AI: Strategy + Marketing (MGT 853)

Deep and Reinforcement Learning (Session 3)

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Yale School of Management

Spring 2024

Agenda for Today's Session

- Deep Learning

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

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

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- Appeal of linear models (e.g. regression) is that it avoids overfitting
- Challenge is that the **true function** f can be anything, not necessarily linear

ML Pipeline

ML Pipeline :

0. Identify Data (y, x)
1. Pre-processing
   Centering, Missing Data/Quality, Outliers, Normalization
2. Data Visualization
   Correlation, Distribution, Model
3. Data Splitting — Test
   Training Validation
4. Feature Engineering
5. Model Selection
6. Hyper parameter Selection
   Human Analyst Decides
7. Learning (Training)
   $y = f(x)$
8. Validation
9. Interpretation
10. Testing ...

Model Complexity: How can we $\uparrow$ or $\downarrow$ it?

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

- Number of parameters
- Number of layers in DL model
- Quadratic terms
- Interaction terms %item

can each impact model complexity.

Deep Learning

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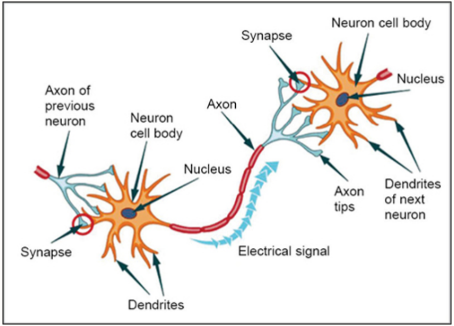

http://www.humanagingcentral.com/brain_page.html

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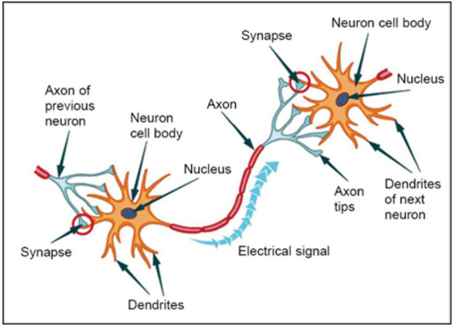

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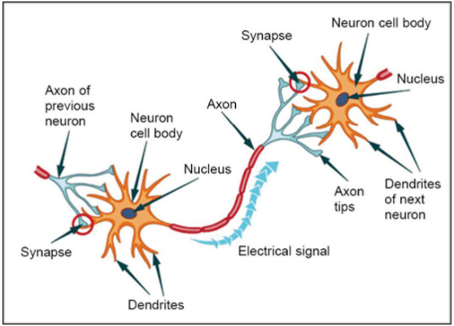

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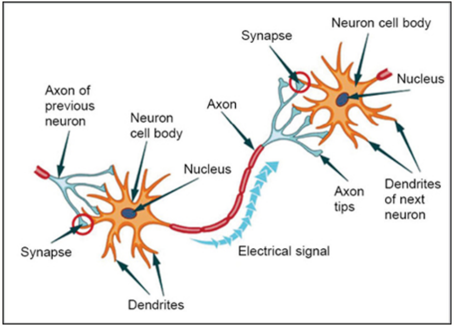

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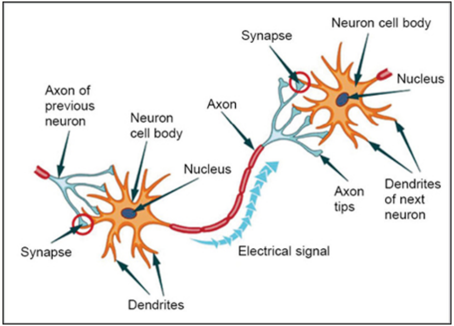
- *Axon* transmits signal to another neuron



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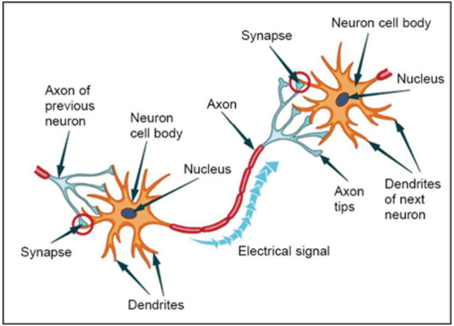
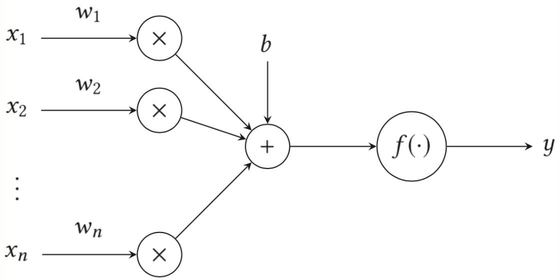
Deep Learning

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.

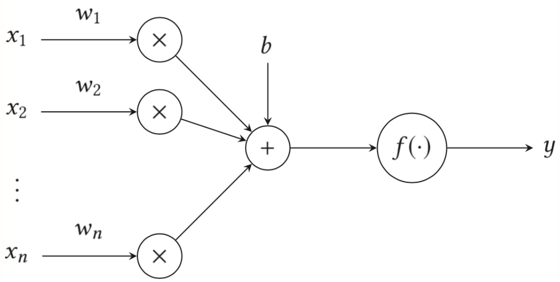
– The New York Times, late 1950s

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

Deep Learning

Perceptron – Basic Element of DL

- Algorithm for Supervised Learning



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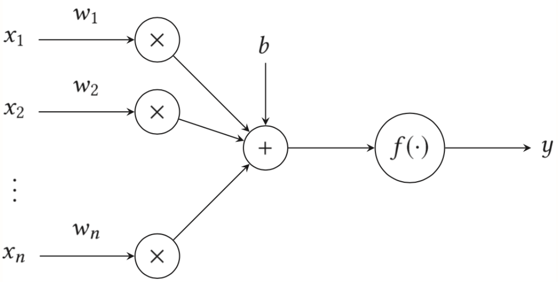

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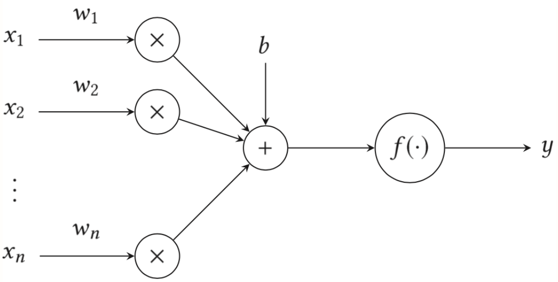

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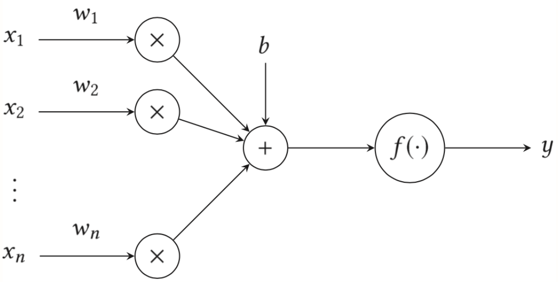

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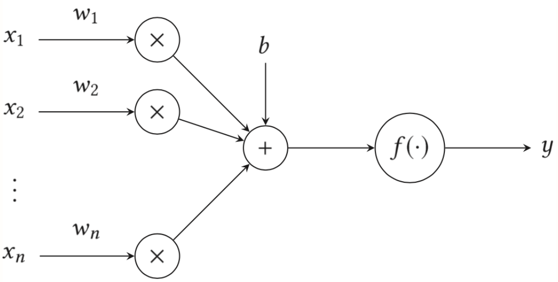
- Proved that Perceptron would automatically learn weights



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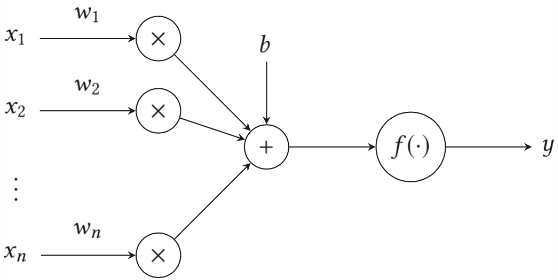

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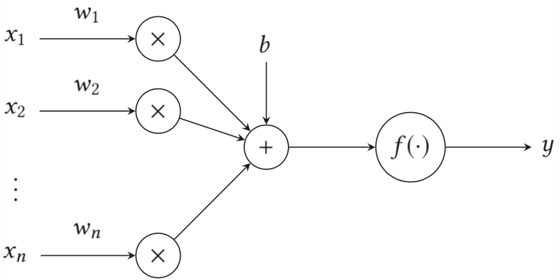

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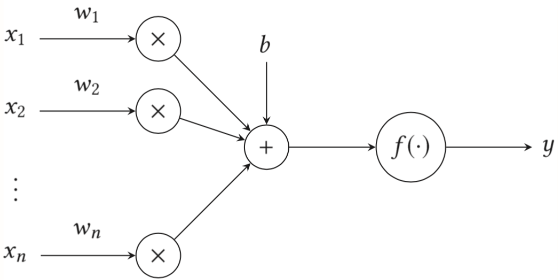

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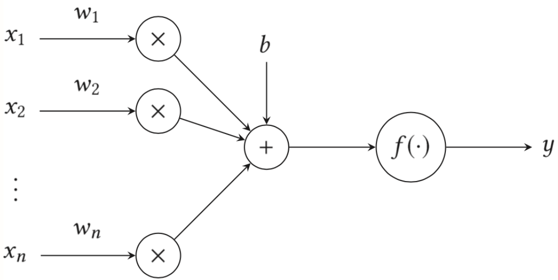

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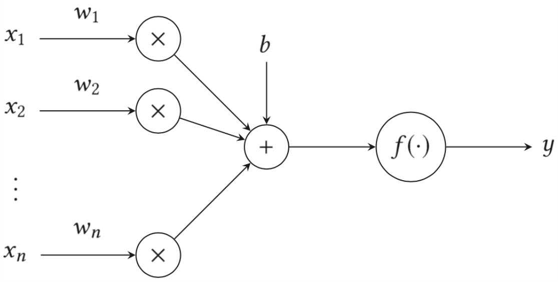
- Turns out you need *some* non-linearity



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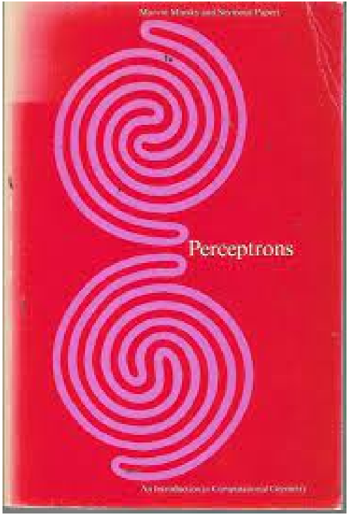

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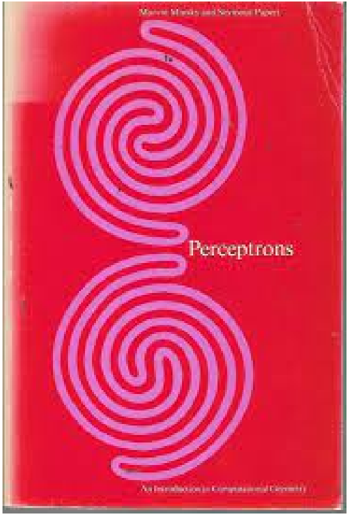

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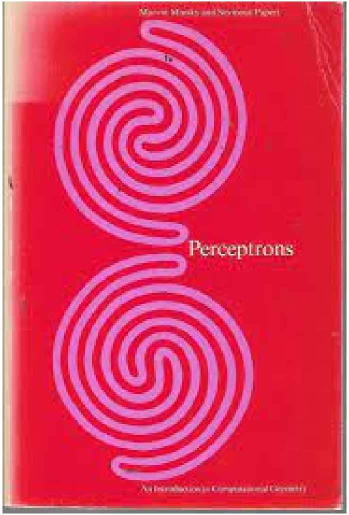

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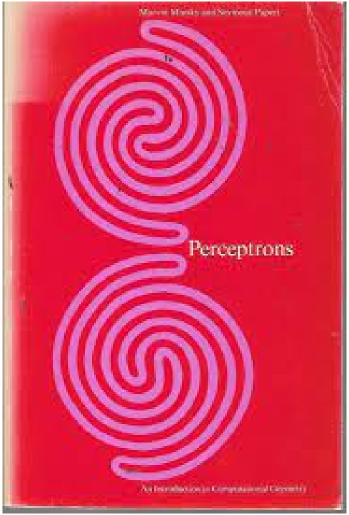

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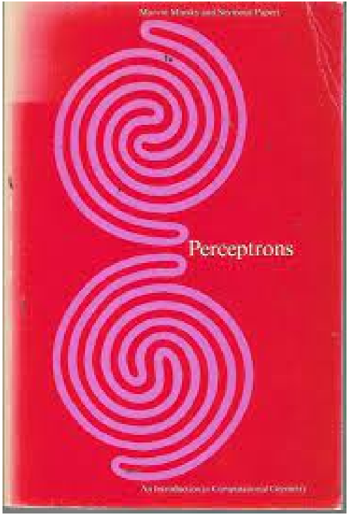
- Many attribute this book with causing an AI winter



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Universal Approximation

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

0893-6080/89 $3.00

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

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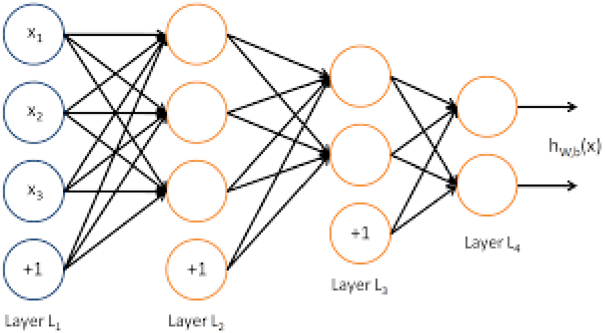

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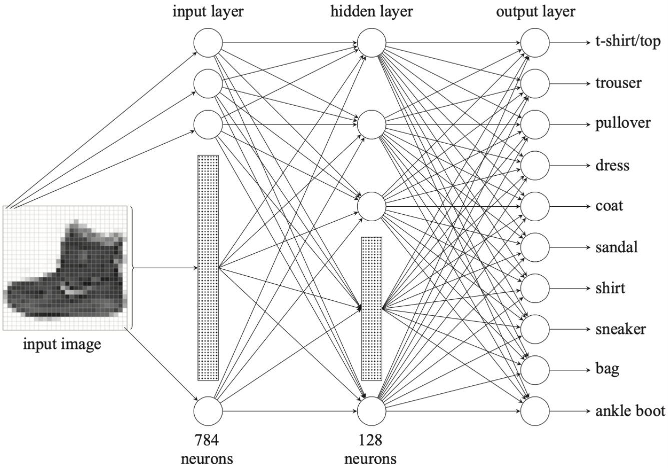
Convolution in Action

https://towardsdatascience.com/intuitively-understanding-convolutions-for-deep-learning-1f6f42faee1

CIFAR10: Clothing Data Set

Source: Algorithms by Louridas, Chapter 6

CIFAR10: Deep Neural Net



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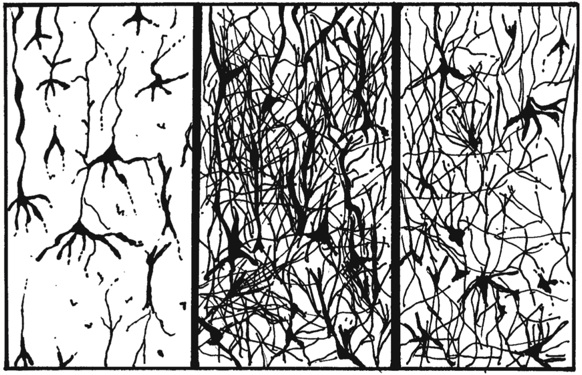
- Is there a connection to how humans learn?

Synaptic Density in Humans varies with age

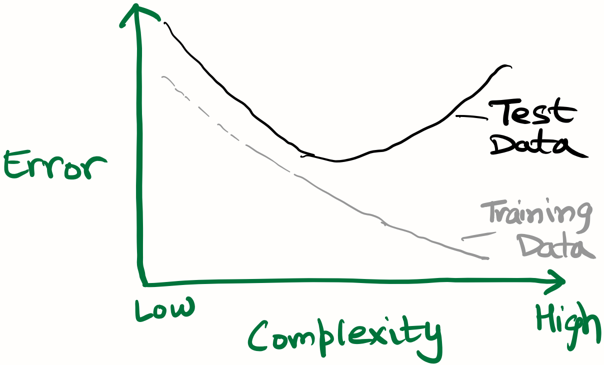


at a child's birth | at 7 years of age | at 15 years of age

Understanding Brain Development in Young Children, Brotherson, 2022

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

Generalization Error and Model Complexity



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

Recurrent Neural Network

RNN

- Images have a spatial regularity (local contiguity)

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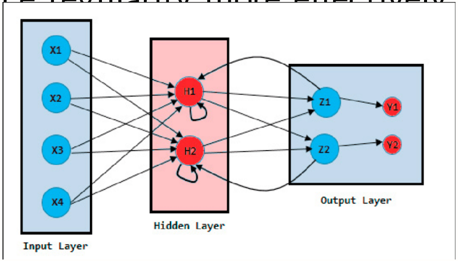
- The output of neurons in “later” layers is given as input to same “earlier” layers

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 Idea

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

LLMs

How do they work?

Some questions with LLMs:

- What are they trained on?

LLMs

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- Why do they hallucinate – create random or nonsense text?

Generative AI Model – Images

Generative AI

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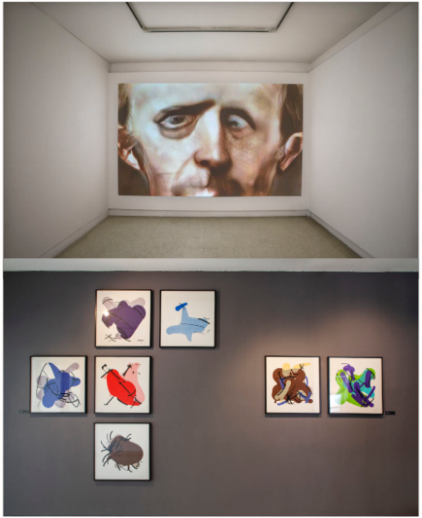
    - AI can create or co-create with humans

Generative AI

Real Paintings by Dali



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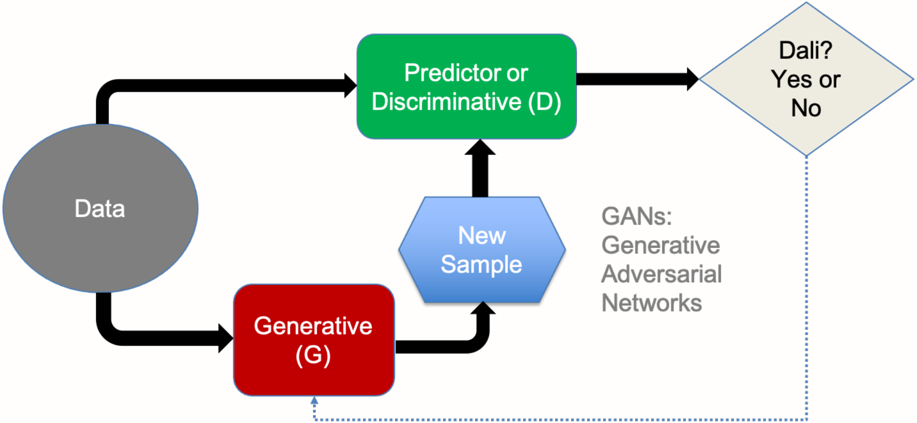

GANs: Generative Adversarial Networks

Reinforcement Learning

Power of RL in Games

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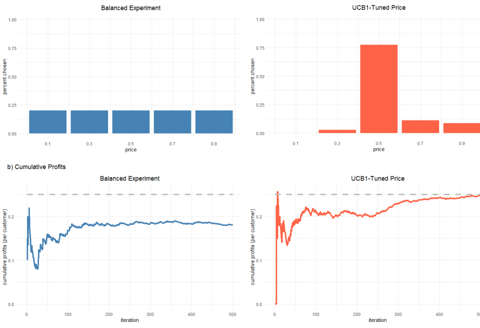
- Critically important to specify the reward function properly

RL in Dynamic Pricing

- When you have a new product we don't know demand



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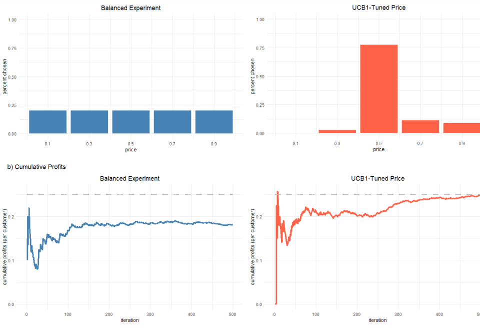

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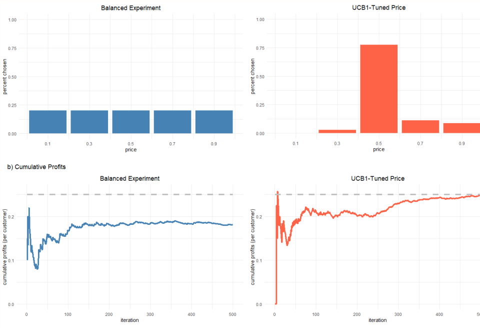

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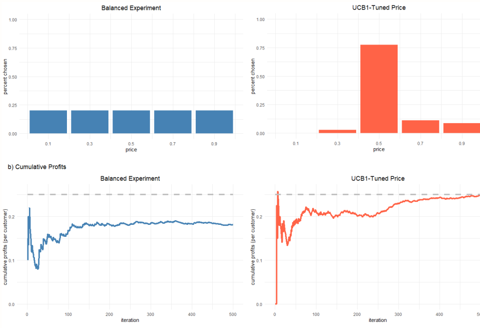

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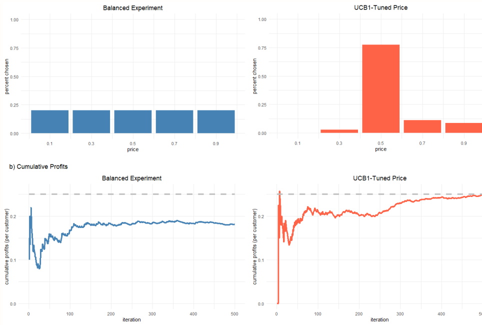

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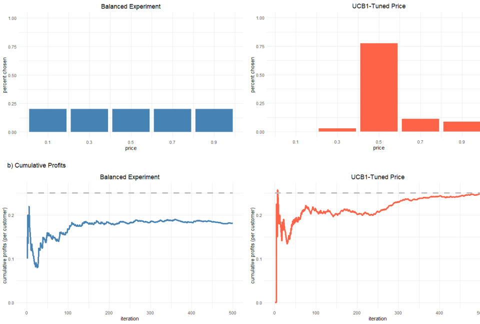

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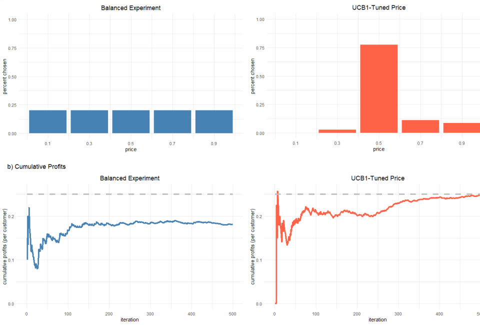

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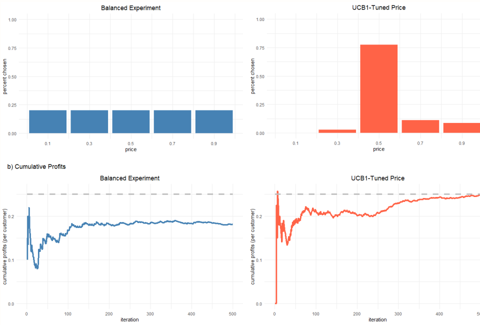
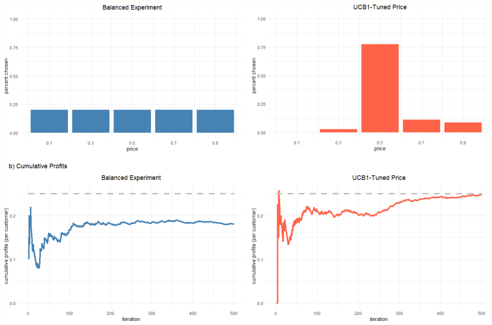


Now let's try this with Chess

RL in Dynamic Pricing

- Blue is Balanced experiment (A/B test), Orange is RL



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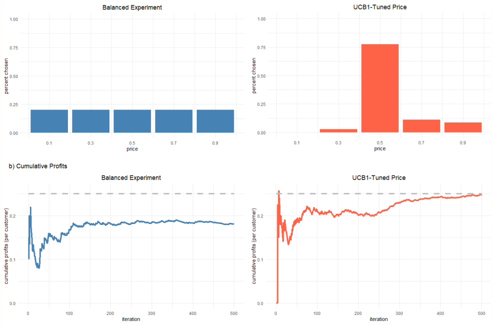

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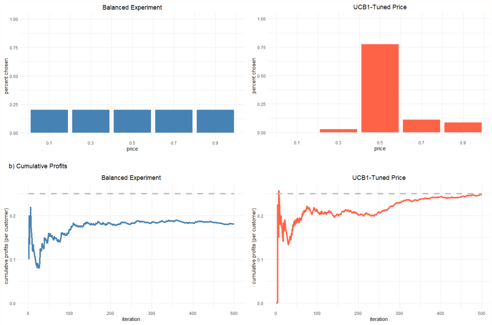

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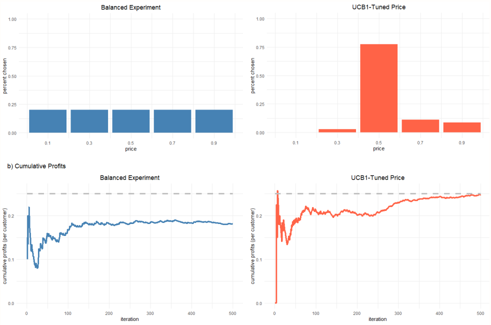
- RL obtains higher profit levels quicker



RL in Robotics

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

Specifying ML Problems (In class exercise)

Let's try this in Groups

- For each case, suggest an (U)nsupervised, (S)upervised **and** (R)einforcement learning approach.
- For (U) and (S) specify what variables you will use as y and X
- For (R), specify the actions (a), states (s), and reward function Π
- What is the goal of your ML model? What metric would you use to measure improvement?

3 Cases – Chose ONE

A) Social media platform like Instagram would like to increase engagement among its users

B) Content firm like Netflix or Spotify would like to recommend new content to its users

C) Apparel retailer like Patagonia would like to improve its product assortment