

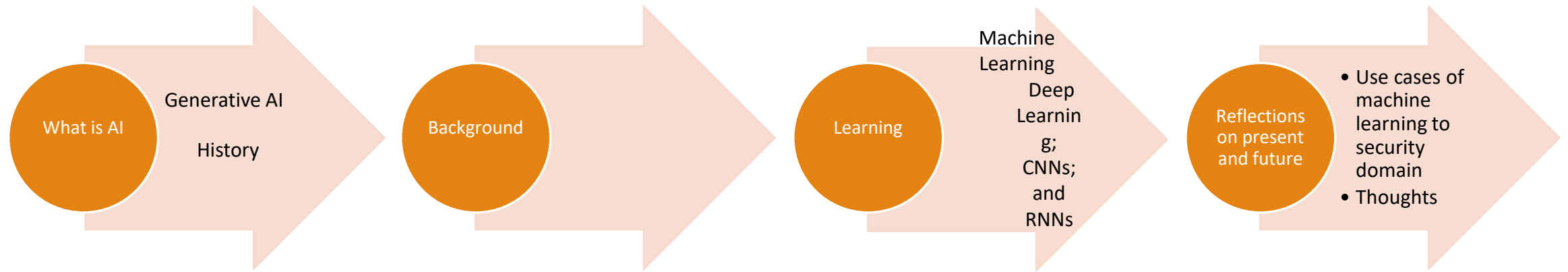
# Foundations of AI and its Future Prospects

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# Overview

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# What is AI

Science and technology to simulate human intelligence by machines and computers

- Examples: Autonomous vehicles, crop analysis; drug discovery; medical diagnosis; Generative AI tools

Machine Learning; Deep Learning; Rule based

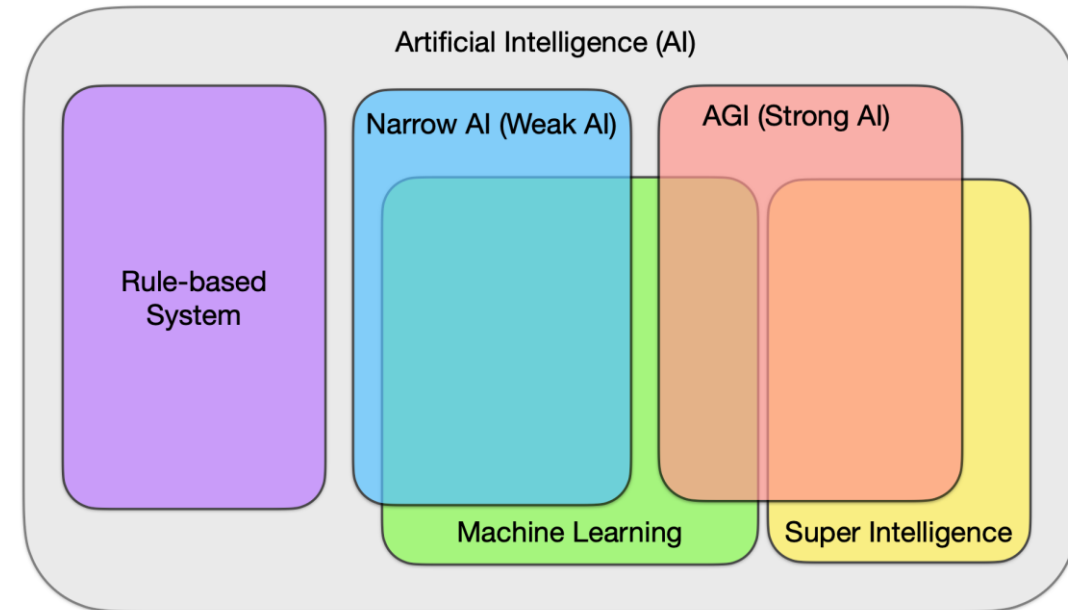
Based on the human decision-making processes that can learn and generalize

## Narrow AI (ANI-Artificial Narrow Intelligence)

- Trained and focused on specific tasks– Apple's Siri, Amazon's Alexa, IBM Watsonx™, Self-Driving Vehicles

## Strong AI (AGI-Artificial General Intelligence or Artificial Super Intelligence)

- Aims for intelligence equivalent to humans—Self aware; consciousness ability to solve problems; plan for the future
- ASI- Surpass the human abilities and intelligence– at present mostly theoretical
- Examples: Superhuman and rogue computer assistant in 2001: A Space Odyssey



# Generative AI



Deep learning that takes raw data (Wikipedia; works of Rembrandt, etc) and can generate statistically probable outputs

Encode a simplified description of training data and generate new work that may be similar but not identical to the original data

# History

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1950

Alan Turing –  
*Computing Machinery  
and Intelligence.*

Can Machines Think?  
Turing Test.



1956

John McCarthy  
“artificial  
intelligence”

Newell, Shaw,  
Simon create the  
first running AI  
software program  
Logic Theorist



1967

Mark Rosenblatt –  
Mark 1  
Perceptron, NN  
that learns

Minsky and Papert  
book Perceptrons  
- argument  
against NN



1980

BP becomes  
widely used



1997

IBMs Deep Blue  
beats world chess  
champion Garry  
Kasparov



2004

John McCarthy  
writes a paper  
“What is Artificial  
Intelligence” and  
defines AI



2011

IBM Watson beats  
champions Ken  
Jennings and  
Brad Rutter at  
Jeopardy



2015

Baidu’s Minwa  
supercomputer  
uses convolutional  
neural networks  
to identify and  
categorize images  
better than an  
average human



2016

DeepMind’s  
AlphaGo program  
using deep neural  
network beats Lee  
Sedol, the world  
Go player  
(possible moves  
14.5 trillion after  
four moves)



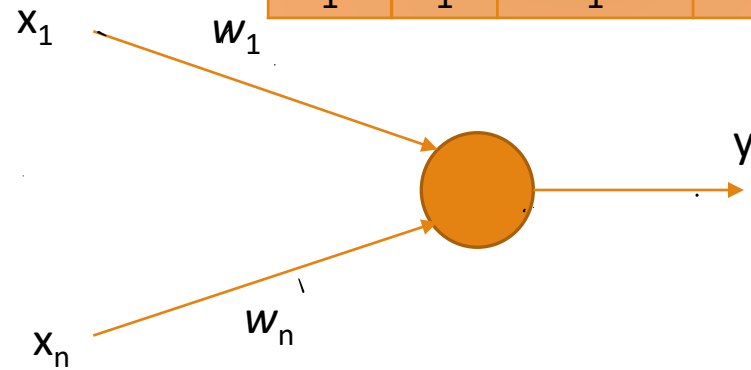
2023

Rise in Large  
Language Models,  
such as ChatGpt

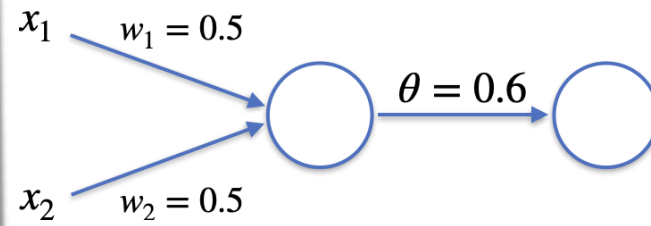
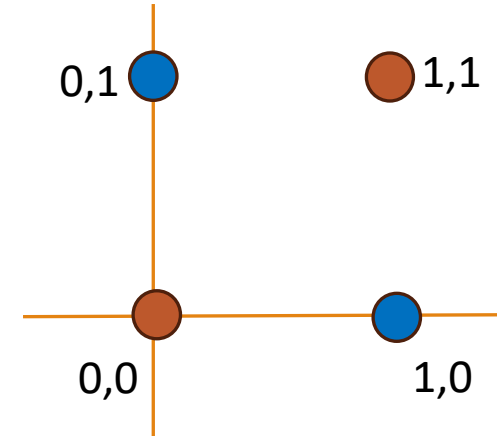
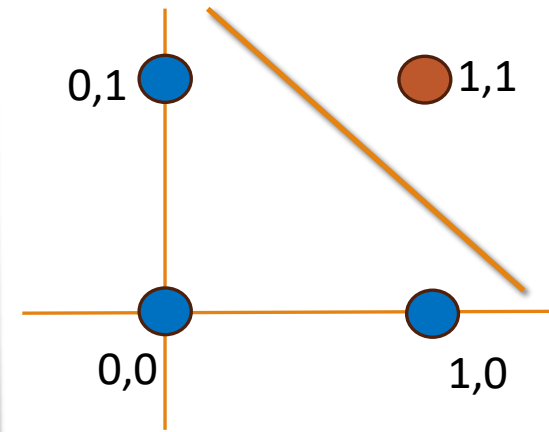
# Background – Neuron --Perceptrons

Implementation of AND XOR?

Input		And	XOR
$x_1$	$x_2$		
0	0	0	0
0	1	0	1
1	0	0	1
1	1	1	0



$$y = f\left(\sum w_i x_i\right) = \begin{cases} 0, & \text{if } f < \theta \\ 1, & \text{if } f \geq \theta \end{cases}$$



$$y = f(x_1 * w_1 + x_2 * w_2)$$

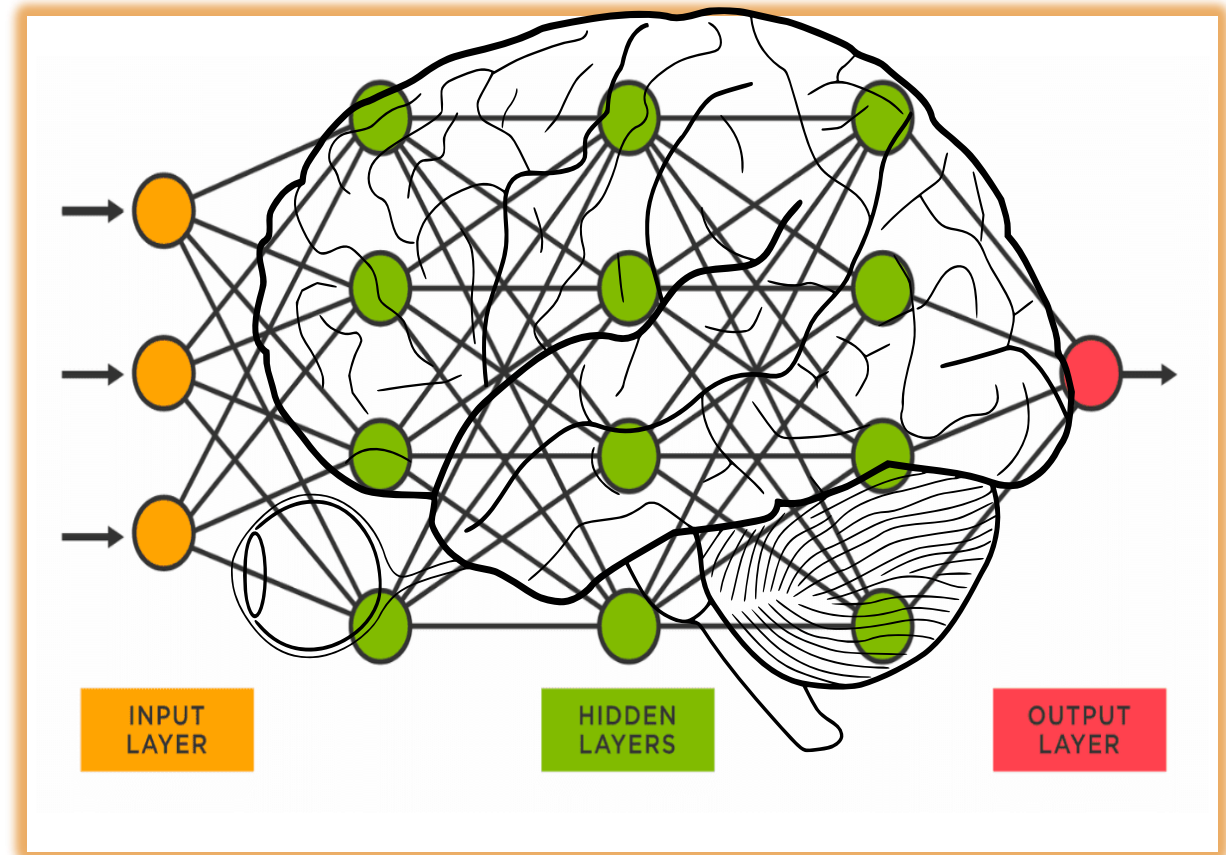
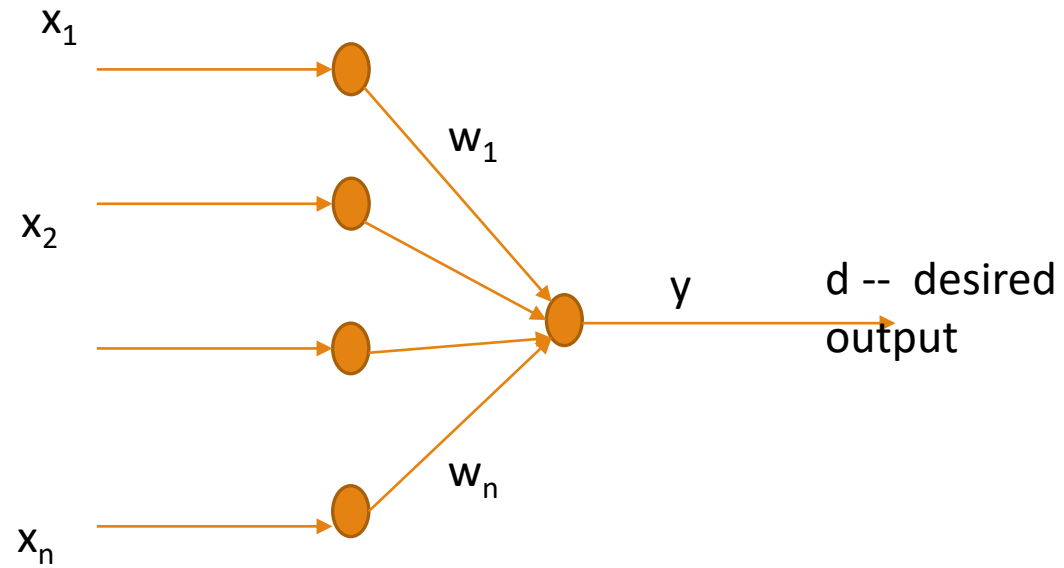
$$y = f(0 \times 0.5 + 0 \times 0.5) = f(0) = 0$$

$$y = f(0 \times 0.5 + 1 \times 0.5) = f(0.5) = 0$$

$$y = f(1 \times 0.5 + 0 \times 0.5) = f(0.5) = 0$$

$$y = f(1 \times 0.5 + 1 \times 0.5) = f(1) = 1$$

# Perceptron



# Machine Learning

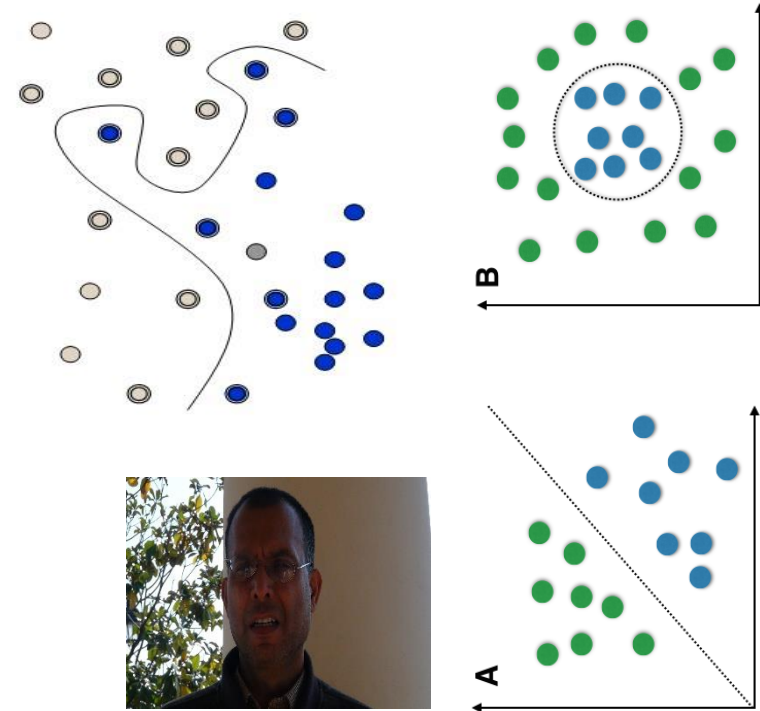
## Machine Learning

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Machine learning covers algorithms that learn from and make predictions on data

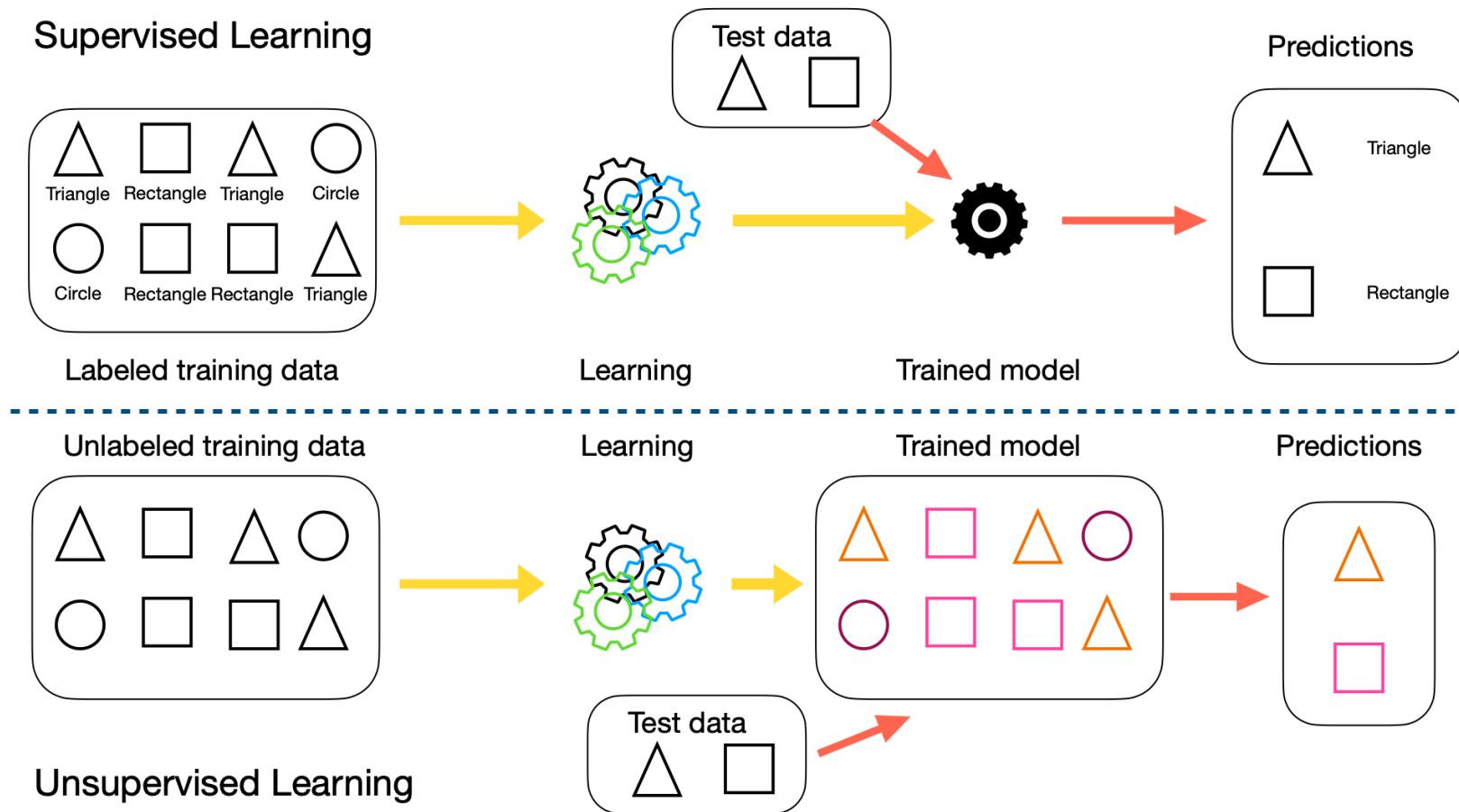
### Characteristics

- Generalization -- programming explicit algorithm is infeasible.
- Approximation is acceptable -- Pattern recognition, Face recognition, Handwriting recognition





# Illustration of a learning system

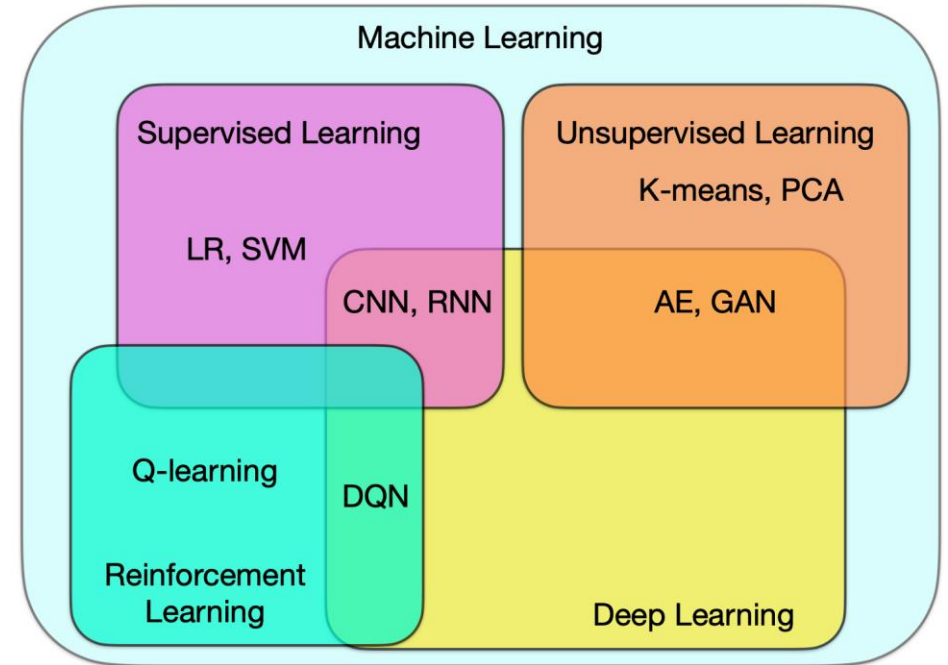


# Deep Learning vs. Machine Learning

Machine learning focuses on the development of algorithms that enable computers to learn from and make decisions based on data.

Deep learning is a specialized subfield of machine learning that uses neural networks with many layers (hence “deep”) to model complex patterns in data.

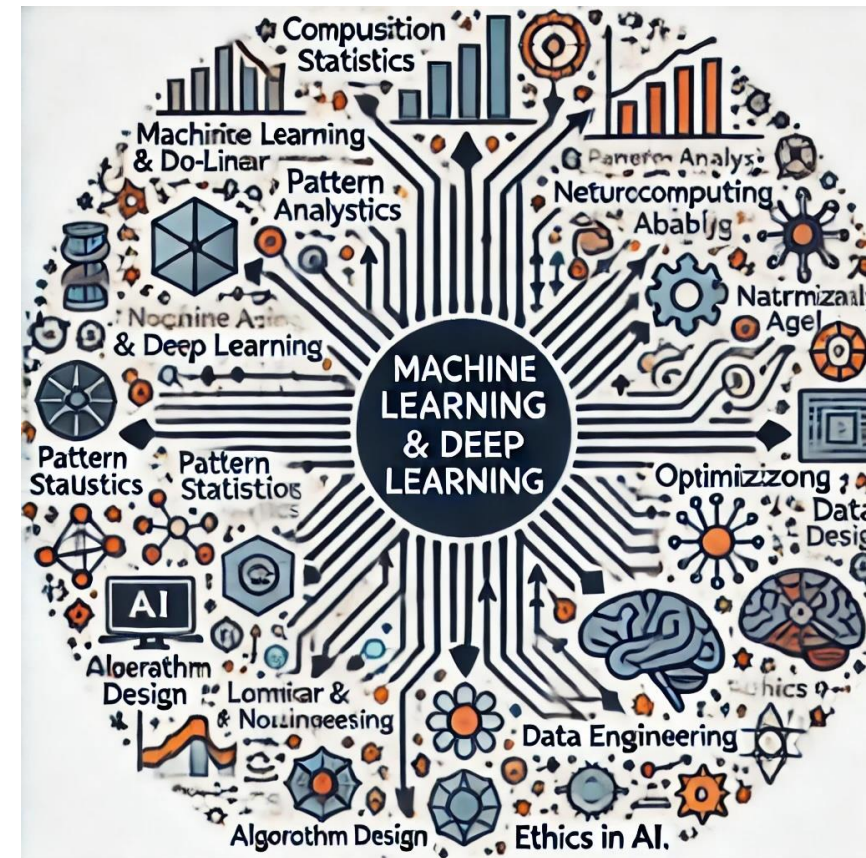
	Machine Learning	Deep Learning
Contemporary Usage	Traditional machine learning algorithms and simpler neural networks	Neural networks with deep architectures
Features	Feature engineering with manually extracted and selected features	Automatically extracted by the neural network
Applications	Well-suited to smaller datasets and problems where interpretability is important	Excels in handling large, complex datasets, especially in CV, NLP, and LLM



# Component fields of Machine Learning

Areas include –

- Computational statistics
- Pattern analysis
- Neurocomputing
- Linear and non-linear algebra
- Optimization
- Algorithm design, etc.



# How deep learning works

Multiple layers of interconnected nodes

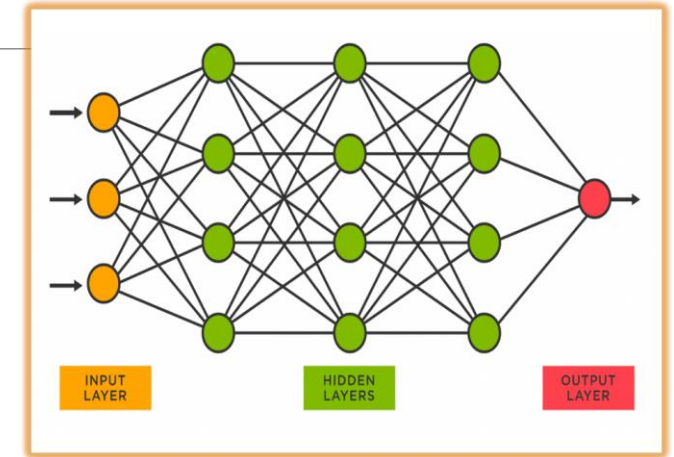
Backpropagation- Error is backpropagated to adjust weights to learn the patterns

Massive set of neurons – require massive resources

High performance graphical processing units – calculations in multiple cores with large memory

Distributed cloud computing is good

Software requirements– typically JAX, PyTorch, TensorFlow



PyTorch

TensorFlow

Jax

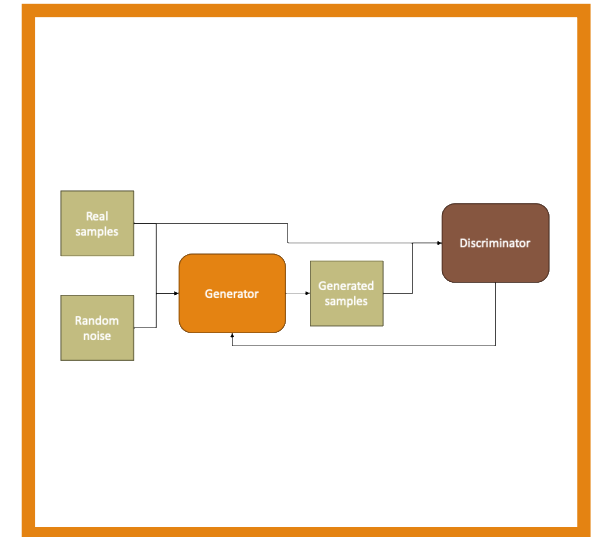
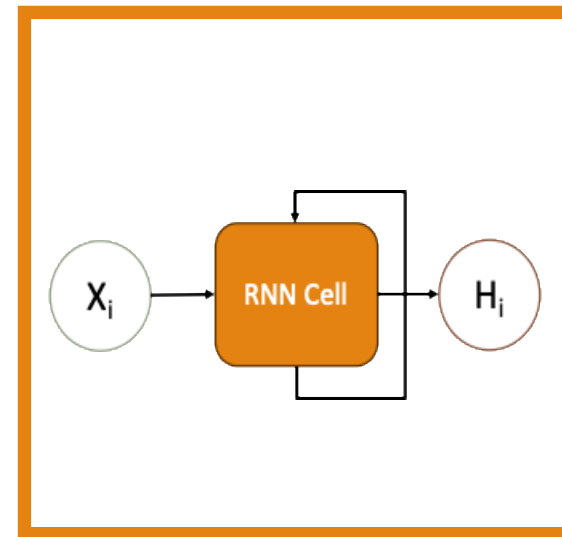
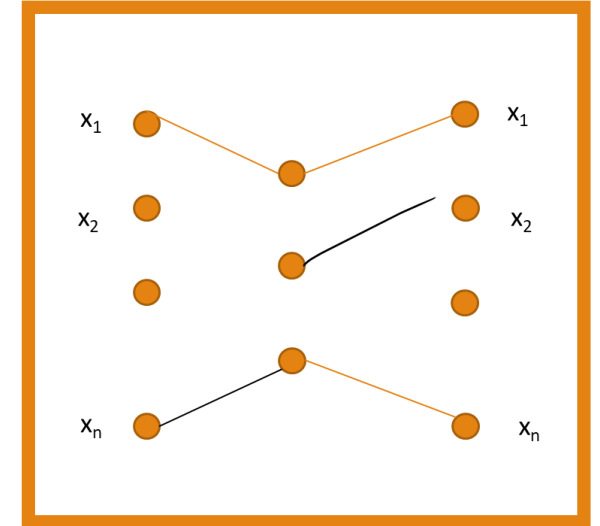
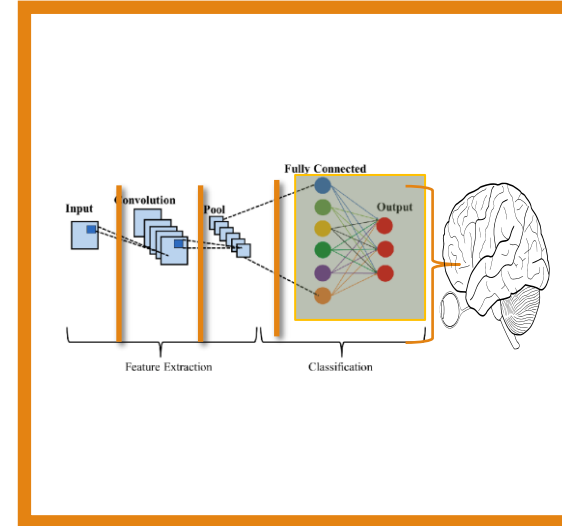
# Types of deep learning -- 1

Convolutional neural networks (CNNs)

Recurrent Neural Networks (RNNs) – Uses a BPTT

Autoencoders and variational autoencoders

Generative Adversarial Networks



# Convolutional Neural Networks

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Used primarily in image processing and vision

At least three main types of layers: a convolutional layer, pooling layer and fully connected (FC) layer.

“convolution”—working and reworking the original input—detailed patterns can be discovered.

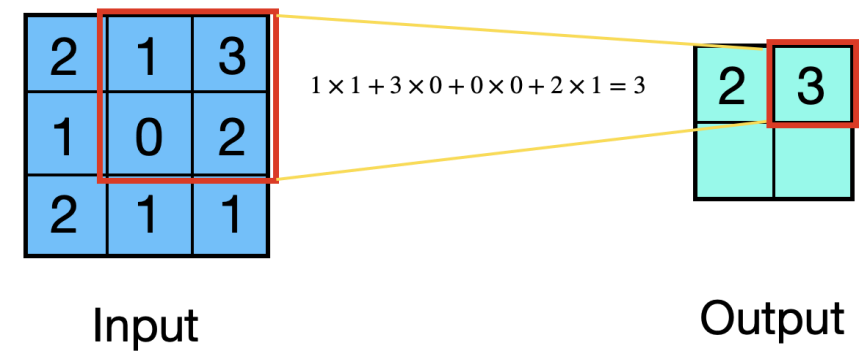
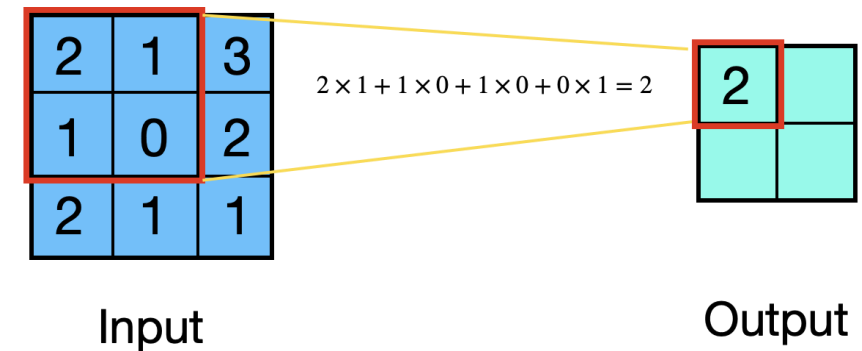
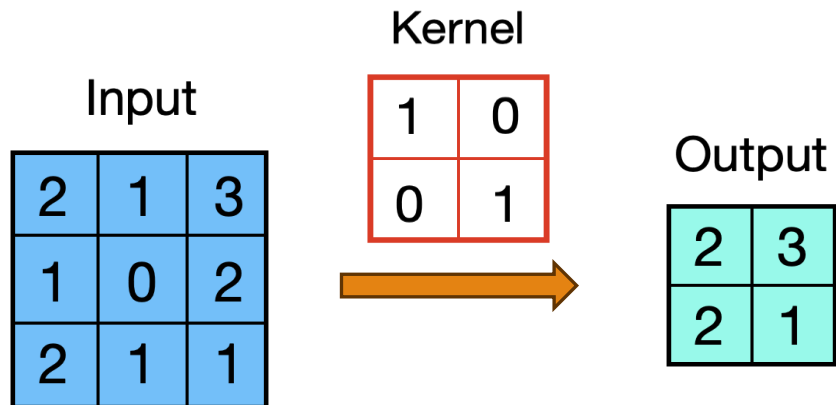
Earlier layers of a CNN detect simple features like colors and edges. As data moves through the layers, the network recognizes larger shapes and eventually identifies the object.

# Convolutional Neural Networks

A simple example shows how CNN works:

Suppose we have a 3\*3 matrix as input.

We apply a CNN layer with a 2\*2 kernel, padding is 0, and stride length is 1



# Recurrent Neural Networks

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used in natural language and [speech recognition](#) applications as they use sequential or time-series data

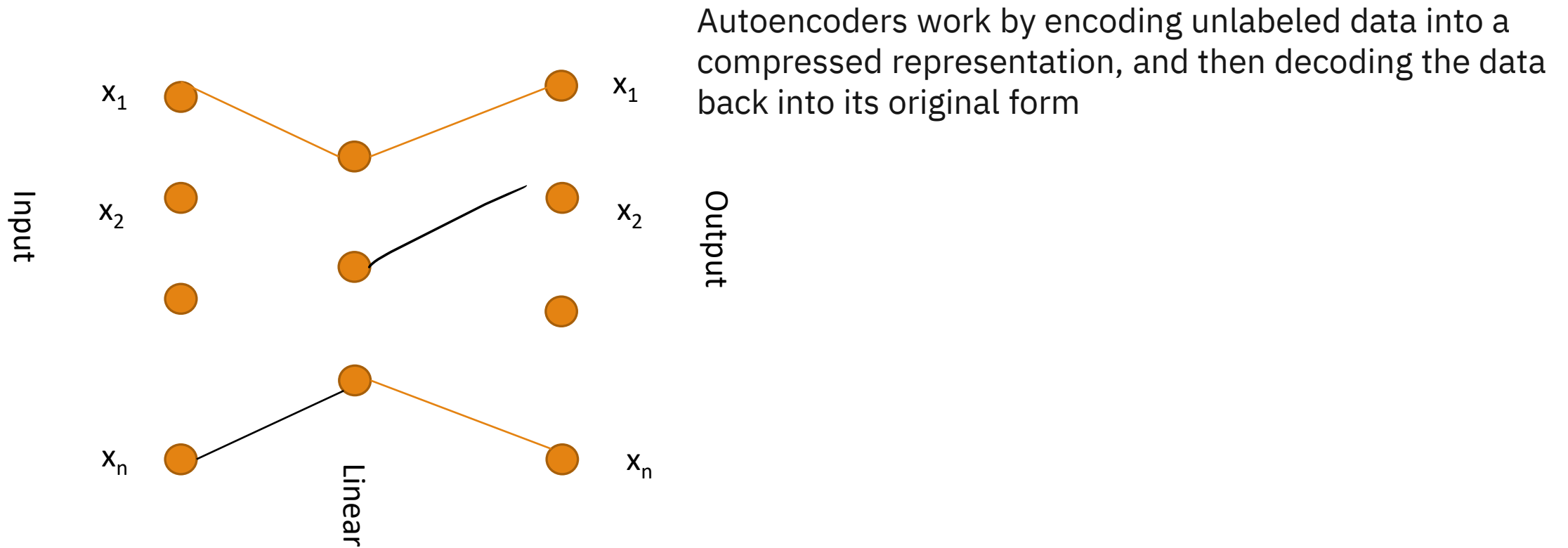
“memory” as they take information from prior inputs to influence the current input and output

Uses Back Propagation through time

BPTT differs from the traditional approach in that BPTT sums errors at each time step,



# Autoencoder



# Generative Adversarial Networks

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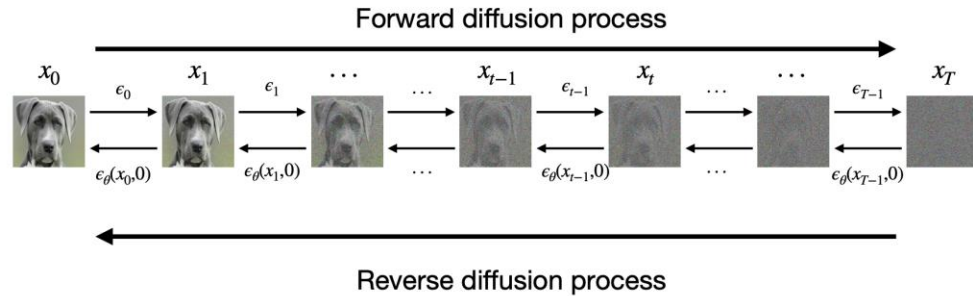
## GANs

- The **generator** creates *something*: images, video or audio and then producing an output with a twist. For example, a horse can be transformed into a zebra with some degree of accuracy. The result depends on the input and how well-trained the layers are in the generative model for this use case.
- The **discriminator** is the adversary, where the *generative* result (fake image) is compared against the *real* images in the dataset. The discriminator tries to distinguish between the real and fake images, video or audio.

# Types of deep learning – Diffusion models

## 1. Forward Diffusion Process

The model starts with a clean image (original image) and gradually adds noise to it over a series of time steps.

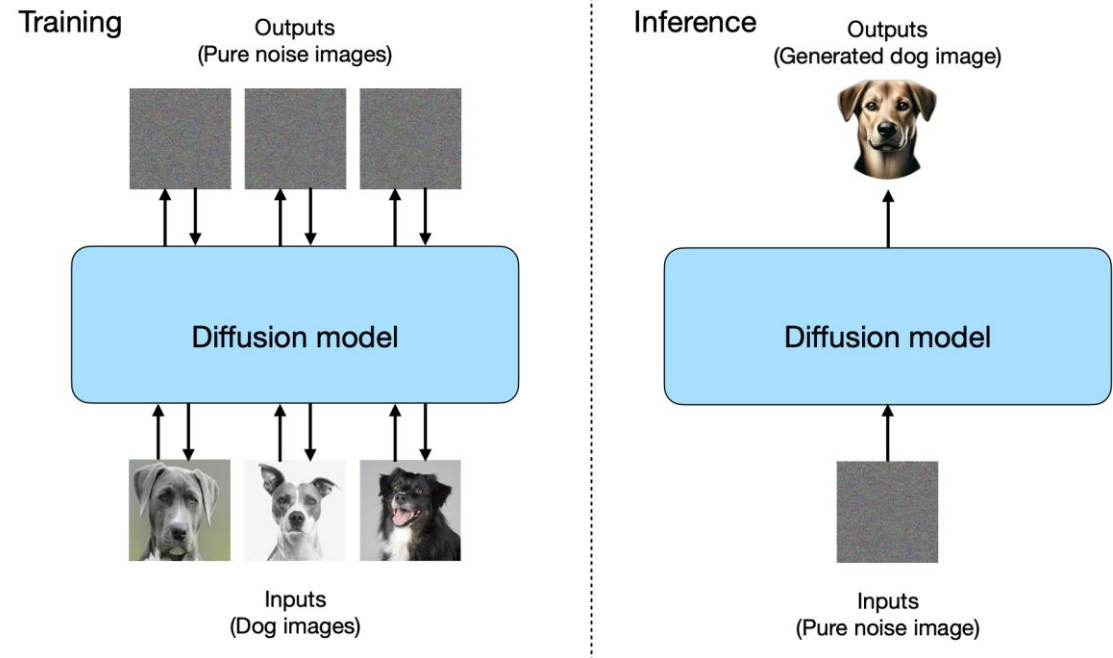


## 2. Reverse Diffusion Process

The goal of the model is to learn the reverse process: given a noisy image at any time step, the model learns to predict the slightly less noisy version of the image from the previous time step.

## 3. Image Generation

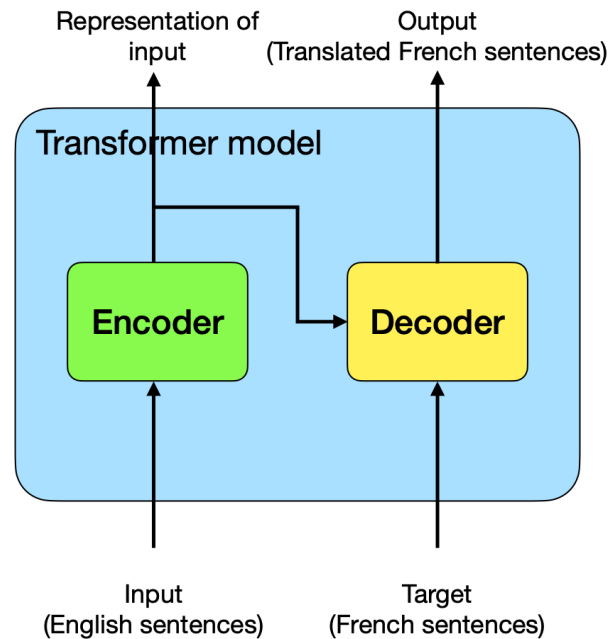
During inference, starting with pure noise, the trained model gradually removes the noise step by step, eventually reconstructing an image that resembles the learned data distribution.



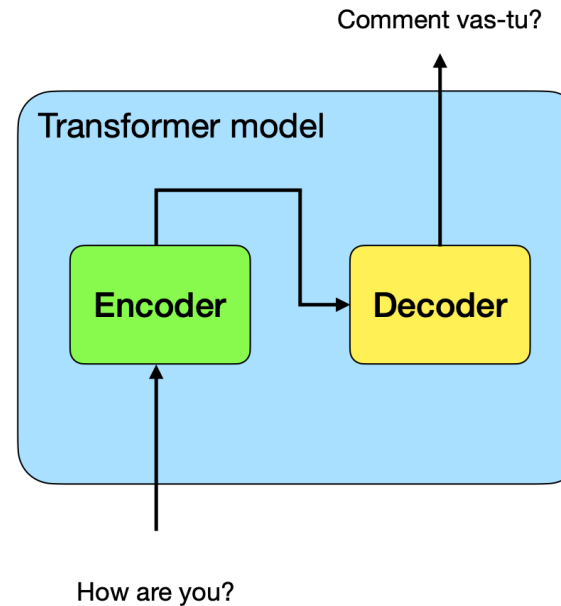
# Types of deep learning – Transformer models

1. **Encoder:** Maps the input sequence to a continuous representation.
2. **Decoder:** Generates the output sequence from the continuous representation provided by the encoder.

Training



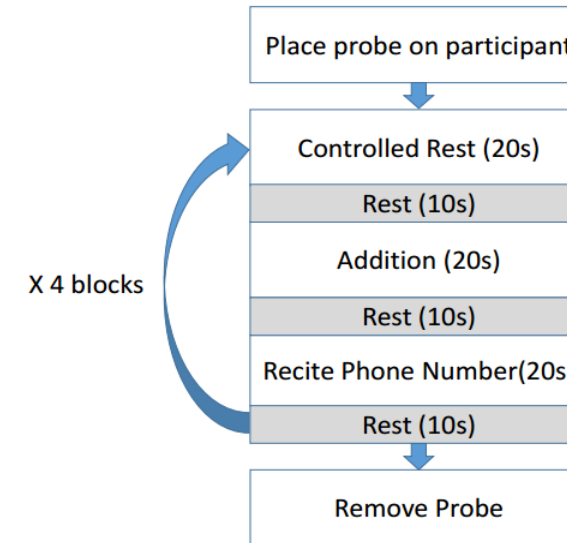
Inference



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Demo Video

## Brain Activity



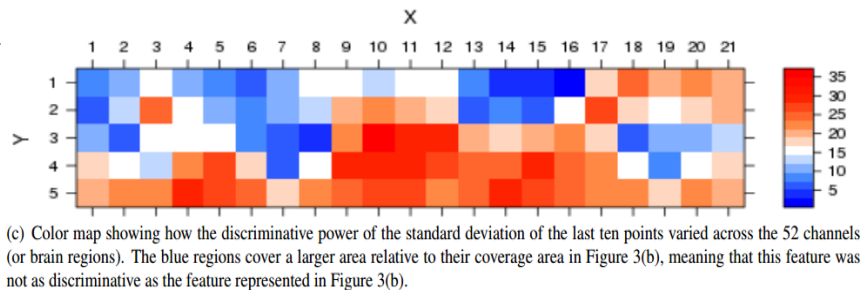
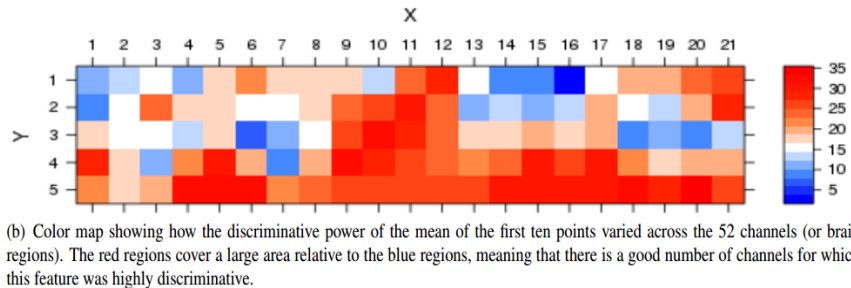
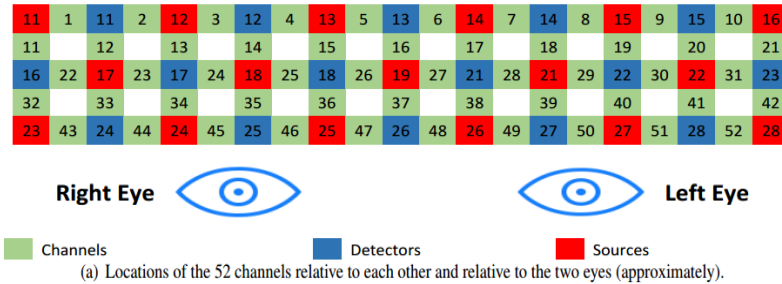
### EXPERIMENT TASKS

- ❖ THREE TASKS CHOSEN BASED UPON A REVIEW OF PSYCHOLOGICAL AND NEUROSCIENCE LITERATURE TO PRODUCE CONSISTENT PATTERNS OF BRAIN ACTIVATION FOR THE LATER IDENTIFICATION OF SUBJECTS.

### EXPERIMENT PROTOCOL

- ❖ 50 PARTICIPANTS (37 MALE, 13 FEMALE) FOR 4 IDENTICAL SESSIONS
- ❖ NEWLY PLACED FNIRS CAP ON THE SUBJECT AT THE BEGINNING OF EACH SESSION,
- ❖ PROBE CENTERED ON EACH PARTICIPANT'S FOREHEAD.

A. Serwadda, V. **Phoha**, S. Poudel, L. Hirshfield, D. Bandara, S. Bratt, *et al.*, "fNIRS: A New Modality for Brain Activity-Based Biometric Authentication," in *The IEEE Seventh International Conference on Biometrics: Theory, Applications and Systems (BTAS 2015)*, Washington, DC, 2015.



Classifier	Mean EER		% Change in EER
	All Channels	Best Channels	
SVM	0.043	0.036	17.1
Naïve Bayes	0.063	0.046	28.3

## Conclusion

- ❖ While there is still a need to evaluate fNIRS for a wider range of mental tasks, these results suggest that fNIRS holds promise as an AA modality.
- ❖ Major part of our ongoing research is to carry out analysis on a wider variety of tasks and to more rigorously evaluate the dependence of authentication performance on specific brain regions.

A. Serwadda, V. **Phoha**, S. Poudel, L. Hirshfield, D. Bandara, S. Bratt, *et al.*, “fNIRS: A New Modality for Brain Activity-Based Biometric Authentication,” in *The IEEE Seventh International Conference on Biometrics: Theory, Applications and Systems (BTAS 2015)*, Washington, DC, 2015.

# LLMs Current and Future



## Near future -Trends

- 1.Small language-based Models
- 2.Development of one-shot and few shot learning
- 3.Complex non-hierarchical Reasoning
- 3.Economic Revolution;
- 4.Lot of Funding and Developer Interest

- Modeling and translating languages
- One-shot and few shot learning
- Explainable AI
- Summarizing Generating and Classifying t
- Image analysis and content recommenda
- Analyzing sentiment in text and images



## Future - Trends

- 1.Contextual and Personalized Content Gen
- 2.Advanced autonomy
- 2.Advanced Conversational Features
- 3.Domain specific and complex Solutions





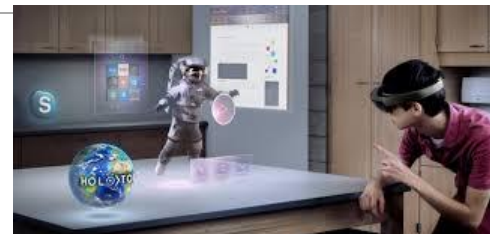
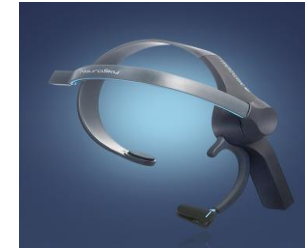
Near Future (3 to 5 years)

Philosophical  
questions

IoT includes wearables; Cloud

Beyond 5 years  
Deep learning directed applications

Augmented Reality By definition  
includes Network centric and IoT



# Current Needs



Faster Solutions to hard problems

Diseases Hunger Energy solved

Less need of physical bodies— people will be minds –augmented by machines

## Can we achieve

Empathy Love Creativity

Ride the train and not jump in front of it

Machines become  
more intelligent  
than humans

Singularity -- a hypothetical future where technology growth is out of control and irreversible.

# Convergence



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Thank you

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