

# DSCI 572: Supervised Learning II

## Lecture 1

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The University of British Columbia

# Agenda

## 1 Overview of AI

## 2 Deep Learning

- Biological Inspiration
- Recurrent Neural Networks
- Convolutional Neural Networks
- ...

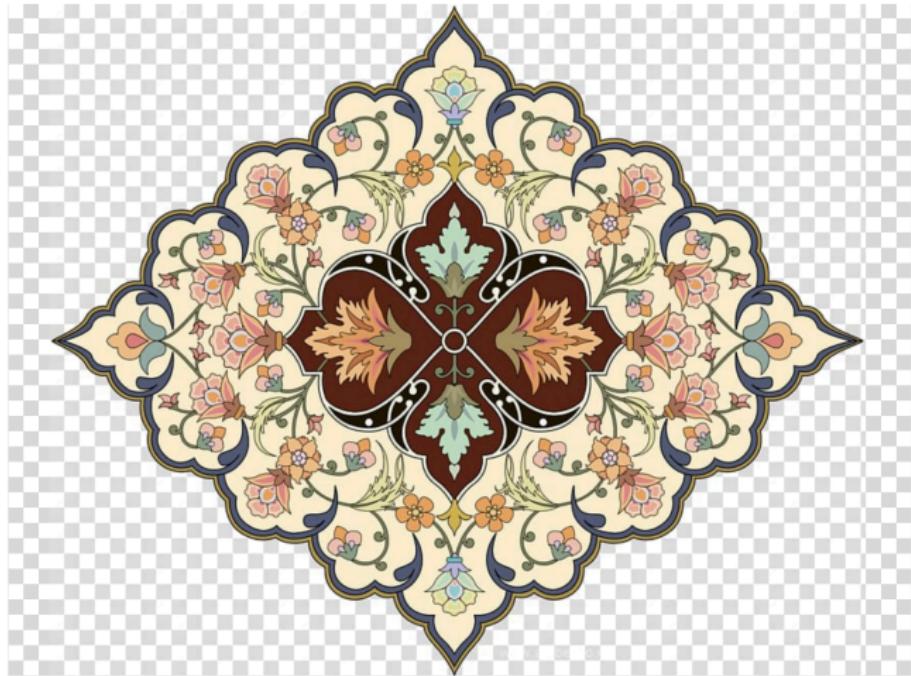
# What is Artificial Intelligence?



Art ...



## Art Contd.



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

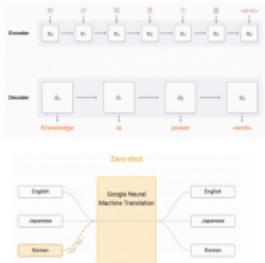
# Can programmable machines become *intelligent*?



Figure: Ada Lovelace. 1842 [Wikipedia]

# Deep Learning & Its Impact

## Machine Translation

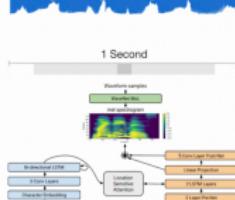
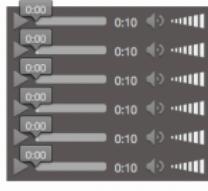


<https://research.googleblog.com/>



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

## Speech



<https://research.googleblog.com/>

## Image (Captioning)



[Microsoft Research: He et al., 2015]



<https://research.googleblog.com/>

# Overview

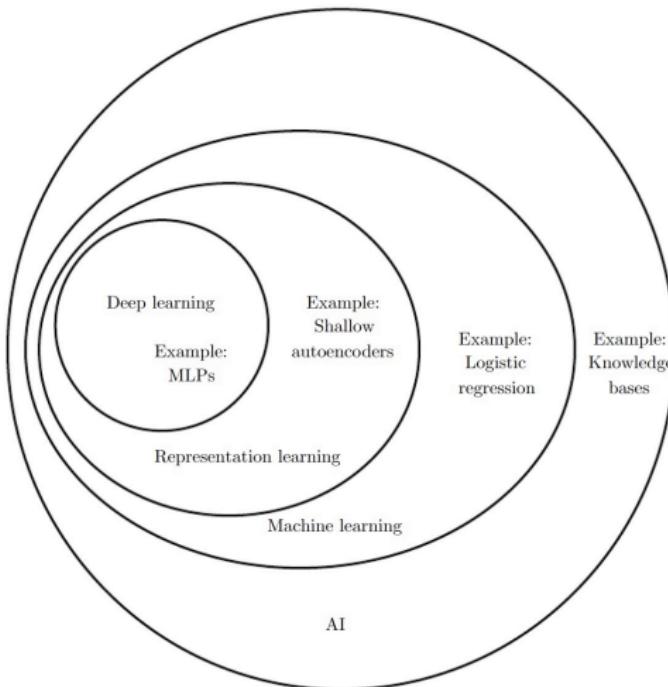


Figure: A Venn diagram situating DL within AI [Goodfellow et al., 2016].

# Biological Inspiration

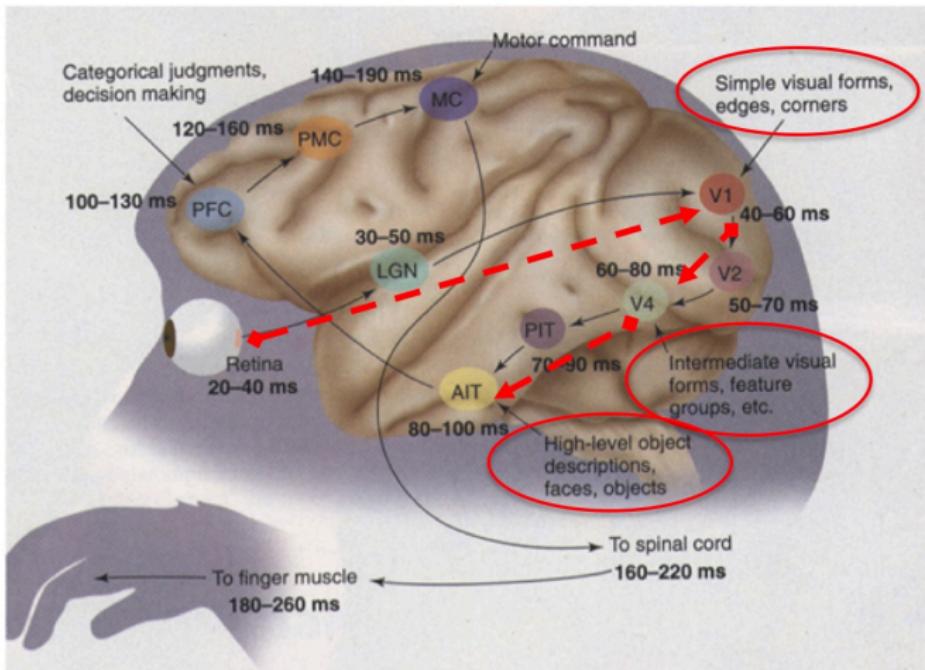


Figure: Visual cortex. [Modified from Simon Thorpe].

# Networks with Multiple Layers

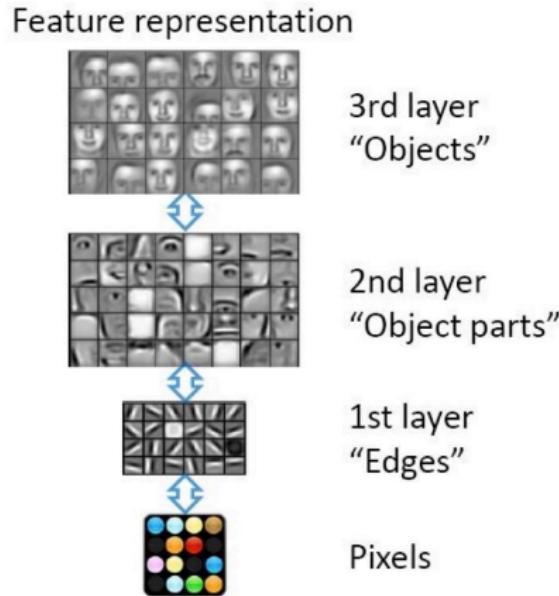


Figure: Learning in stages

# Information processing in a neuron

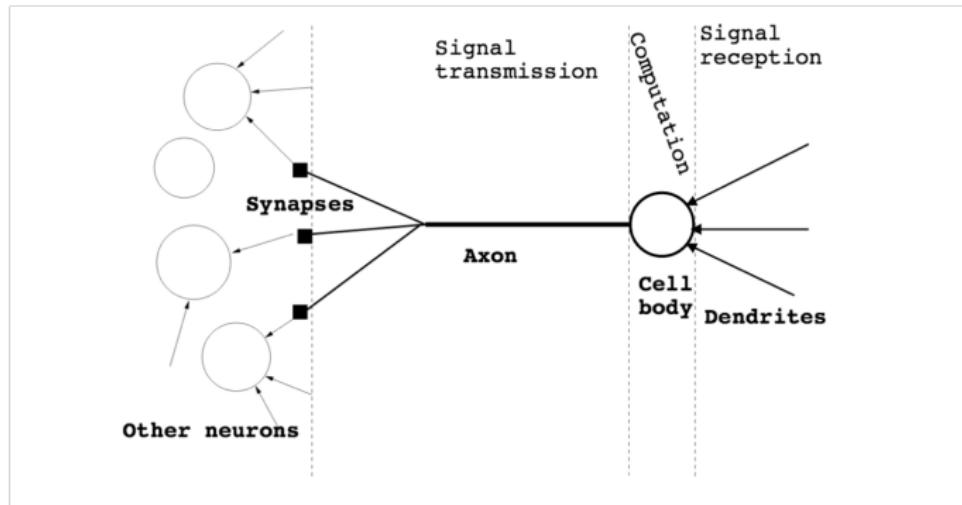


Figure: Information processing in a neuron. [Hyvarinen, Hurri, & Hoyer, 2009]

## Neuron With Input

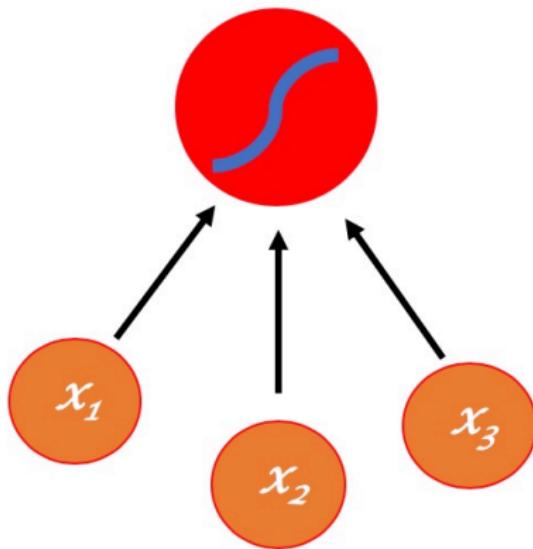


Figure: Input is a vector of  $\mathbf{x}$  with three units, each taking an index  $j$

# A Vector For Connection Weights

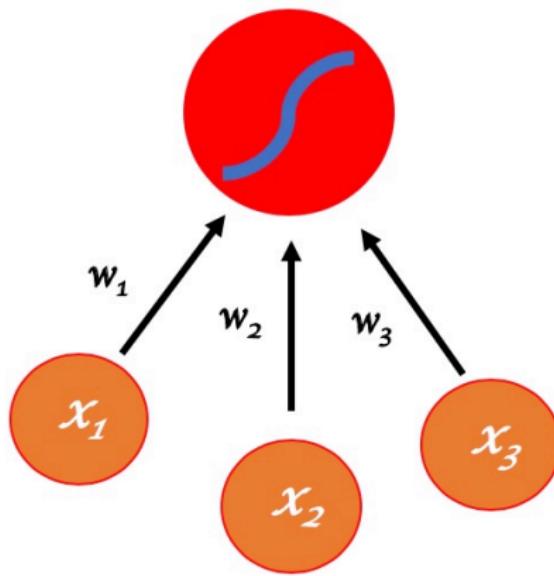


Figure: A vector of free parameters  $w$  with several items, each taking an index  $i$

# A Bias Unit

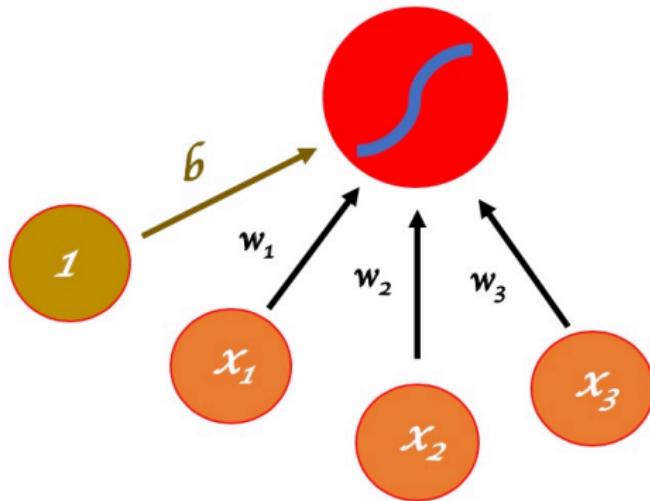


Figure: A bias unit  $b$ , equal to 1

# A Deep Neural Network

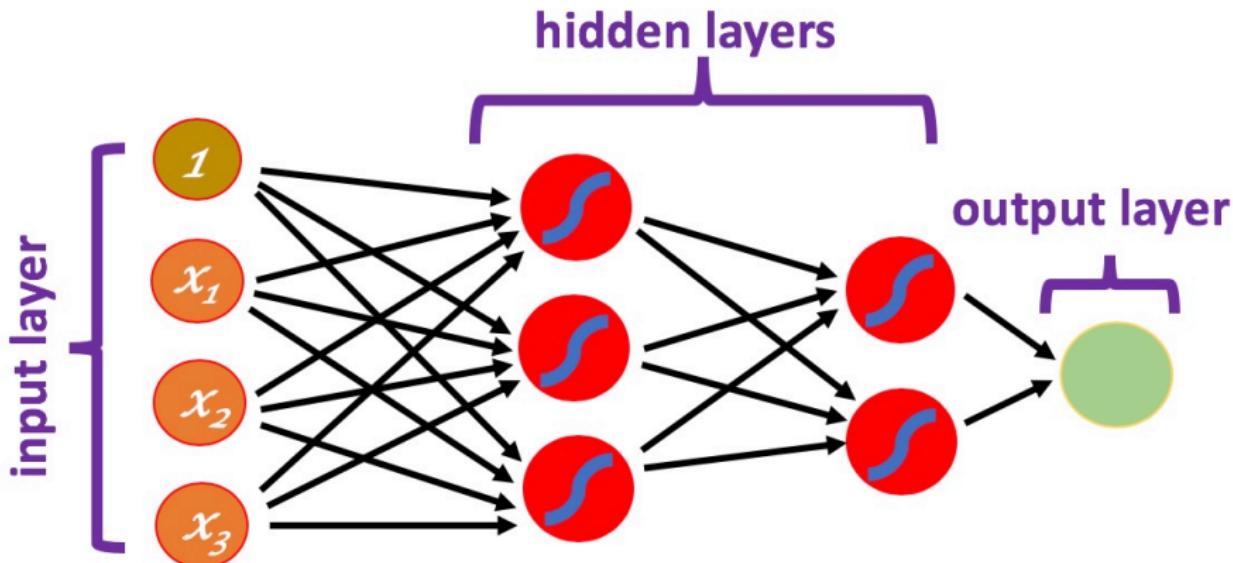


Figure: A **deep neural network**. The network has **2 hidden layers**.

# RNN With Output

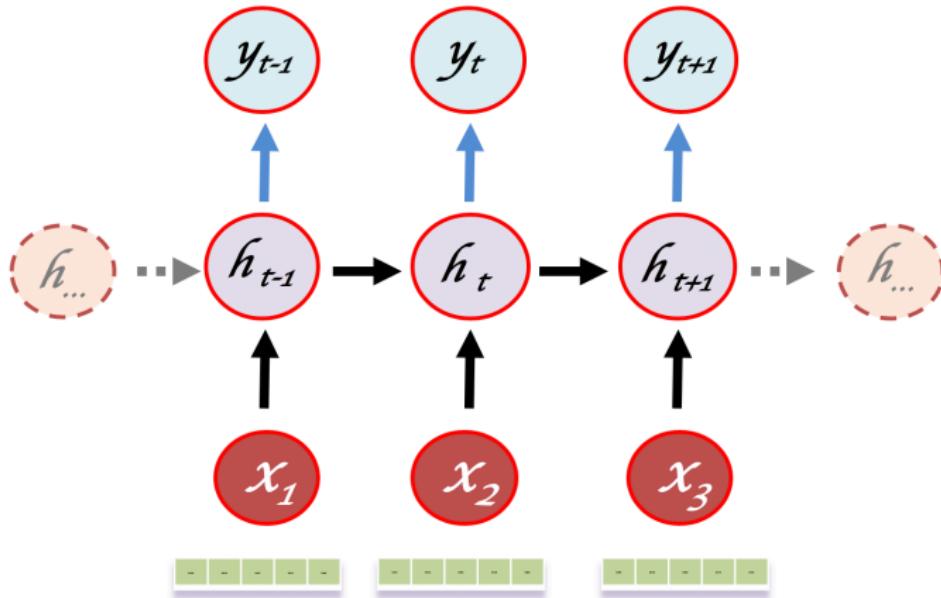


Figure: RNN is a generative model (can output a  $y$  at each time step).

# Bidirectional RNNs

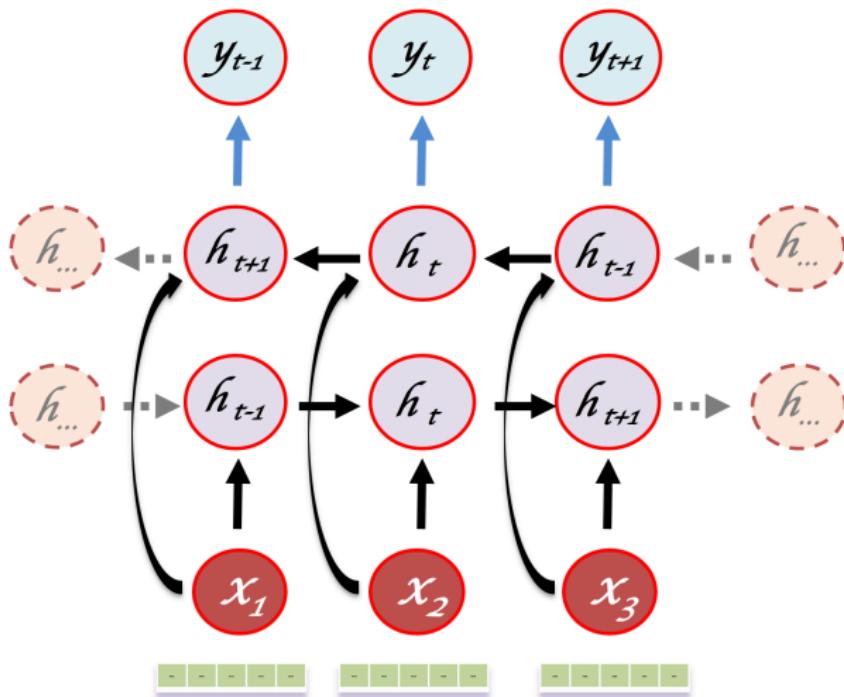


Figure: A bidirectional RNN (BiRNN).

# Seq2Seq Models

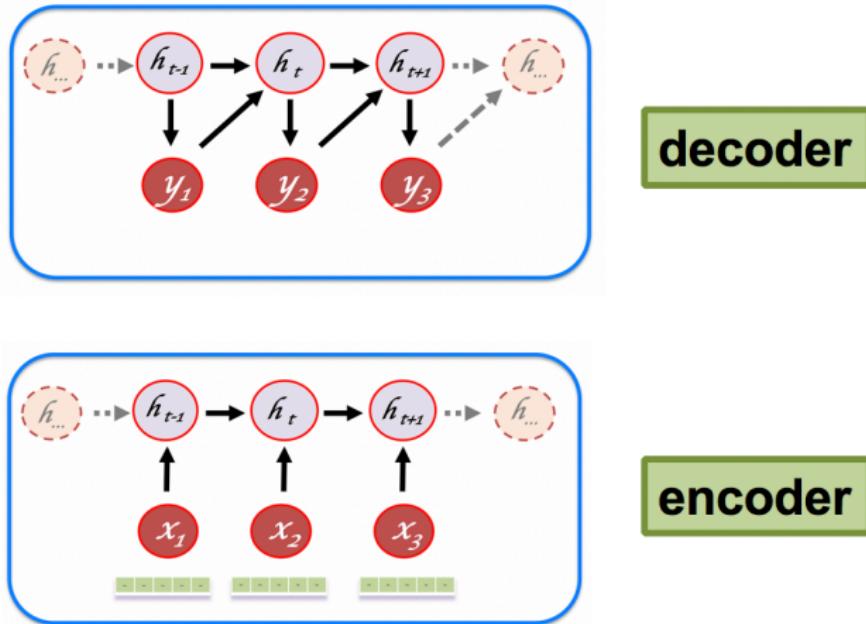


Figure: An Encoder and decoder.

# Seq2Seq Models has Encoder Context

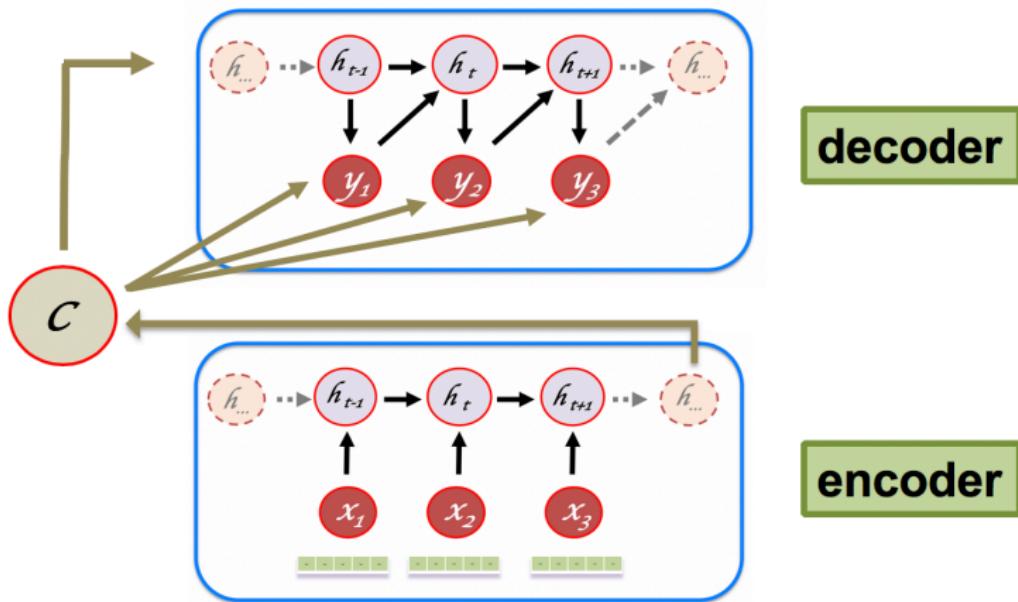
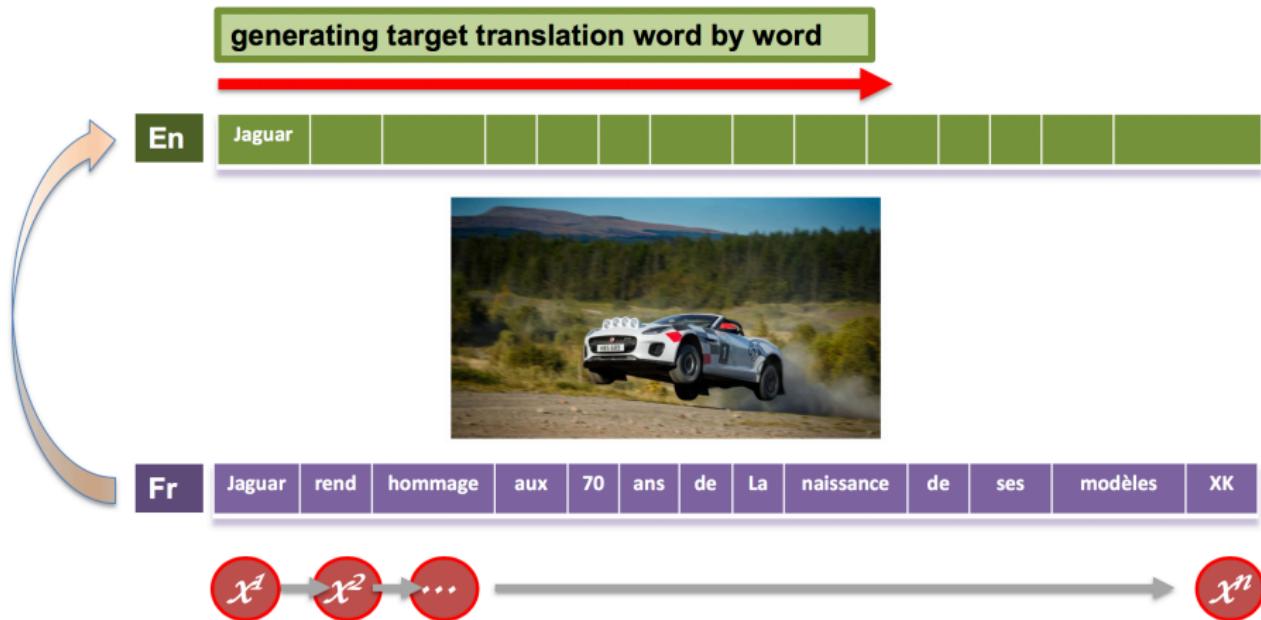
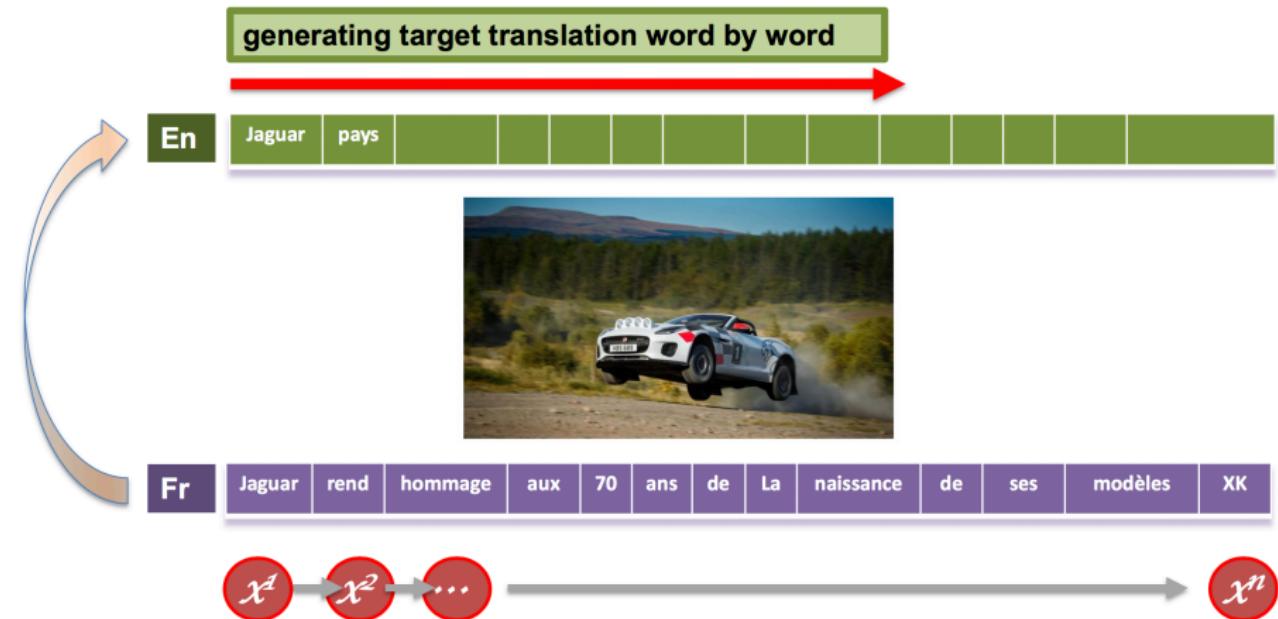


Figure: An Encoder and decoder connected via a **context vector  $C$** .

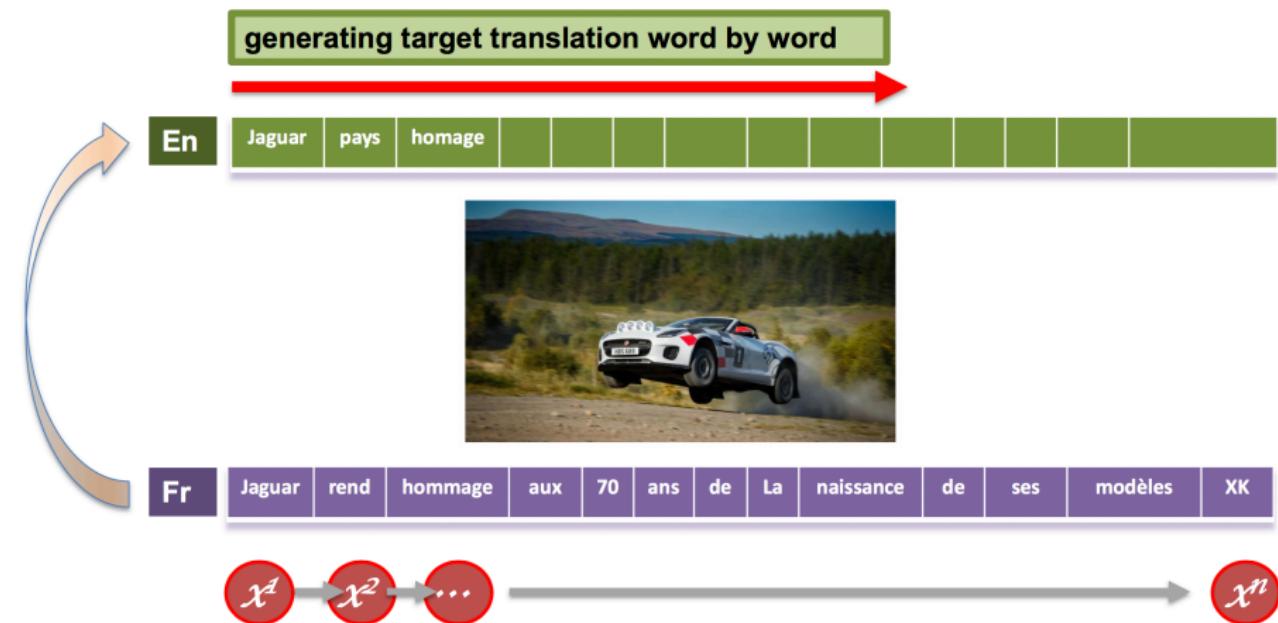
# Generating Target (En) One Word at a Time



# 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

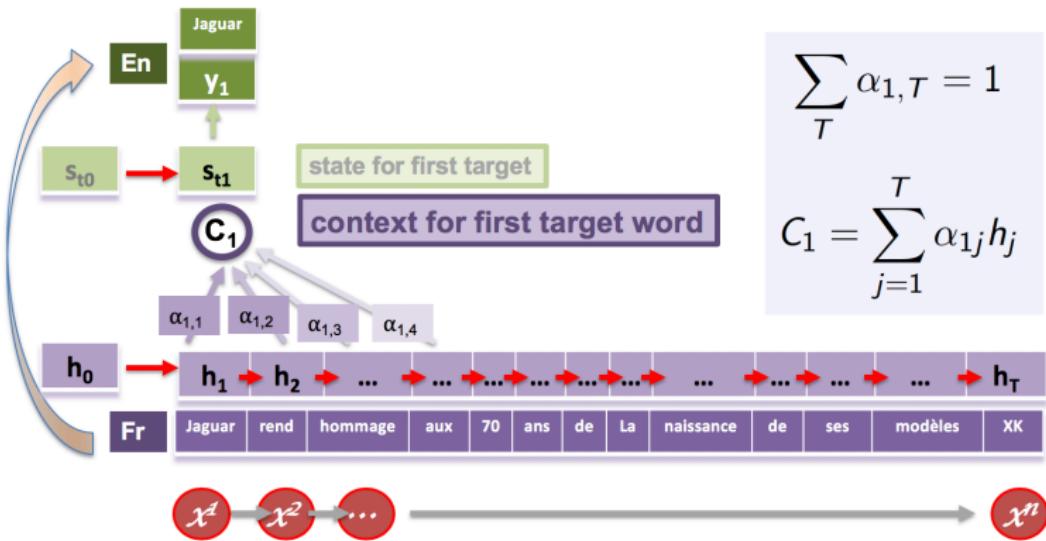


Fr

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



# Context For State One



## Context Ingredients

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

# Convolutional Neural Networks

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

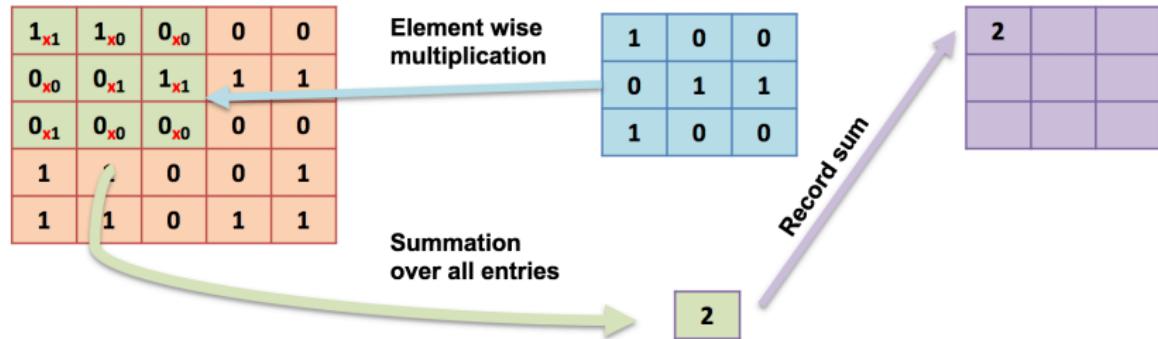


Figure: Filling in the first cell.

# Convolving 2

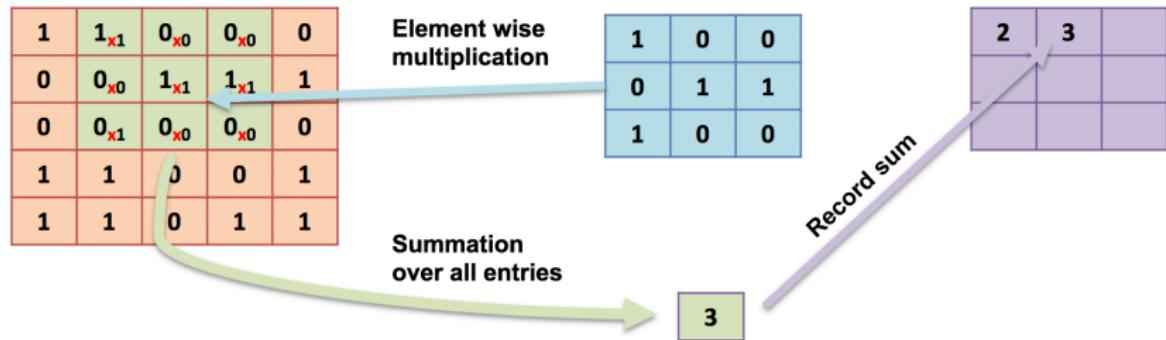


Figure: Filling in the second cell.

# Convolving 3

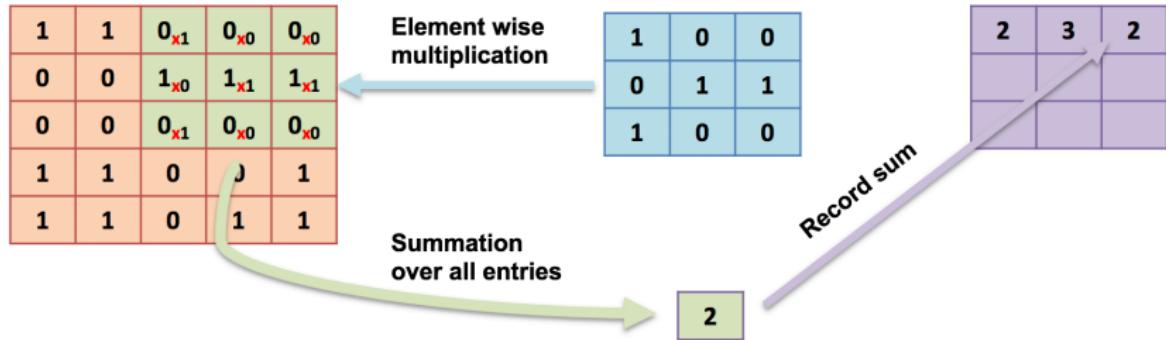


Figure: Filling in the third cell.

# Convolving 4

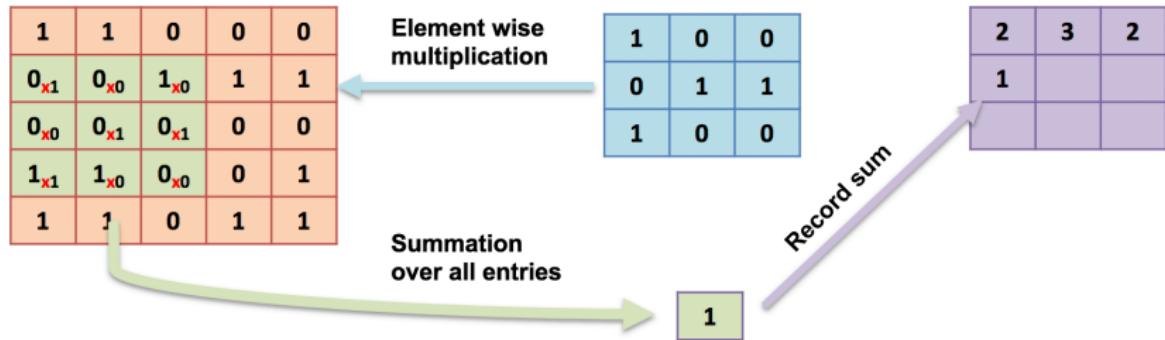
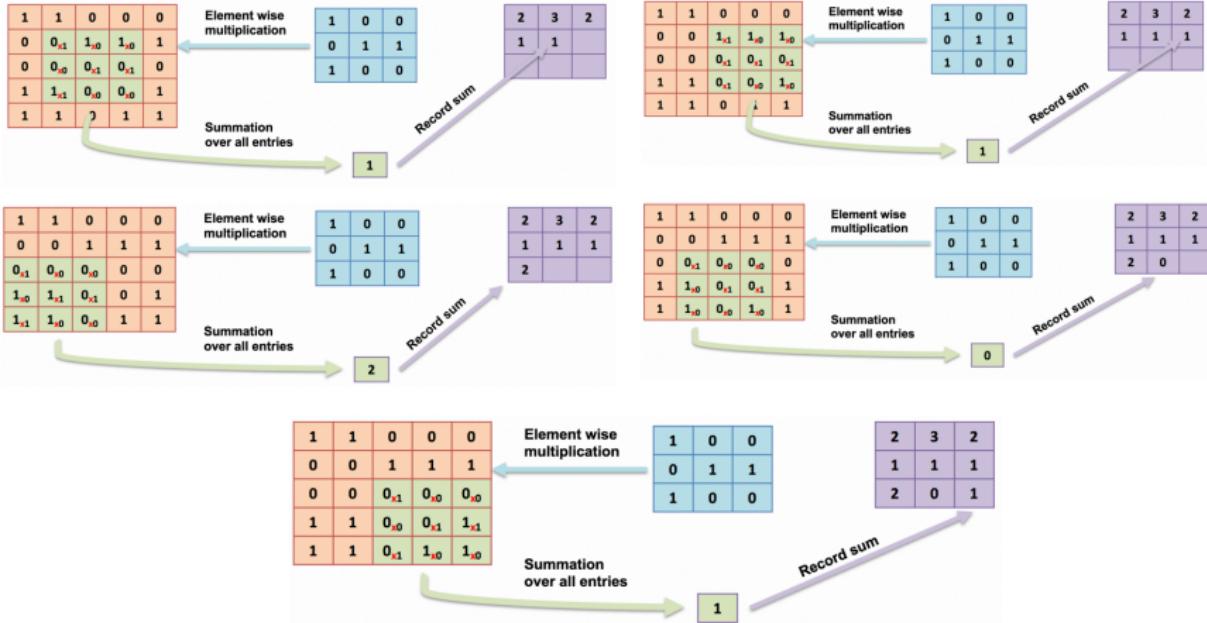


Figure: Filling in the fourth cell.

## Convolving 5-9



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

# Convolving With 10 Kernels

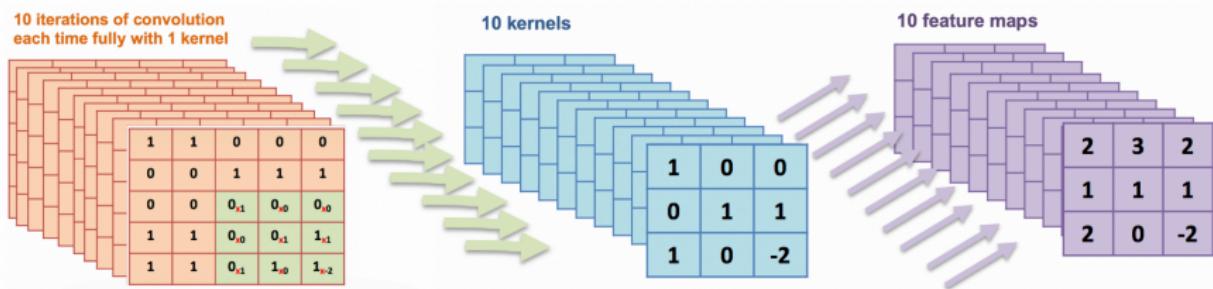
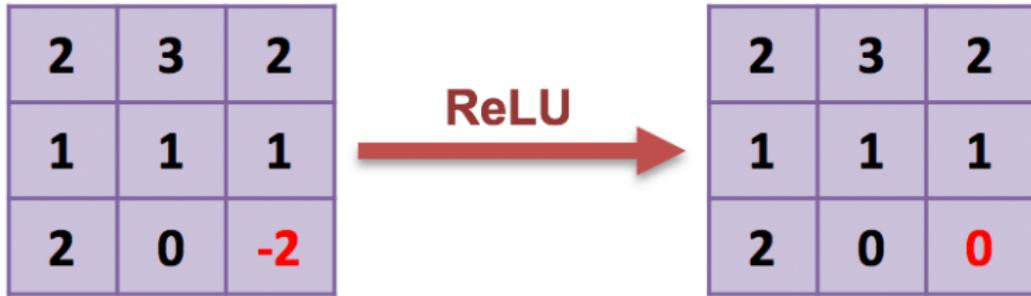


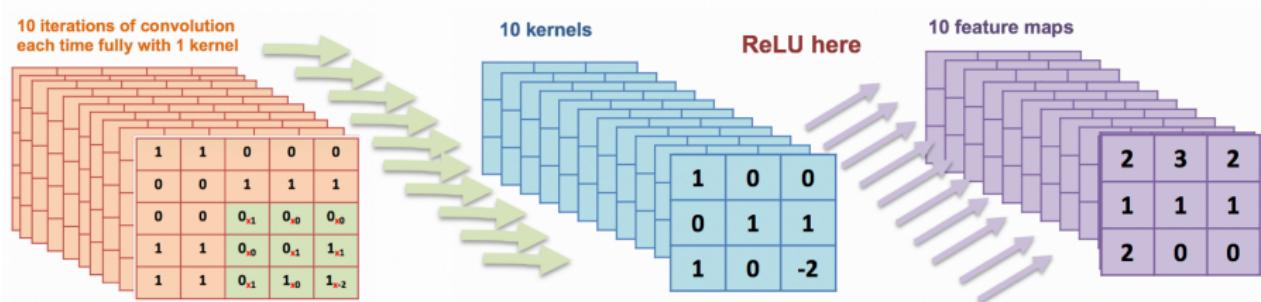
Figure: Convolving with 10 kernels, each with different values, we acquire 10 different feature maps.

# 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.

## Attention Is All You Need

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# Transformer *Contd.*

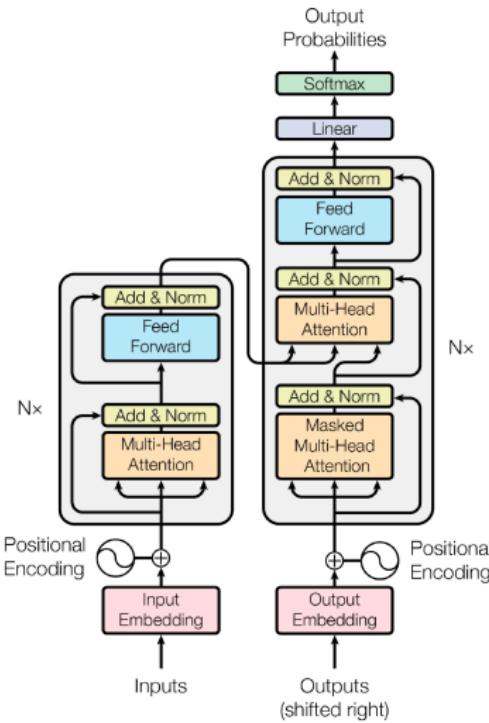
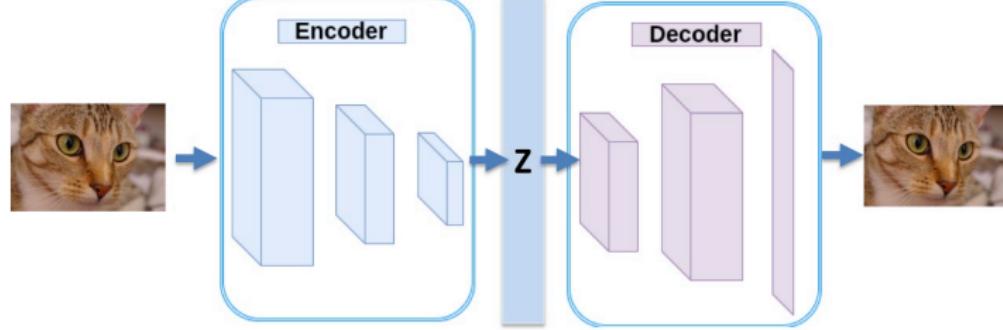


Figure: Transformer: Model Architecture.

# (Variational) Autoencoders



**Figure:** A variational autoencoder. It has an **encoder** (left) and a **decoder** (right).

# Generative Adversarial Networks

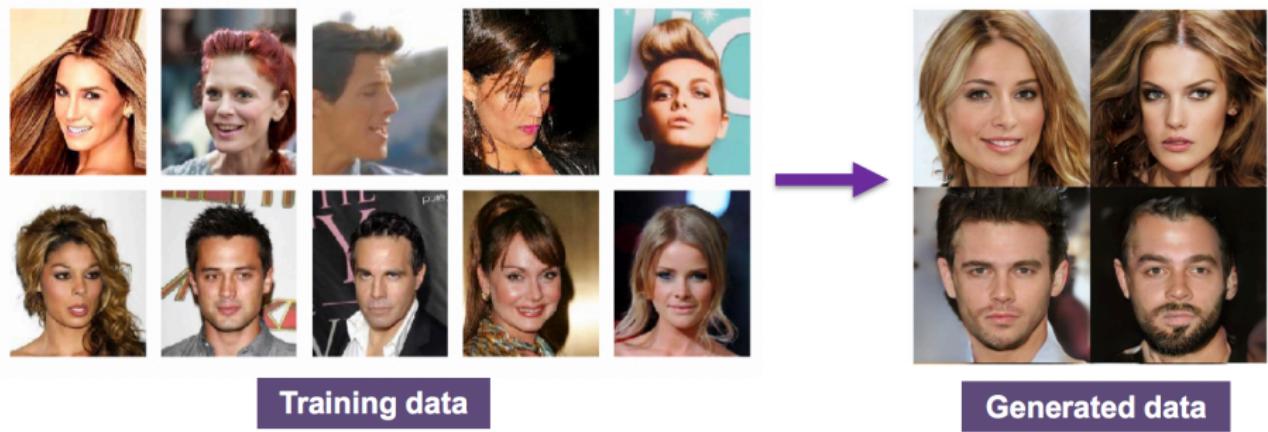


Figure: [From Karras et al, 2017; see paper]

# GAN-Generated Images

goldfish



indigo bunting



redshank



saint bernard



Figure: [From Zhang et al, 2018; see paper]

# Thank You!

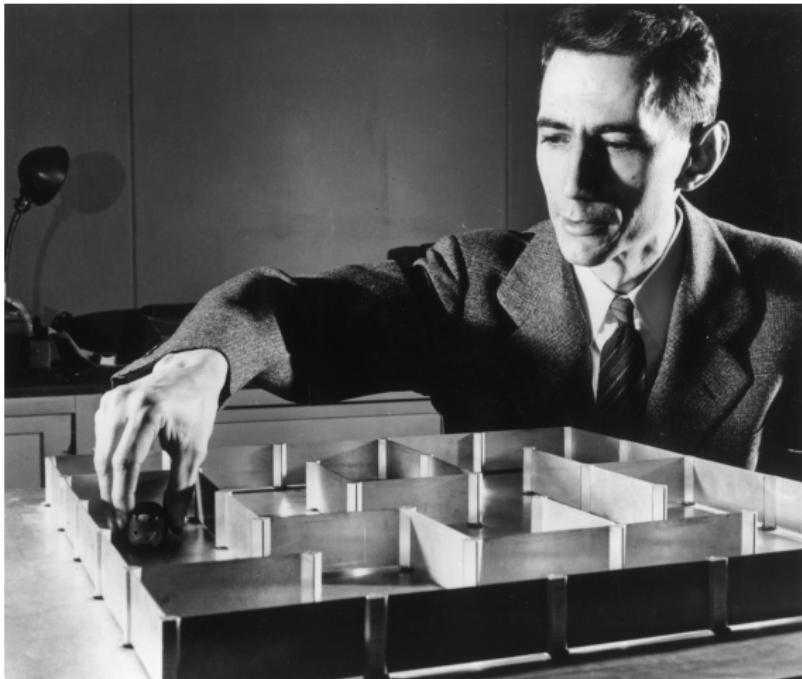


Figure: Claude Shannon. [From Time]