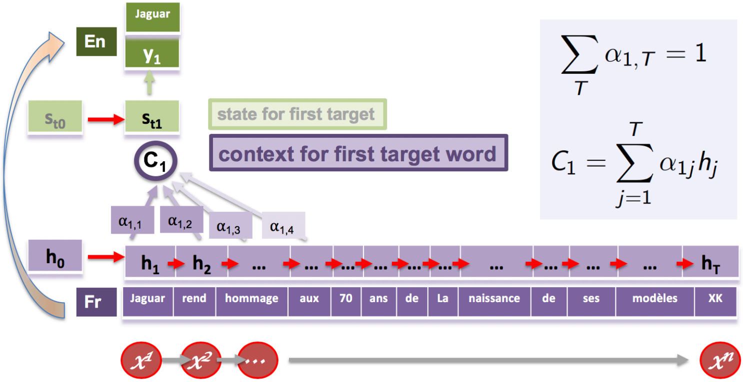
generating target translation word by word

En	Jaguar	pays	homage	to	the	70	years	of	the	birth	of	its	XK	models

Fr	Jaguar	rend	hommage	aux	70	ans	de	La	naissance	de	ses	modèles	XK

$x^1 \rightarrow x^2 \rightarrow \cdots \rightarrow x^n$

Context For State One



$$\sum_{T} \alpha_{1,T} = 1$$

$$C_1 = \sum_{j=1}^{T} \alpha_{1j} h_j$$

Context Ingredients

- α: **attention weights**. (*We will learn these weights*)
- h: **activation from source**

5 x 5 matrix (e.g., input image)

1	1	0	0	0
0	0	1	1	1
0	0	0	0	0
1	1	0	0	1
1	1	0	1	1

3 x 3 kernel (*aka* filter)

1	0	0
0	1	1
1	0	0

Desired feature map

Figure: **Input**: 5 x 5 matrix/2D Tensor. We will convolve with a 3 x 3 kernel, with a `stride` of 1. Our goal is to acquire an feature map (filling in the 3 x 3 matrix on right-hand side).

Convolving 1

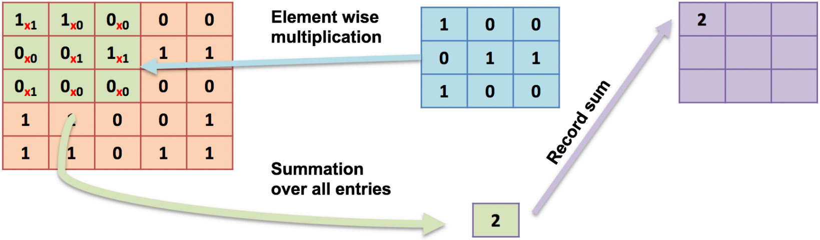


Figure: Filling in the first cell.

Convolving 2

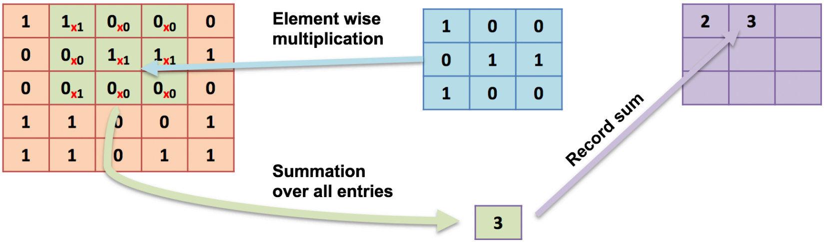


Figure: Filling in the second cell.

Convolving 3

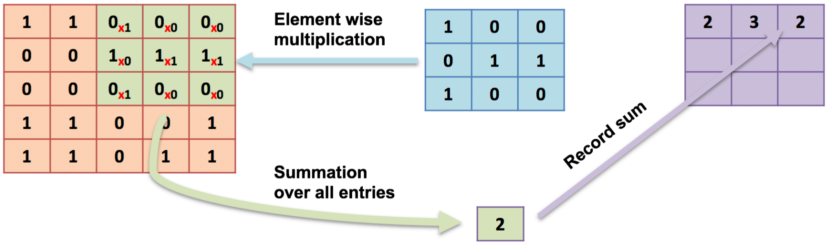


Figure: Filling in the third cell.

Convolving 4

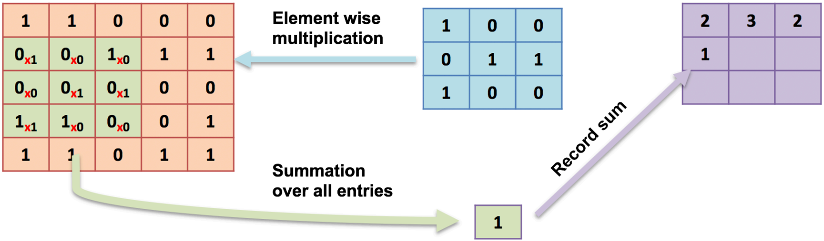


Figure: Filling in the fourth cell.

Convolving 5-9

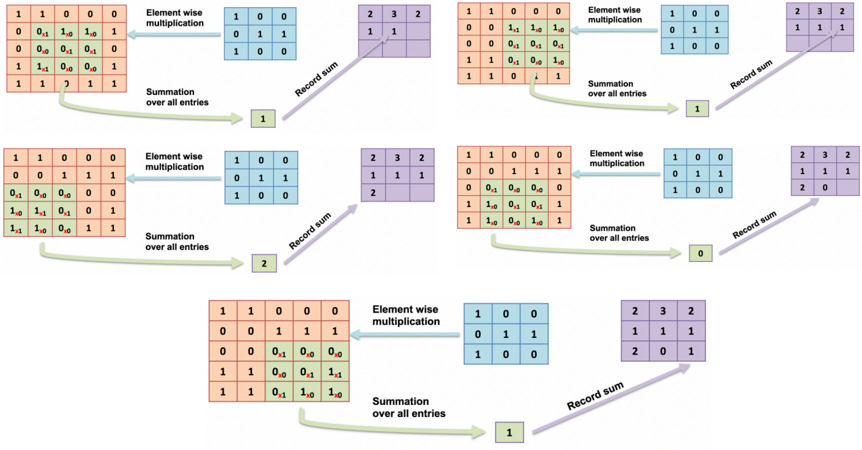


Figure: Filling in the fifth-to-ninth cells.

Convolving With 10 Kernels

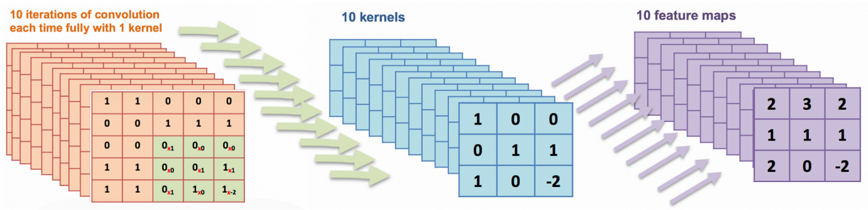


Figure: Convolving with 10 kernels, each with different values, we acquire 10 different feature maps.

Non-Linearity

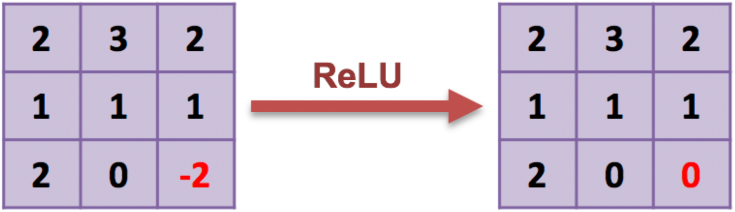


Figure: We actually apply a non-linear function like ReLU on the output of convolution operations such that we end up with meaningful feature maps.

Convolution With Non-Linearity

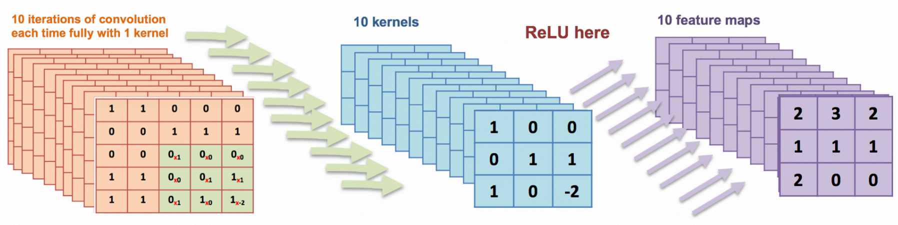


Figure: We actually apply a non-linear function like ReLU on the output of convolution operations such that we end up with meaningful feature maps.

Thank You!

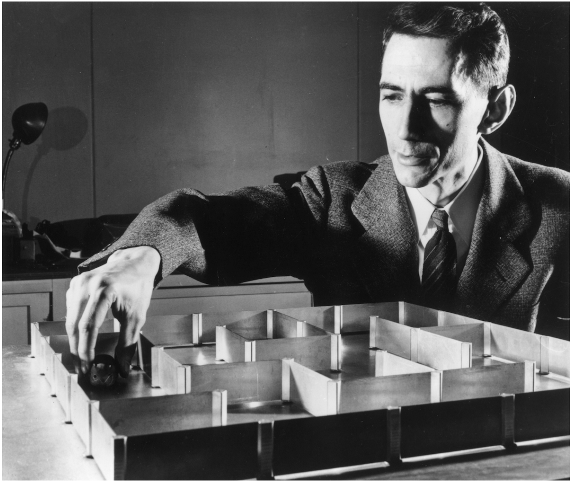


Figure: Claude Shannon. [From Time]