AI: Strategy + Marketing (MGT 853)

Deep and Reinforcement Learning (Session 3)

Vineet Kumar

Yale School of Management
Spring 2025

Group Logistics:

https://docs.google.com/spreadsheets/d/1TOBHukKLPpt8MEC03sXTQrdgEzt_fZ2gnL50E1sWc8s/edit?gid=896101207#gid=896101207

Agenda for Today's Session

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- Generative Models
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- In-class Exercise on using (U)nsupervised, (S)upervised and (R)einforcement Learning

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- We want to learn a good f so that $\boxed{y \approx f(x)}$ both within **training** data ("data seen by algo") as well as **test** data ("data *unseen* by algo")

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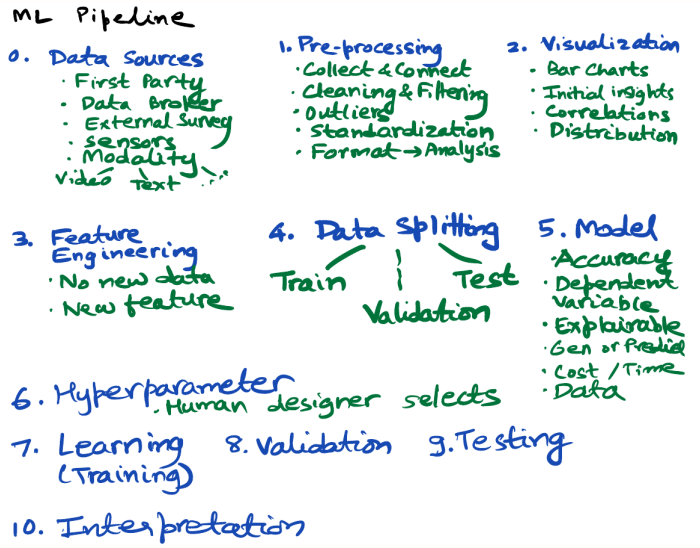
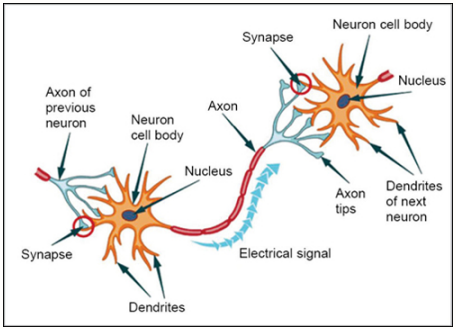
- Challenge is that the **true function** f can be anything, not necessarily linear

ML Pipeline


ML Pipeline
0. Data Sources
· First Party
· Data Broker
· External Survey
· Sensors
· Modality
Video Text
1. Pre-processing
· Collect & Connect
· Cleaning & Filtering
· Outliers
· Standardization
· Format → Analysis
2. Visualization
· Bar Charts
· Initial insights
· Correlations
· Distribution
3. Feature Engineering
· No new data
· New feature
4. Data Splitting
Train
Test
Validation
5. Model
· Accuracy
· Dependent Variable
· Explainable
· Gen or Predict
· Cost / Time
· Data
6. Hyperparameter
· Human designer selects
7. Learning (Training)
8. Validation
9. Testing
10. Interpretation

Deep Learning

- Foundation of Deep Learning built in the 1950s-1960s



http://www.humanagingcentral.com/brain_page.html

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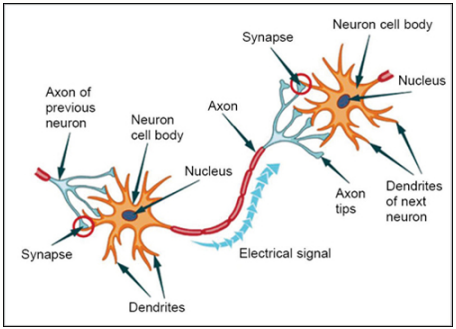

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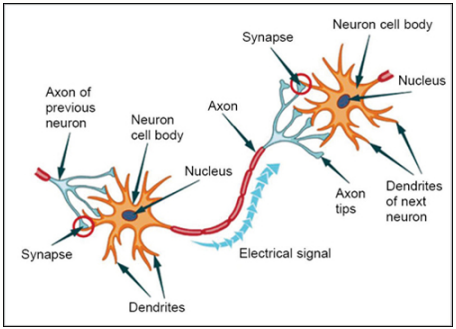

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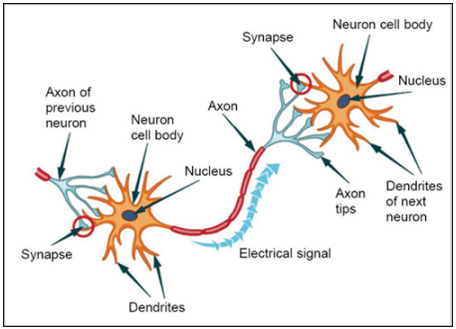

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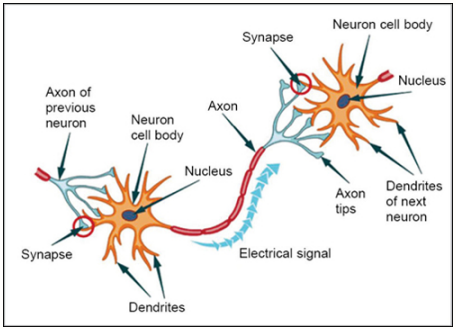
- *Axon* transmits signal to another neuron



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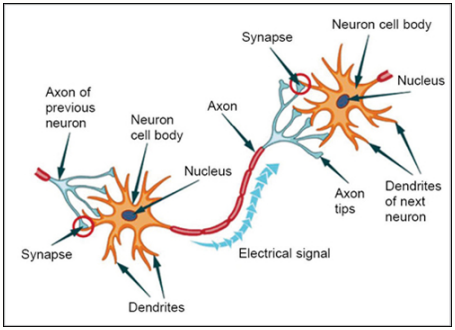
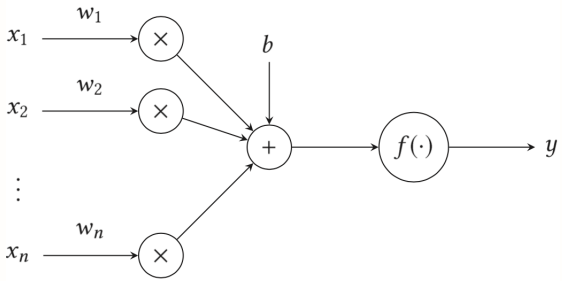
Deep Learning

Connecting Brain Neurons to Artificial Neurons

Perceptrons were motivated by the human brain, which was built up of billions of neurons





Rosenblatt's Perceptron

Later Perceptrons will be able to recognize people and call out their names and instantly translate speech in one language to speech or writing in another language, it was predicted.

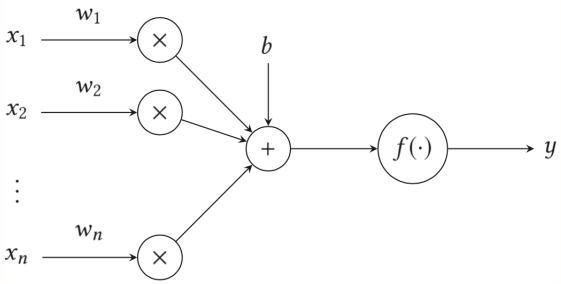
– The New York Times, late 1950s

https://news.cornell.edu/stories/2019/09/professors-perceptron-paved-way-ai-60-years-too-soon

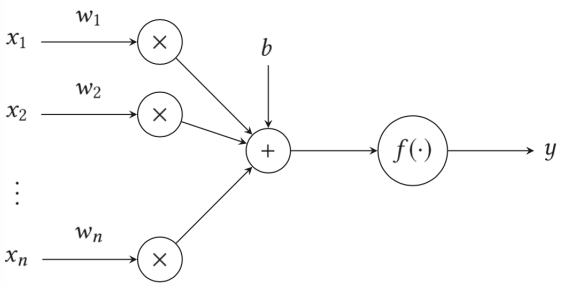
Deep Learning

Perceptron – Basic Element of DL

- Algorithm for Supervised Learning



- Algorithm for Supervised Learning
  - Classification: $y = 0$ or 1



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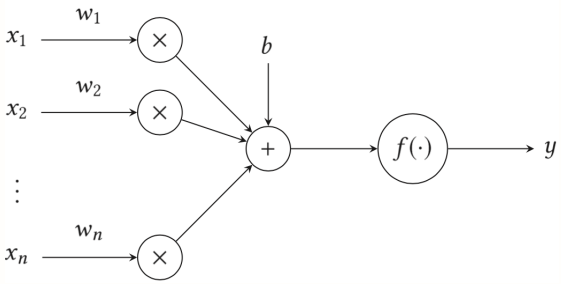
- Parameters: Bias (b or w_0), Weights ($w_1, \ldots, w_n$)



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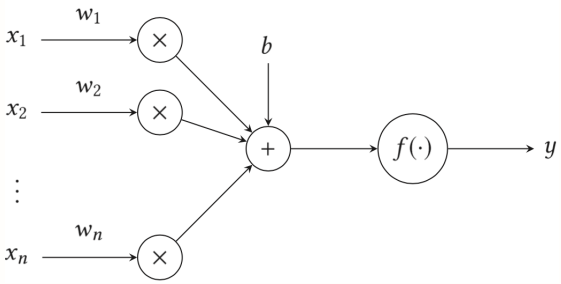

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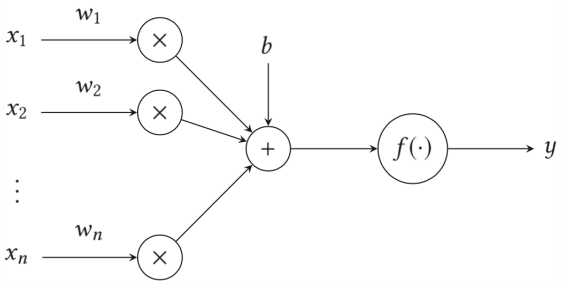
- Proved that Perceptron would automatically learn weights



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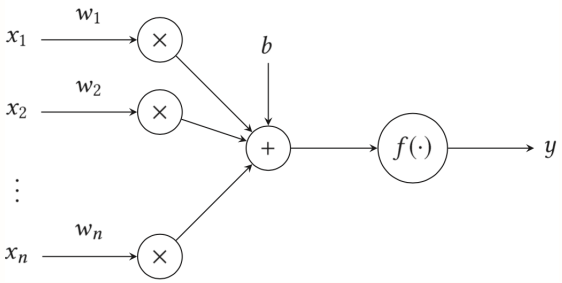
Perceptron – Activation Function

- *Activation function and weights* – what is being learned (nothing else)



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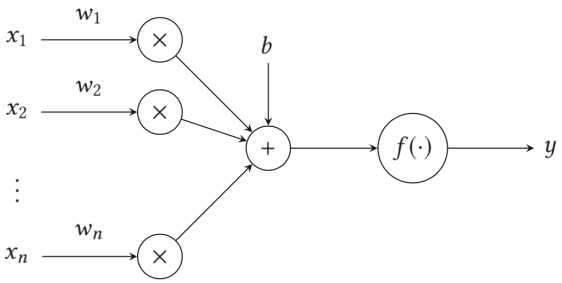

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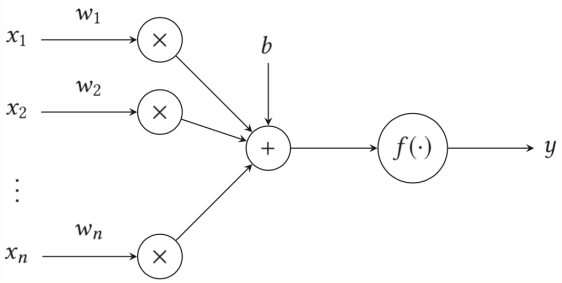

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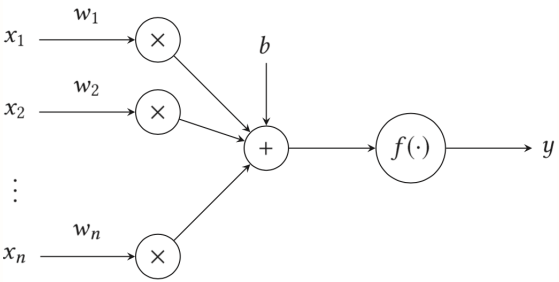

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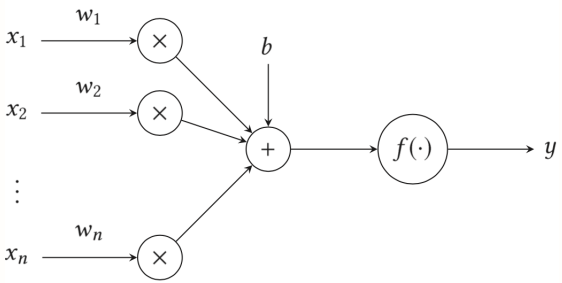
- $\boxed{f(x) = w_0 + w_1 x_1 + \ldots w_n x_n}$
- Turns out you need *some* non-linearity



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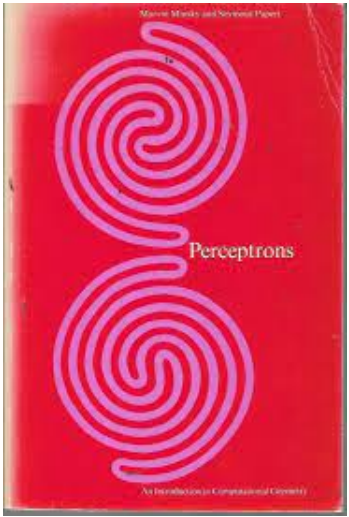
Minsky: The Exclusive OR (XOR) Problem

- History of AI was altered by a book titled "Perceptrons" (1969)



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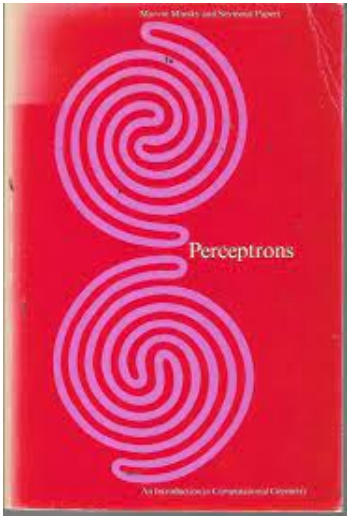

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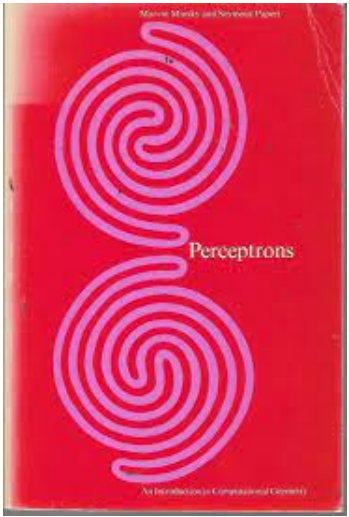

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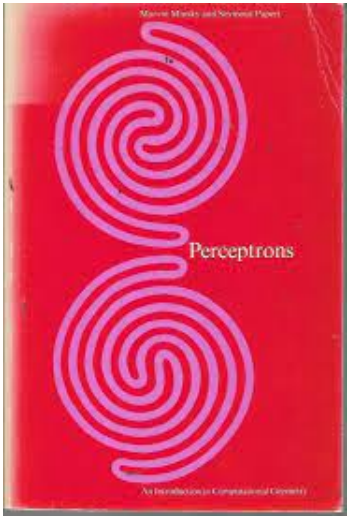

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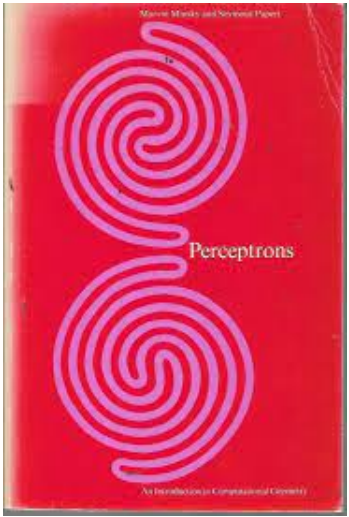
- *Many attribute this book with causing an AI winter*



What is the Exclusive OR (XOR) Problem?

- Perceptrons were proven to be incapable of learning this function

x_1	x_2	$y = XOR(x_1, x_2)$
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Universal Approximation

Can approximate any "reasonable" function

Neural Networks, Vol. 2, pp. 359–366, 1989
Printed in the USA. All rights reserved.

ORIGINAL CONTRIBUTION

Multilayer Feedforward Networks are Universal Approximators

KURT HORNIK

Technische Universität Wien

MAXWELL STINCHCOMBE AND HALBERT WHITE

University of California, San Diego

(*Received* 16 *September* 1988; *revised and accepted* 9 *March* 1989)

Abstract—*This paper rigorously establishes that standard multilayer feedforward networks with as few as one hidden layer using arbitrary squashing functions are capable of approximating any Borel measurable function from one finite dimensional space to another to any desired degree of accuracy, provided sufficiently many hidden units are available. In this sense, multilayer feedforward networks are a class of universal approximators.*

Keywords—Feedforward networks, Universal approximation, Mapping networks, Network representation capability, Stone-Weierstrass Theorem, Squashing functions, Sigma-Pi networks, Back-propagation networks.

https://cognitivemedium.com/magic_paper/assets/Hornik.pdf

Universal Approximation

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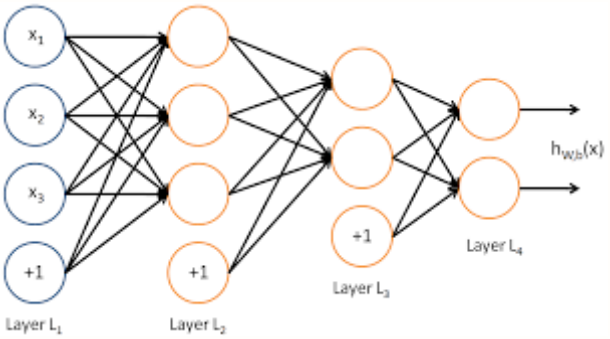


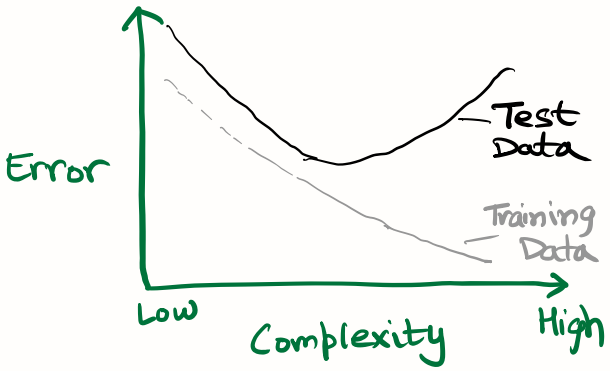
Model Complexity in Deep Learning

How can we ↑ or ↓ it?

Assume *data does not change*, same set of y and X variables

- Number of connections (weights or parameters)
- Depth: Number of layers in DL model
- Width: Maximum number of nodes in a layer
- Which is more important, width or depth?
  - Width is Less Important than Depth in ReLU Neural Networks

Generalization Error and Model Complexity



Complex models explain *training* data better but not *test* data
$\Longrightarrow$ we need validation and test data that is separate (no leakage) from training data

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Regularization is a set of techniques for reducing model complexity and increasing generalization ability

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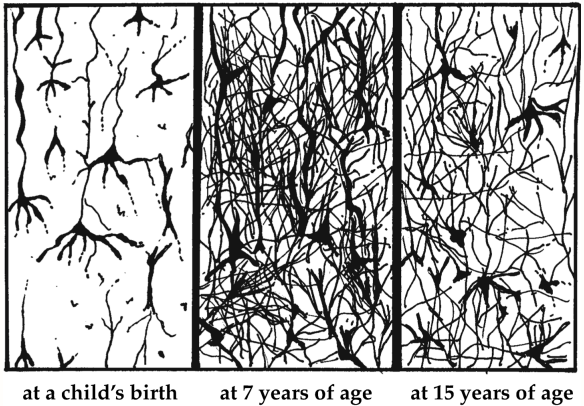
- Is there a connection to how humans learn?

Synaptic Density in Humans varies with age



Understanding Brain Development in Young Children, Brotherson, 2022

Children typically have more synapses (connections between neurons) than adults

Deep Learning: Digit Recognition

Link to MNIST Colab Notebook

- How to recognize digits – why?

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Convolutional Neural Network

CNN

- Specialized type of Deep NN for image data

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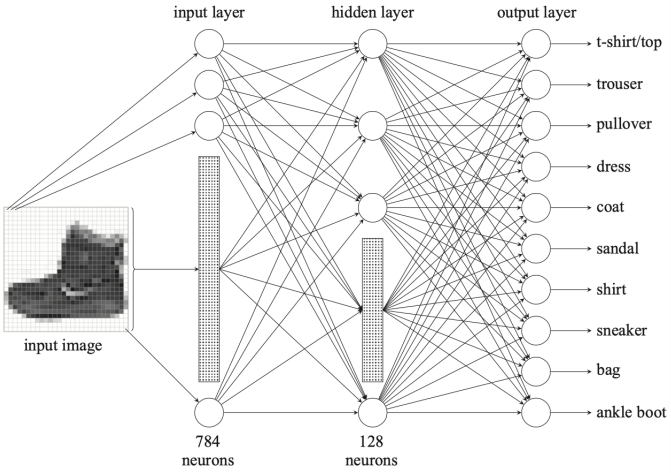
Convolution in Action

https://towardsdatascience.com/convolutional-networks-intuitively-and-exhaustively-explained-ab08f6353

CIFAR10: Clothing Data Set

Source: Algorithms by Louridas, Chapter 6

CIFAR10: Deep Neural Net



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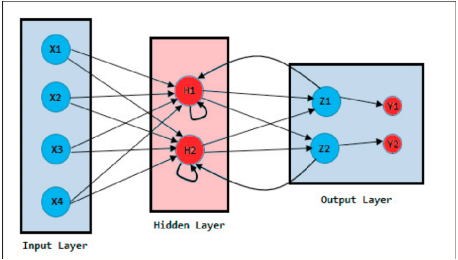
- RNNs accommodate and model these patterns by altering the structure of the feedforward networks
- The output of neurons in "later" layers is given as input to same "earlier" layers

Recurrent Neural Network

RNN

- Not just feedforward: Allow connections to go "backwards"
- Can learn sequence regularity more effectively



https://www.researchgate.net/figure/Basic-Architecture-of-Recurrent-Neural-Network-22-23_fig2_325668211

Generative AI Models for Text – Large Language Models (LLMs)

LLMs

How do they work?

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- Why is language predictable?

LLMs

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Some questions with LLMs:

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- Why do they show different outputs each time you ask the same thing?
- What is the architecture?
- Why do they hallucinate – create random or nonsense text?

Generative AI Model – Images

Generative AI

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Generative AI

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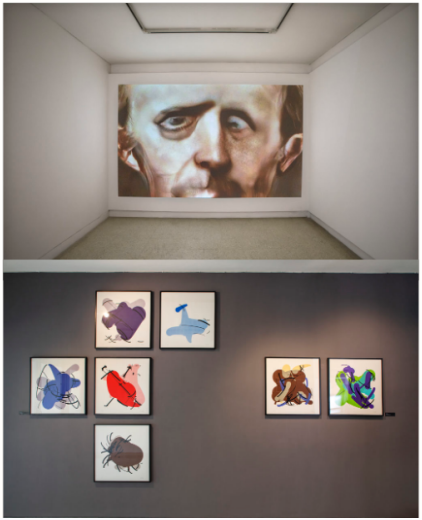
  - AI can do not just prediction but also generation
  - AI can create or co-create with humans

Generative AI

Real Paintings by Dali



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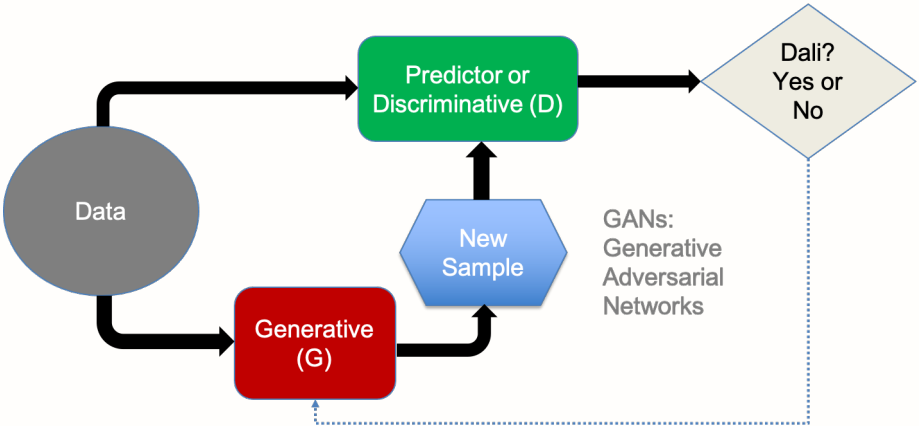

Reinforcement Learning

Power of RL in Games

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  https://www.youtube.com/watch?v=tXlM99xPQC8

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- *Critically important to specify the reward function properly*: A Story

Now let's try this with Chess

RL in Robotics

Takeaways

- Neural Nets and Deep learning developed in the 1980s provide the foundation for Deep learning
- Deep learning can approximate almost any function $y = f(x)$
- Different architectures used for different kinds of problems
- Generative AI: LLMs are based on deep learning with transformer architecture
  - Use self-supervised learning
- Generative AI images: often use Generative Adversarial Networks which experiment and try to fool a predictor
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- Reinforcement Learning is used when you have the ability to experiment
  - Works without any data (Alpha *Zero*)

Next Class: Prediction to Decision

- Everything we have looked at up until now has focused on prediction problems
- What data is typically used, labels (y) and predictors (X)
  - Structured, Unstructured (Text, Images, Audio, Video,...)
- Building blocks of ML models
- Specifying prediction problems provides a foundation for **converting** a problem to a prediction problem