

AI: Strategy + Marketing (MGT 853)

Deep and Reinforcement Learning (Session 3)

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Yale School of Management
Spring 2025

Agenda for Today's Session

- Deep Learning

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 - What is DL? What are the types of DL?

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 - why “deep” needed?
- Generative Models
- Reinforcement Learning
- In-class Exercise on using (U)nsupervised, (S)upervised and (R)einforcement Learning

What is the Learning Goal?

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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

3. Feature Engineering

- No new data
- New feature

6. Hyperparameter

Human designer selects

7. Learning (Training)

1. Pre-processing

- Collect & Connect
- Cleaning & Filtering
- Outliers
- Standardization
- Format → Analysis

2. Visualization

- Bar Charts
- Initial insights
- Correlations
- Distribution

4. Data Splitting



5. Model

- Accuracy
- Dependent variable
- Explorable
- Gen or Predict
- Cost / Time
- Data

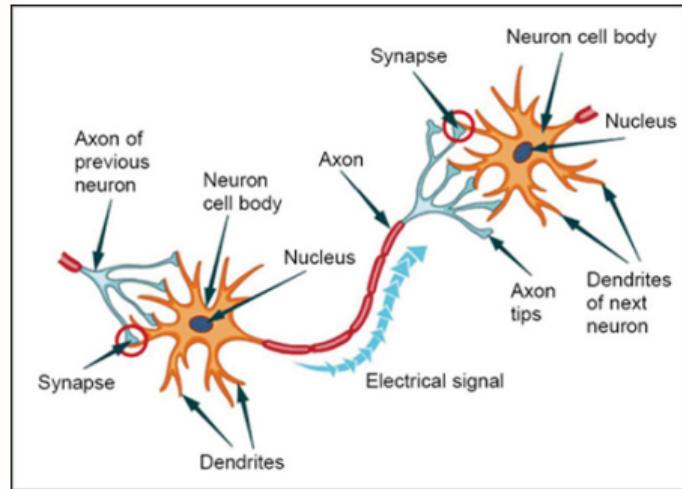
8. Validation

9. Testing

10. Interpretation

Deep Learning

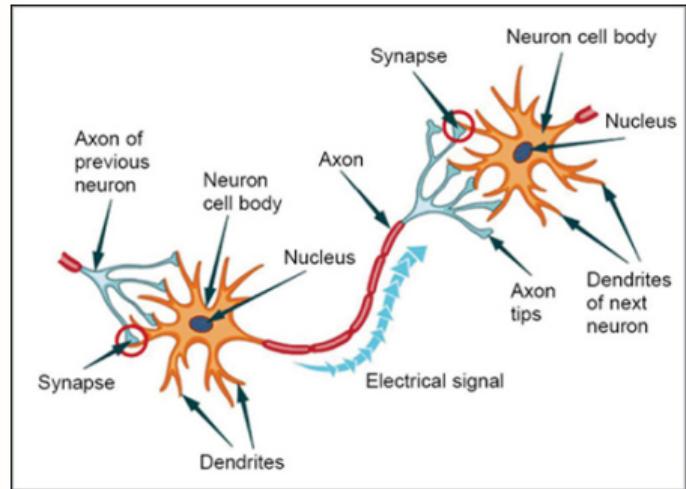
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http://www.humanagingcentral.com/brain_page.html

Deep Learning

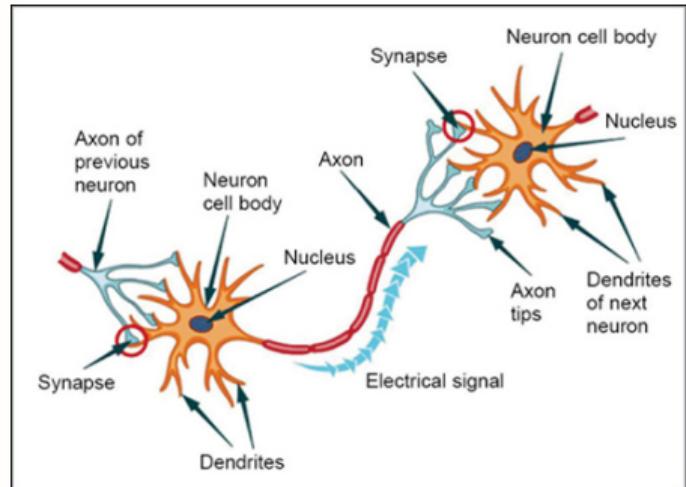
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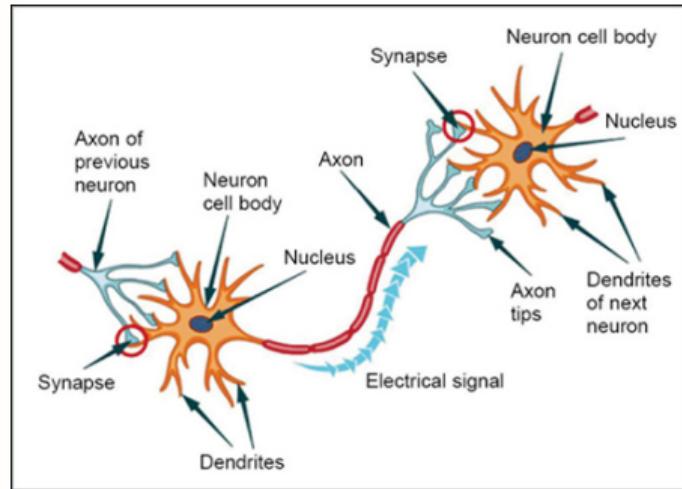
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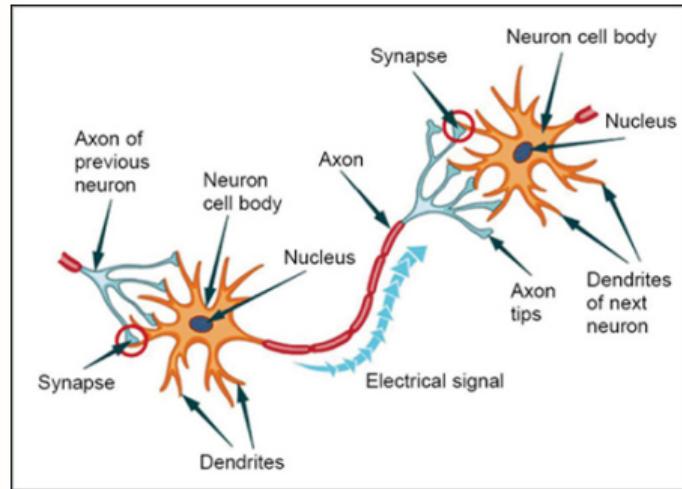
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- *Axon* transmits signal to another neuron

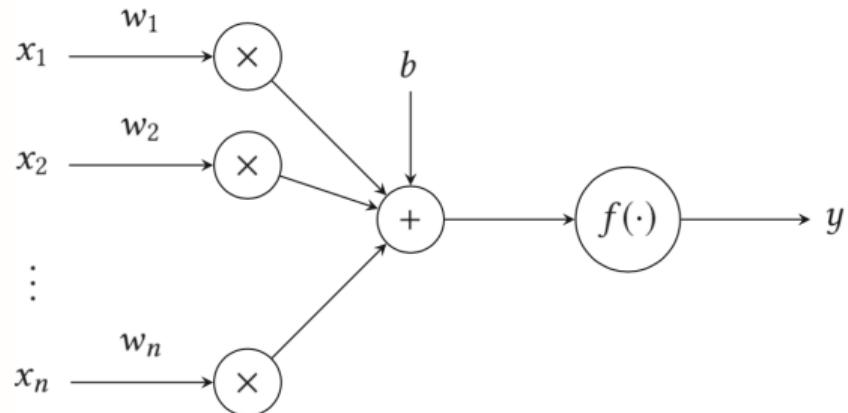
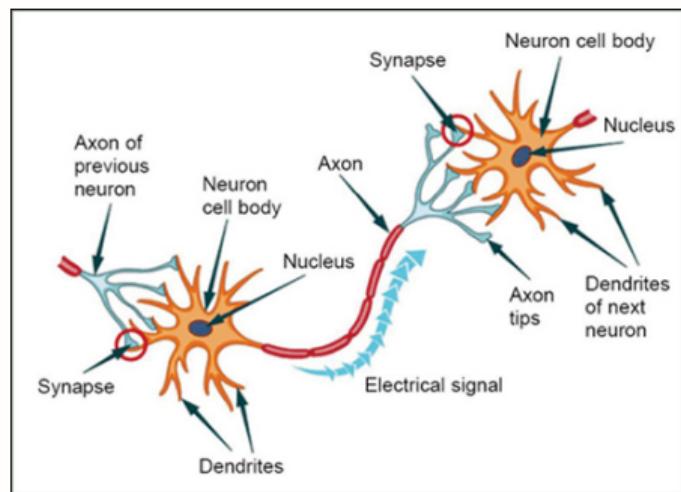


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Deep Learning

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.



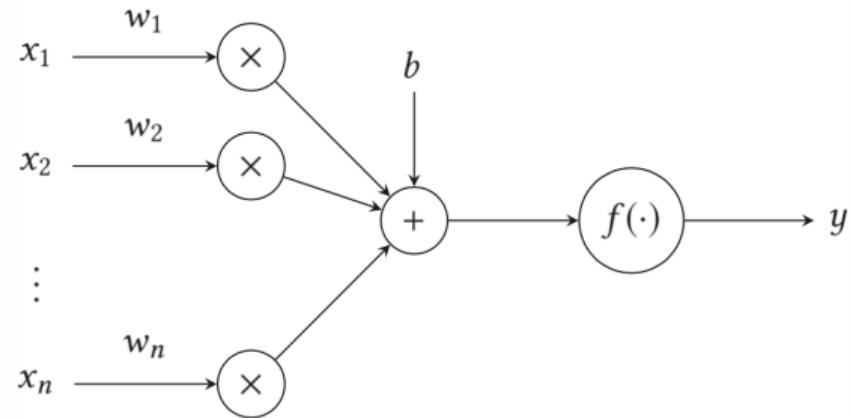
– The New York Times, late 1950s

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

Deep Learning

Perceptron – Basic Element of DL

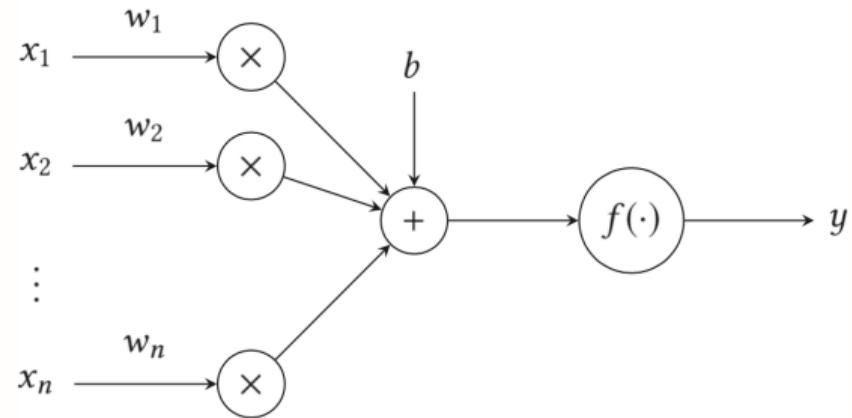
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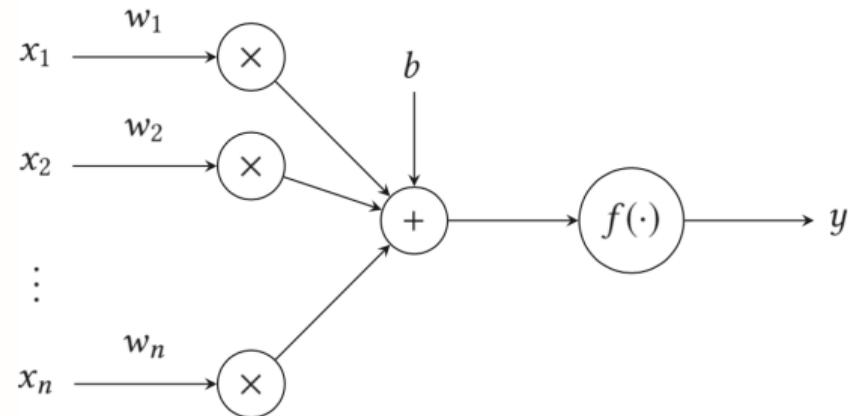
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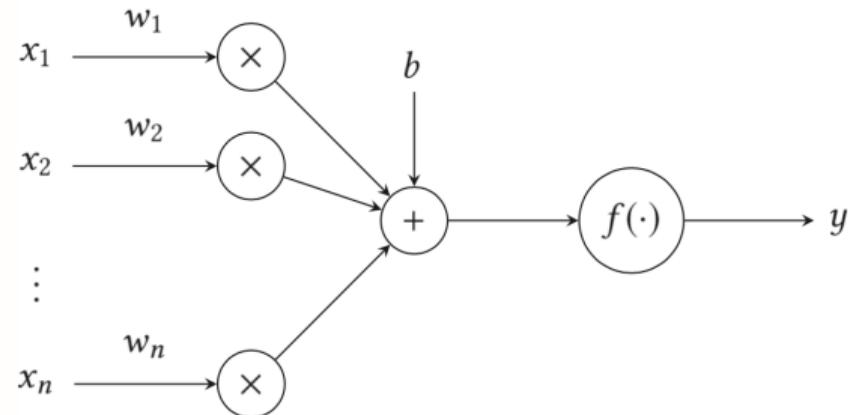
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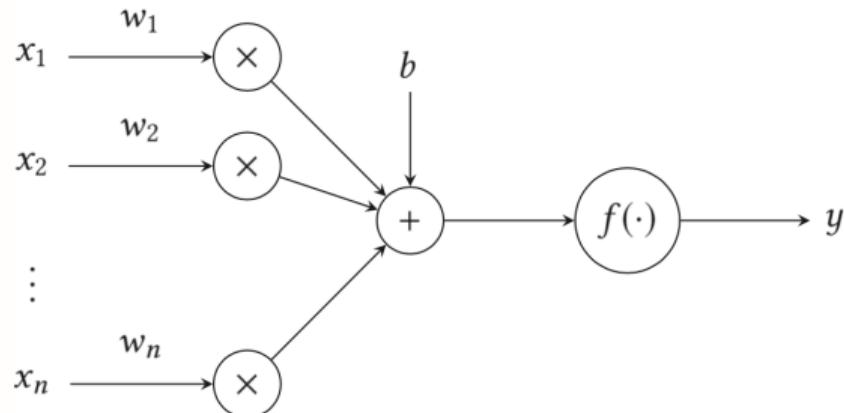
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- Activation function $f(\cdot)$



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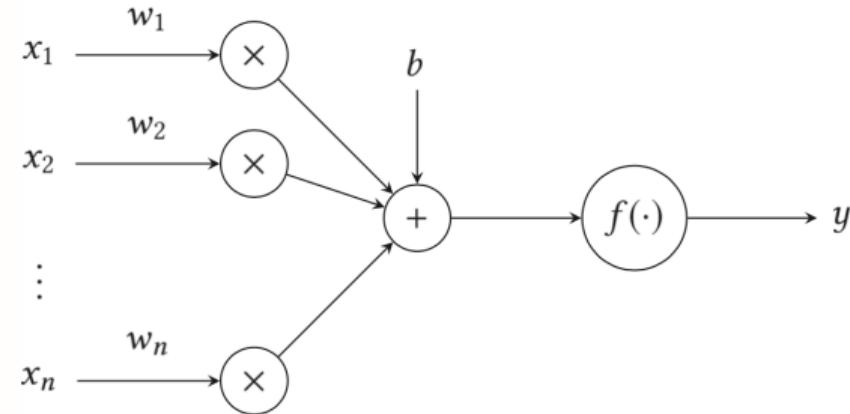
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- Proved that Perceptron would automatically learn weights



Deep Learning

Perceptron – Activation Function

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

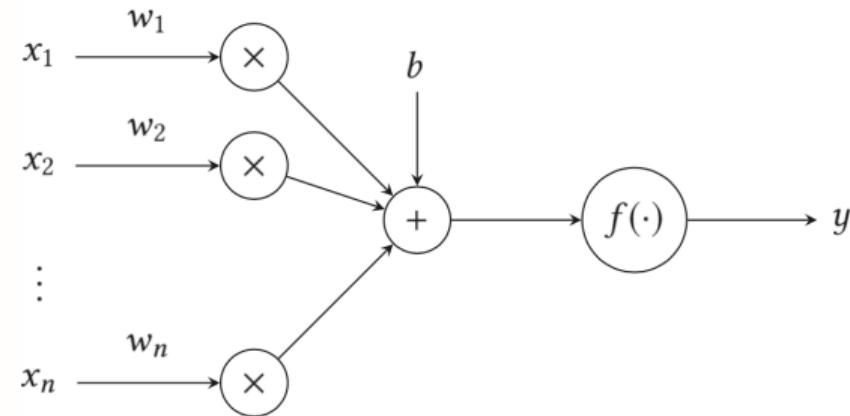


Activation functions like Sigmoid, ReLU, or even a step function

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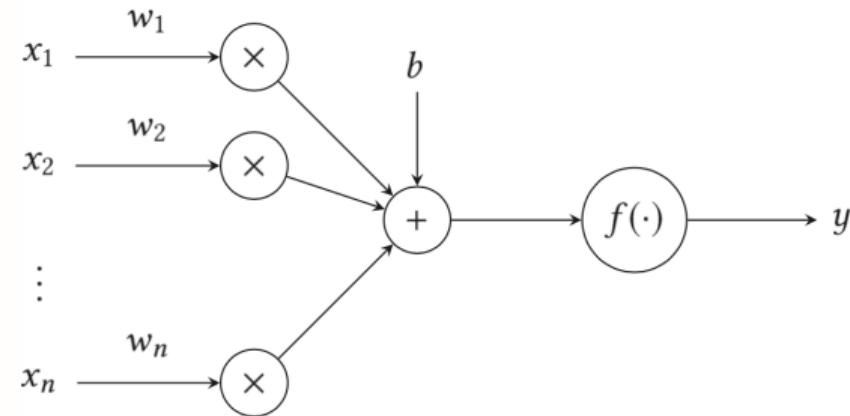


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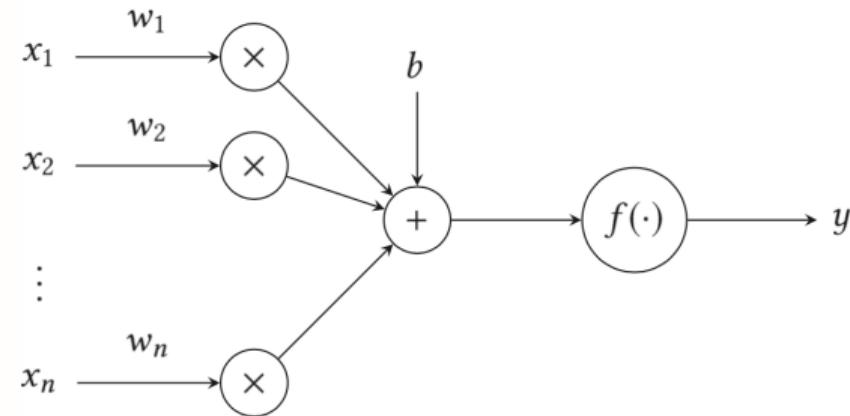


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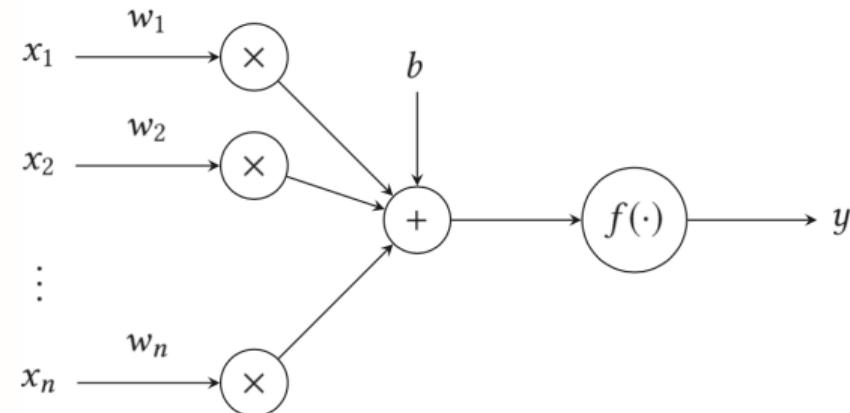


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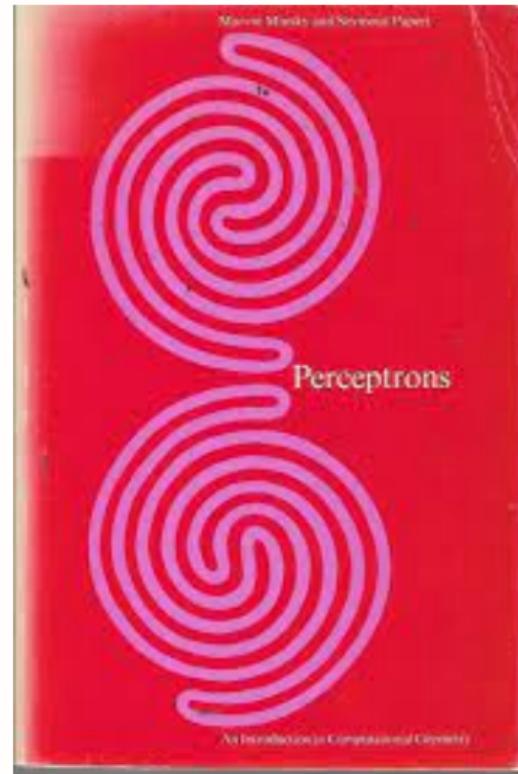
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- Turns out you need some non-linearity



Activation functions like Sigmoid, ReLU, or even a step function

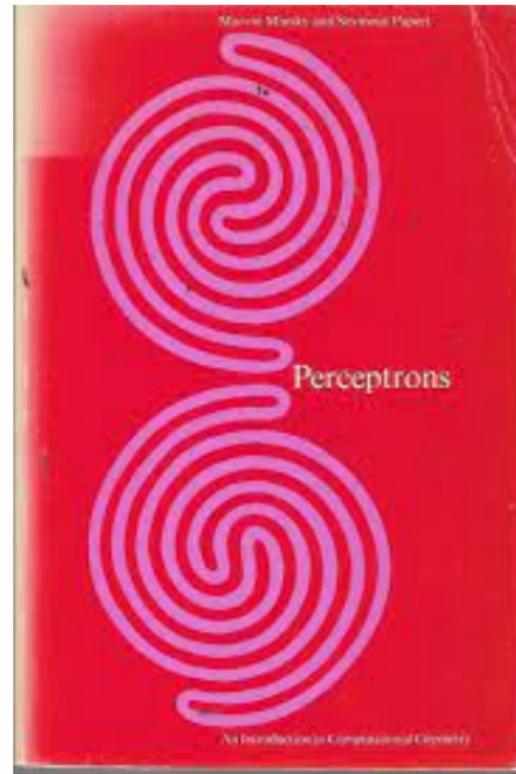
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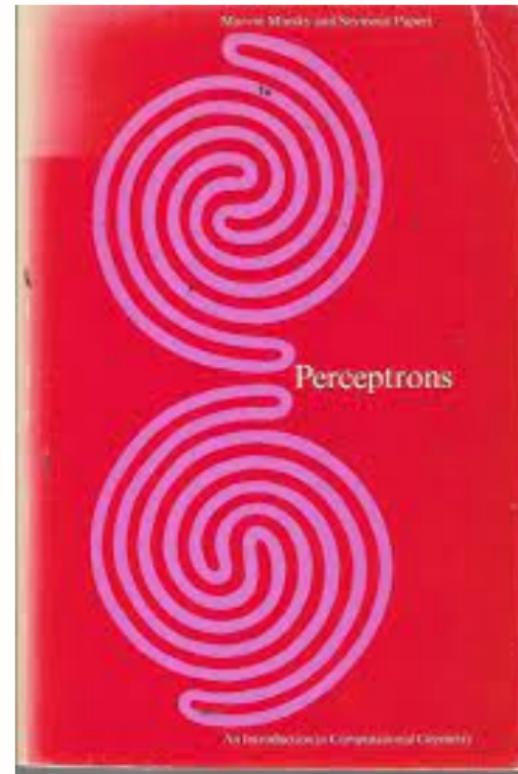
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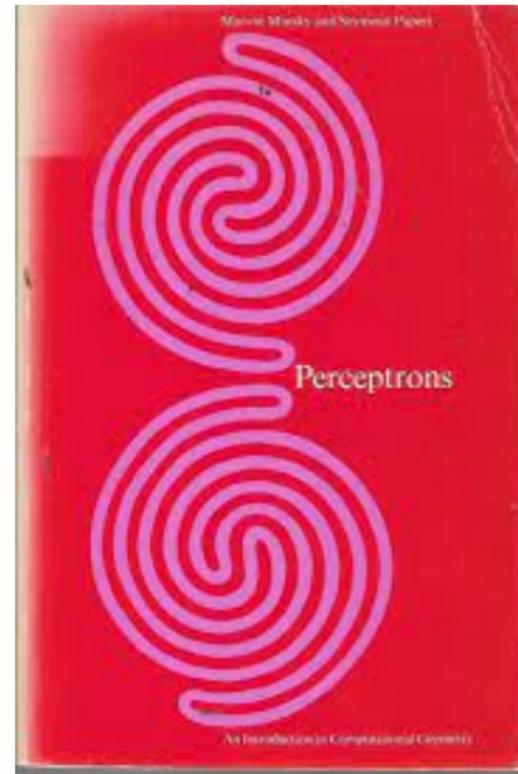
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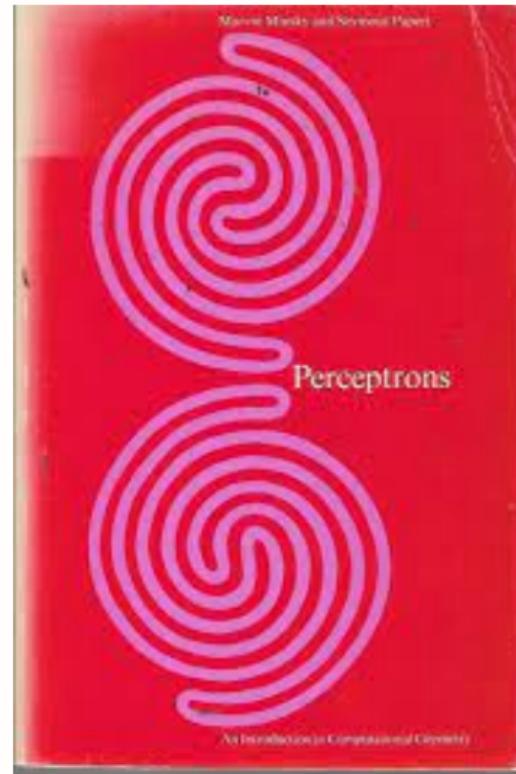
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- *Many attribute this book with causing an AI winter*



What is the Exclusive OR (XOR) Problem?

- Perceptrons were proven to be incapable of learning this function

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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.

0893-6080/89 \$3.00
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ORIGINAL CONTRIBUTION

Multilayer Feedforward Networks are Universal Approximators

KURT HORNICK

Technische Universität Wien

MAXWELL STINCHCOMBE AND HALBERT WHITE

University of California, San Diego

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

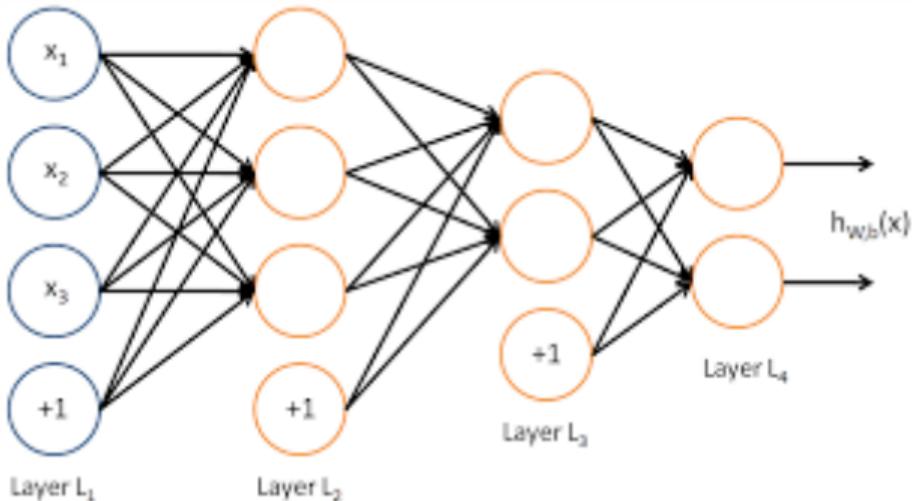
Abstract—This paper rigorously establishes that standard multilayer feedforward networks with as few as one hidden layer using arbitrary squashing functions are capable of approximating any Borel measurable function from one finite dimensional space to another to any desired degree of accuracy, provided 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

Can approximate any “reasonable” function



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
⇒ we need validation and test data that is separate (no leakage)
from training data



Deep Net Architecture

Regularization

What is Regularization?

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

- Deep Learning models can become complex very quickly

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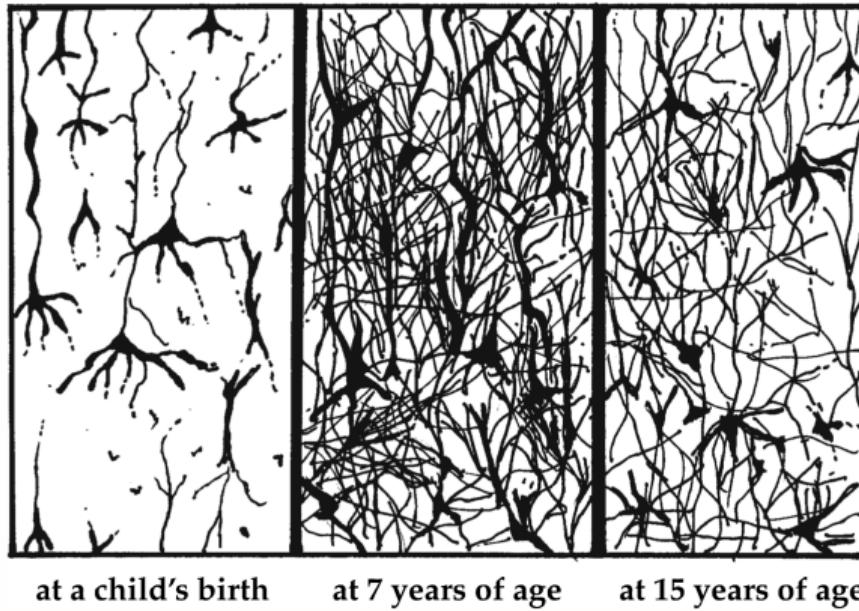
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- Achieve higher performance on test data by making a model simpler
- Is there a connection to how humans learn?

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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- How to recognize digits – why?
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- 60,000 training and 10,000 test images
- Human error rate is about 2%
- Deep Learning models (CNN) achieve 0.5% error rate
 - Other ML models require a lot of feature engineering done by hand



Convolutional Neural Network

CNN

- Specialized type of Deep NN for image data

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Convolution in Action

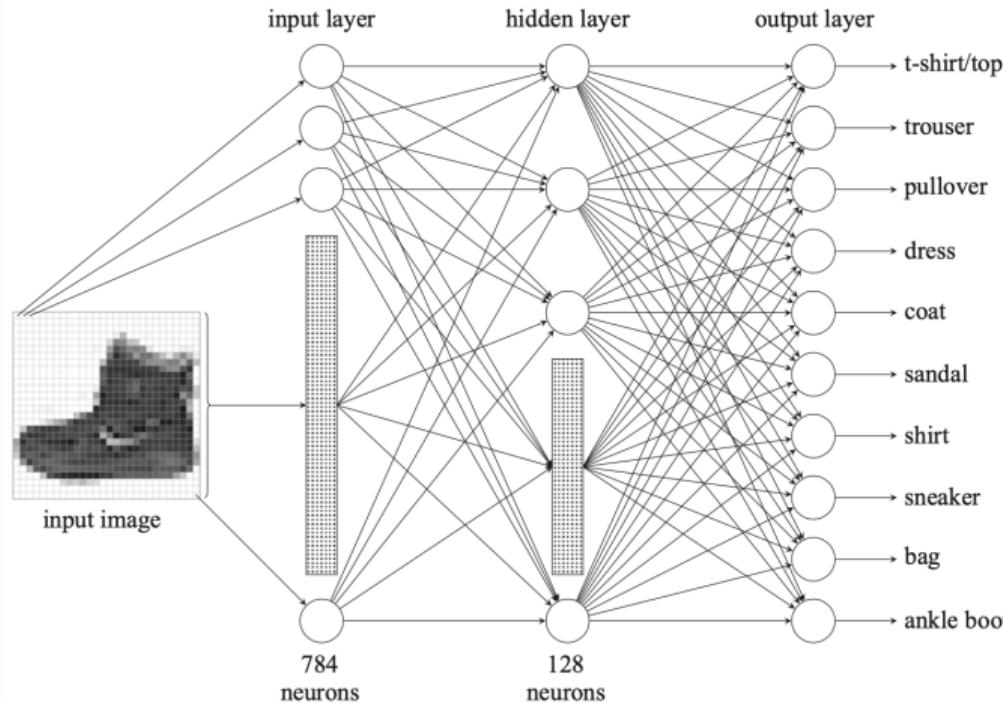
<https://towardsdatascience.com/convolutional-networks-intuitively-and-exhaustively-explained-ab08f6353>

CIFAR10: Clothing Data Set



Source: Algorithms by Louridas, Chapter 6

CIFAR10: Deep Neural Net



Source: Algorithms by Louridas, Chapter 6

Recurrent Neural Network

RNN

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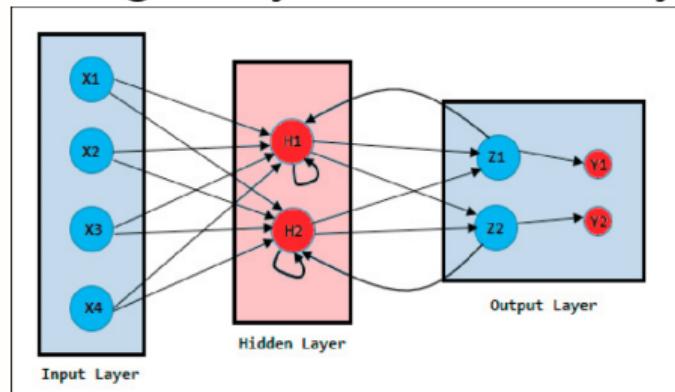
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- Next word prediction leverages this:
 - Start a sentence with the word "I" (very different from "Our")
- RNNs accommodate and model these patterns by altering the structure of the feedforward networks
- The output of neurons in “later” layers is 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?

- Let's say we start a sentence with "I"

LLMs

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- Why is language predictable?

LLMs

How do they work?

Some questions with LLMs:

- What are they trained on?

LLMs

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Some questions with LLMs:

- What are they trained on?
 - Are they trained with supervised or unsupervised learning?

LLMs

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- What is the architecture?
- Why do they hallucinate – create random or nonsense text?

Generative AI Model – Images

Generative AI

- Can AI actually be part of the creation process?

Generative AI

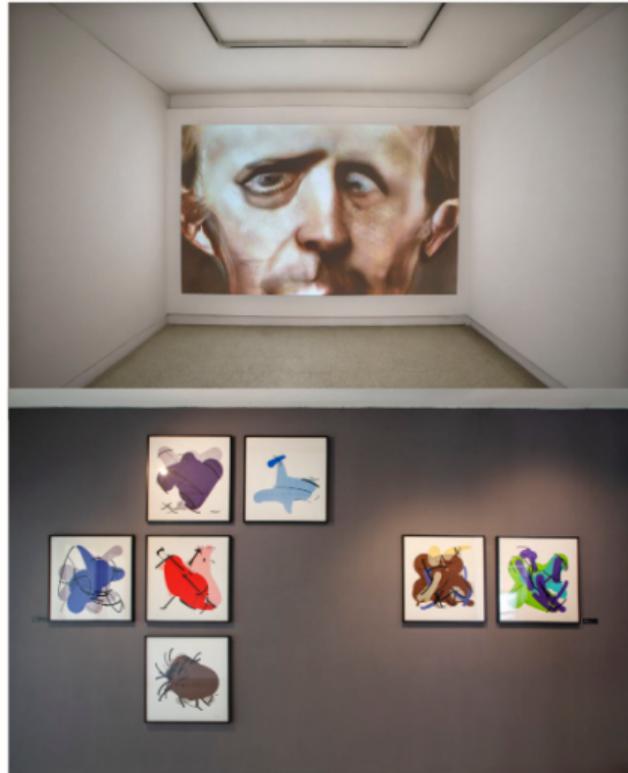
- Can AI actually be part of the creation process?
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Generative AI

- Can AI actually be part of the creation process?
 - AI can do not just prediction but also generation
 - AI can create or co-create with humans

Generative AI

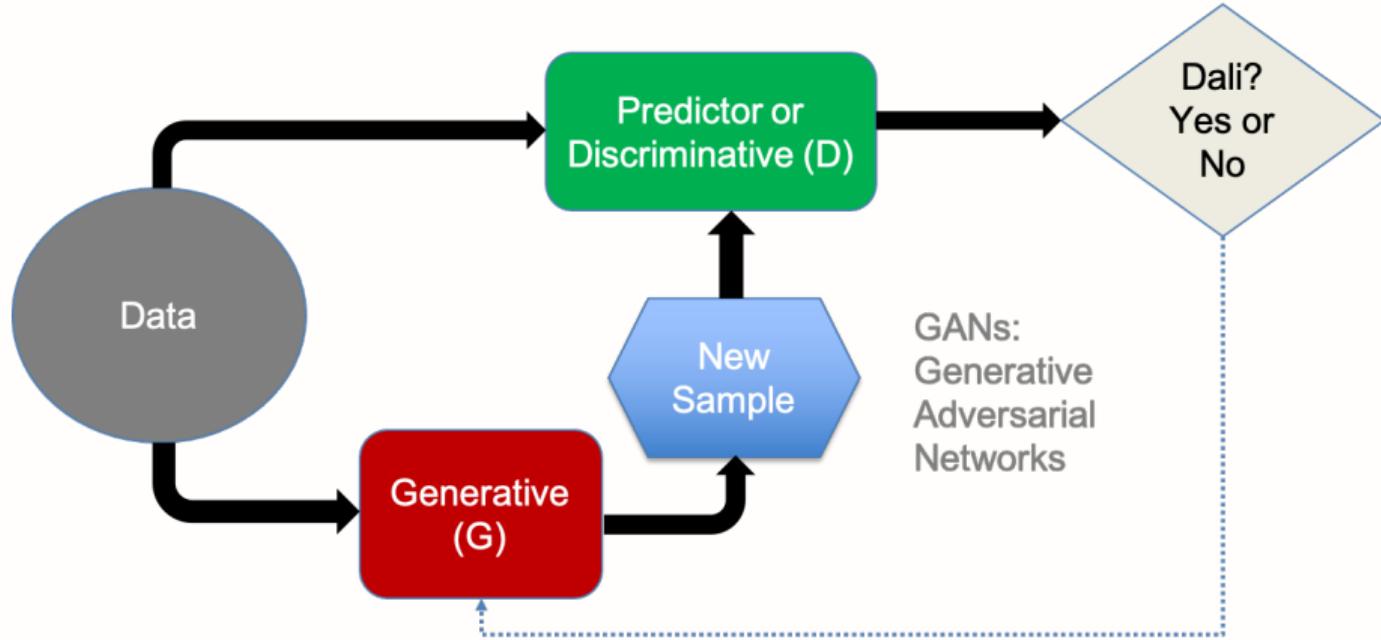
Real Paintings by Dali



Generative AI



Generative AI



Reinforcement Learning

Power of RL in Games

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- Defeated AlphaGo 100–0

<https://www.youtube.com/watch?v=tX1M99xPQC8>



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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
- Reinforcement Learning is used when you have the ability to experiment

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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