ECE408 / CS483 / CSE408
Summer 2025

Applied Parallel Programming

Lecture 16: Machine Learning and Deep Learning

What Will You Learn Today?

- application areas for machine learning
- basic strategy for machine learning applications
- extension to deep learning (mostly a research pitch)
- concept of a multi-layer perceptron

Perspective is Important

Chips are cheaper than ever.

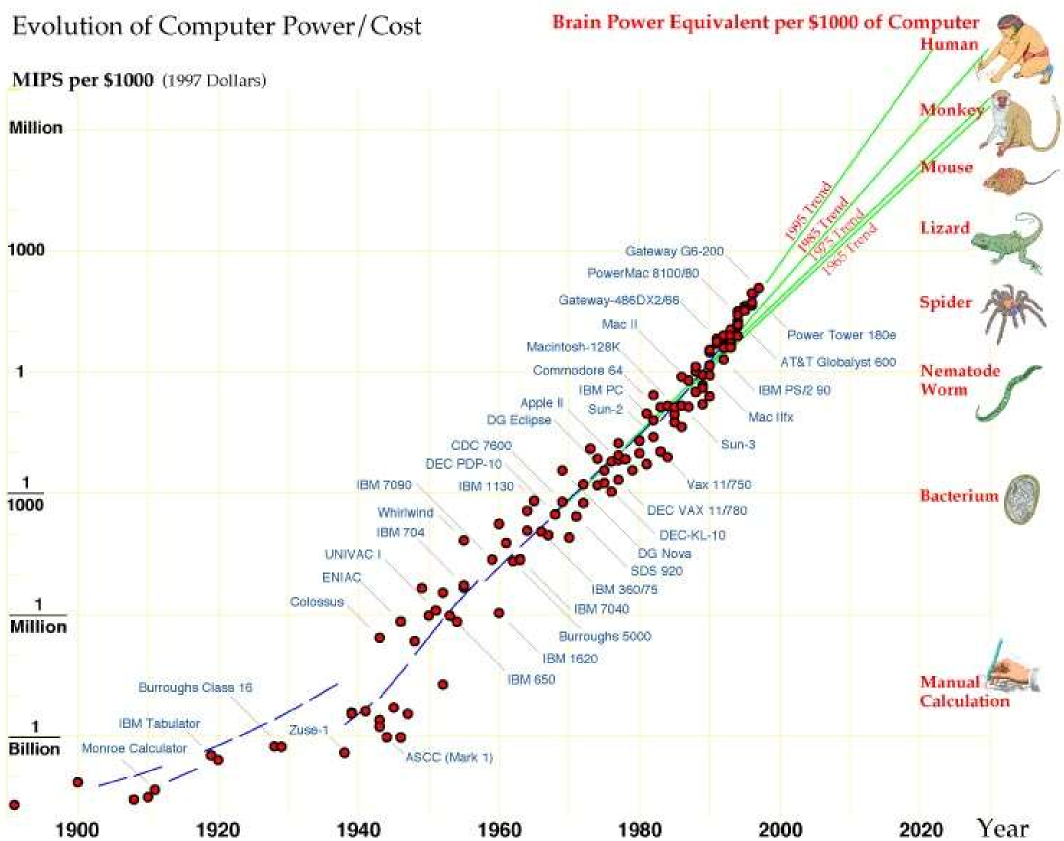
Unlike humans, digital systems offer

- **high-speed computation**,
- **low capital investment**
  (purchase vs. training a human), and
- **negligible operations cost** (no salary!).

If computer outperforms (or even matches)
a **human, use a computer**.

Industry has done so for 40-50 years now.

Evolution of Computer Power/Cost



Hans Moravec, 1997

Computing has evolved under the premise that some day, computing machines will be able to mimic general human intelligence.

From a computing power perspective, Moore's Law has fueled the idea of the intelligent machine. Hardware has gotten 2x faster every 18 months.

The software, though, has been a vexing open question.

https://jetpress.org/volume1/moravec.htm

What is Machine Learning?

machine learning: important method of building applications whose logic is not fully understood

Typically **by example**:

- **use labeled data** (matched input-output pairs)
- **to represent** desired **relationship**.

Iteratively adjust program logic to produce desired/approximate answers (called **training**).

Types of Learning Tasks

- classification
  - Map each input to a category
  - Ex: object recognition, chip defect detection
- regression
  - Numerical prediction from a sequence
  - Ex: predict tomorrow's temperature
- transcription
  - Unstructured data into textual form
  - Ex: optical character recognition

More Advanced Learning Tasks

- translation
  - Convert a sequence of symbols in one language to a sequence of symbols in another
- structured output
  - Convert an input to a vector with important relationships between elements
  - Ex: natural language sentence into grammatical structure
- others
  - Anomaly detection, synthesis, sampling, imputation, denoising, density estimation, genetic variant calling

Test Cycle Time is Important

You've all written code…

- code, test, code, test, code, test
- integrate, test, test, test
- and test again!

But how long is the code, test cycle?

Depends what you're building.

What's your longest?

Your Cycle Times are Probably Small

In college, **10k lines** took **½ hour** to compile on my PC.

In grad. school, **100k lines** took

- **½ hour** to compile on my workstation, or
- **2 minutes** on our cluster (research platform).

In ECE435 (networking lab), students needed

- **½ hour** to reinstall Linux after a bad bug.
- (Ever had a good bug?)

Gene sequencing / applications can take **two weeks**.

We're all a little spoiled…

Why Machine Learning Again?

In 2007, **programmable GPUs accelerated the training cycle**.

Today, **new chip designs** for learning applications **have further accelerated**.

Led to a resurgence of interest

- in Computer Vision, Speech Recognition, Document Translation, Self Driving Cars, Data Science…
- all tasks that **human brains solve regularly**, **but** for which **we** have **struggled to express solutions** systematically.

Why Machine Learning Now?

- **Computing Power**
  - GPU computing hardware and programming interfaces such as CUDA has enabled very fast research cycle of deep neural net training
- **Data**
  - Lots of cheap sensors, cloud storage, IoT, photo sharing, etc.
- **Needs**
  - Autonomous Vehicles, Smart Devices, Security, Societal Comfort with Tech, Health Care

Many Problems are Still Hard

Speed is not a panacea.

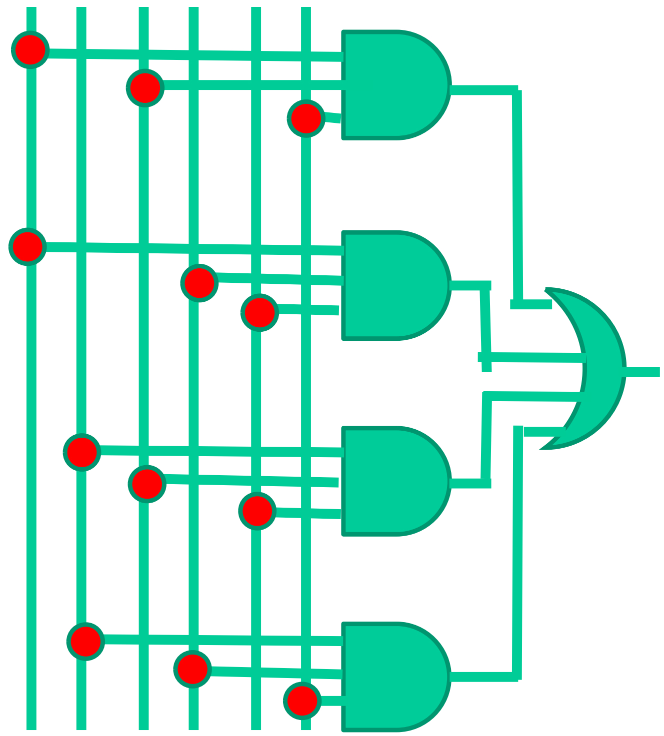
- Many **tasks still require human insight**
  - for network structure and feature selection
  - for effective input and output formats, and
  - for production of high-quality labeled data.

- Other trends sometimes help: ubiquitous computing enables crowdsourcing, for example.

Many Problems Have Systematic Solutons

Example: building a Boolean function from a truth table.

Input			output
a	b	c	
0	0	0	0
0	0	1	1
0	1	0	1
0	1	1	0
1	0	0	1
1	0	1	0
1	1	0	0
1	1	1	1



What if We Lack a Truth Table?

- Make enough observations to construct a rule
  - 000 → 0
  - 011 → 0
  - 100 → 1
  - 110 → 0

- If we cover all input patterns,
  we can construct a truth table!

Many Problems are Too Large

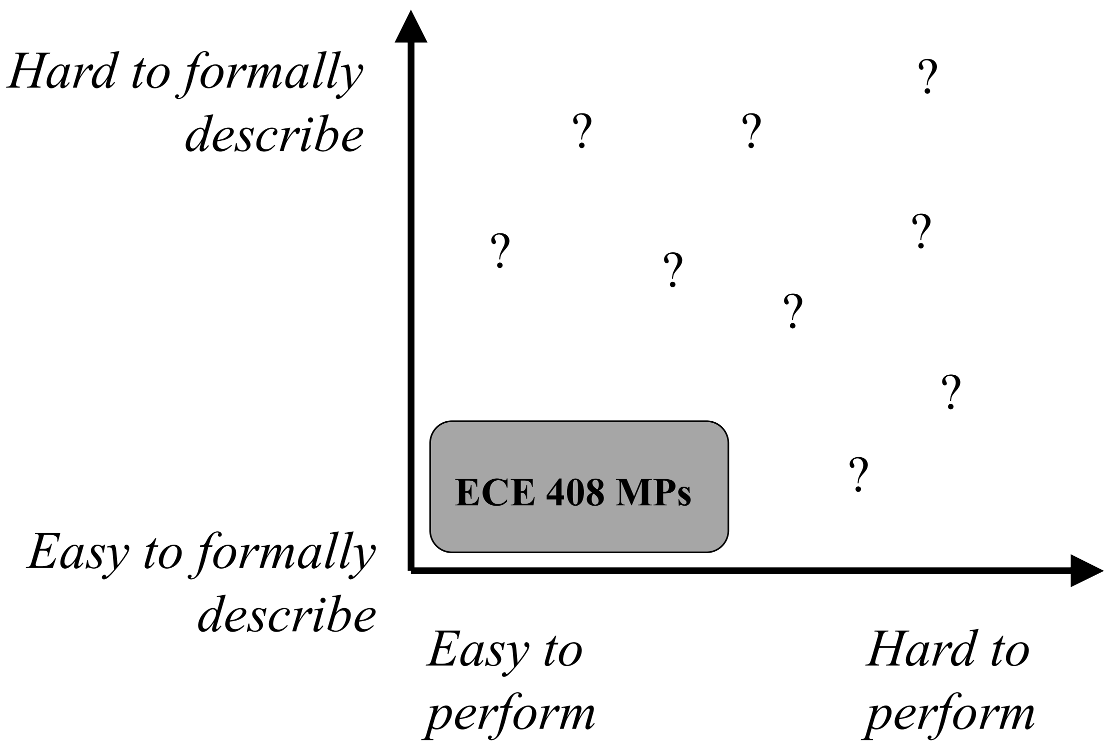
- The logic formulation of a 32x32-pixel (small) image recognition problem involves
  - 1024*8 bit input,
  - which will have a truth table of 2^{8196} entries
- If we managed to collect and label 1 billion ($\sim 2^{32}$) images as training data
  - We cover only $2^{32} / 2^{8196} = 1/ 2^{8164}$ of the truth table
  - Solution - learning processes that exploits features

Features in our logic example

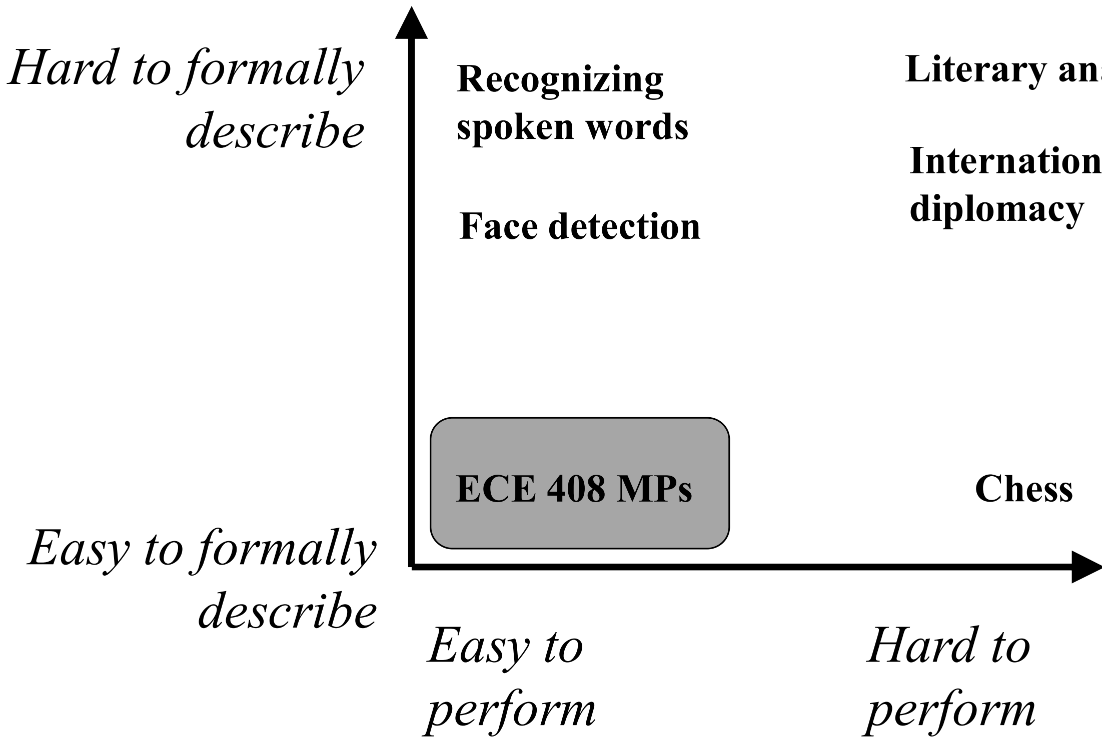
Input			output
a	b	c	
0	0	0	0
0	0	1	1
0	1	0	1
0	1	1	0
1	0	0	1
1	0	1	0
1	1	0	0
1	1	1	1

Feature 1: bit patterns with odd number of 1's result in output 1
Feature 2: bit patterns with even number of 1's result in output 0

Types of Problems



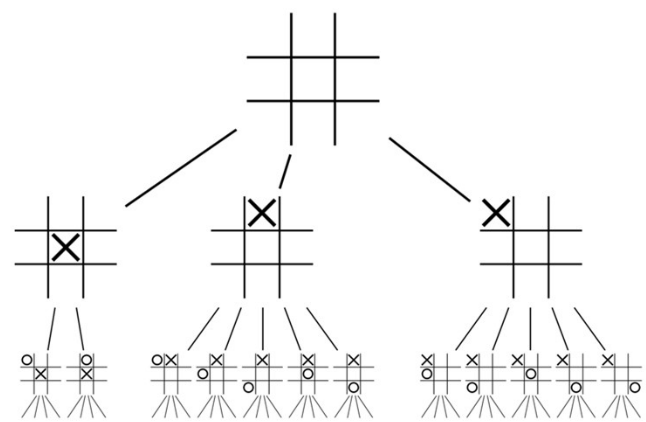
Types of Problems



Algorithm complexity, parallelism, and data bandwidth)

Chess as an AI Success (1)

- Easy to formalize
  - 64 locations, 32 pieces
  - Well-defined, allowable moves
- Score each leaf in a tree of possible board positions
- Proceed down path that results in best position



2-ply game tree for tic-tac-toe

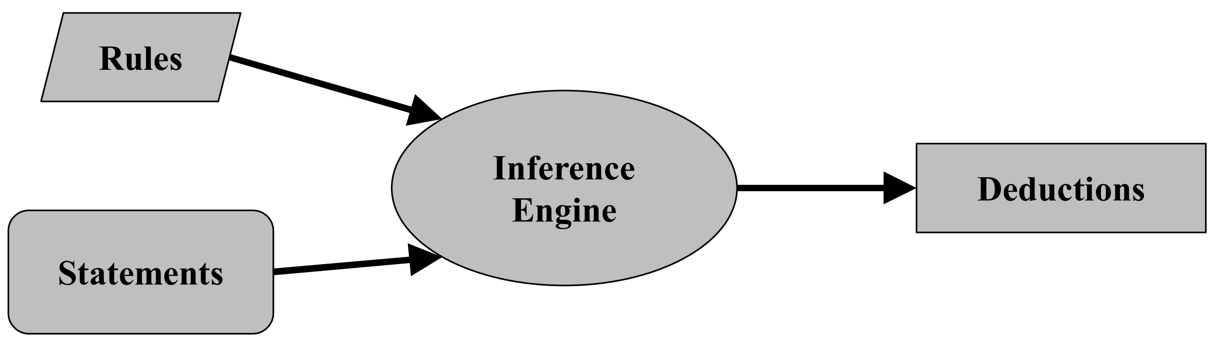
Chess as an AI Success (2)

Deep Blue defeated Gary Kasparov in 1997

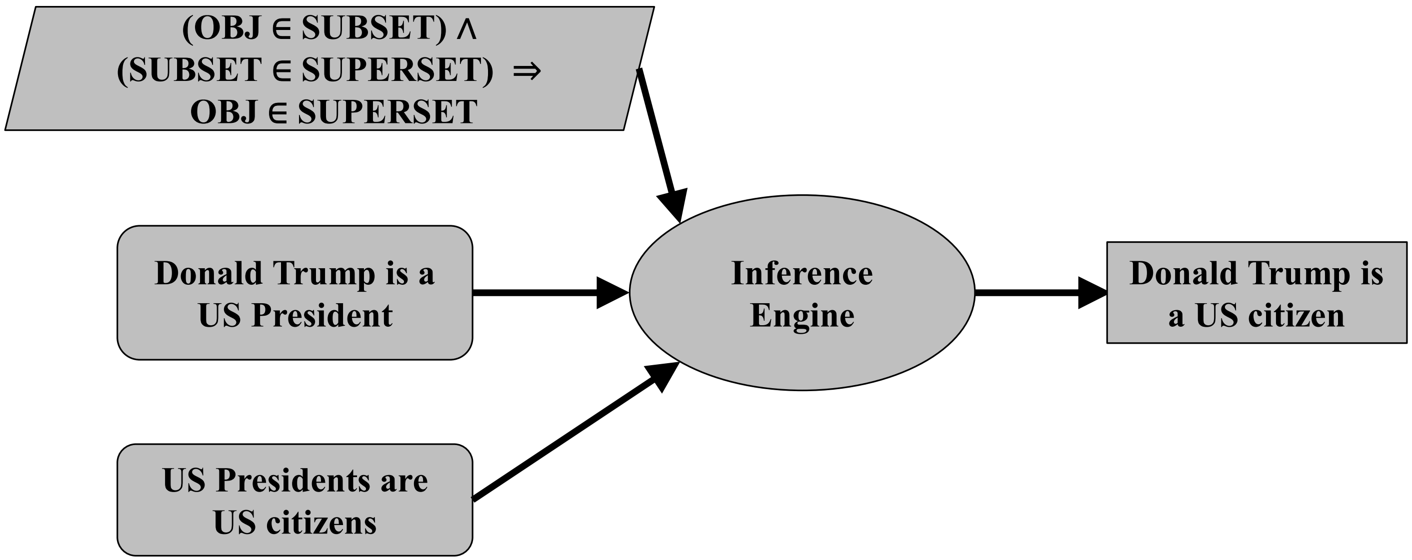
- Hard to perform
  - ~30 legal moves per position
  - 1,015 moves for 10-ply lookahead
  - 30 years of compute at 1M positions/sec
- Heuristics, pruning, parallel search, fast computers

Cyc: Extending Rule-based Systems to the Real World

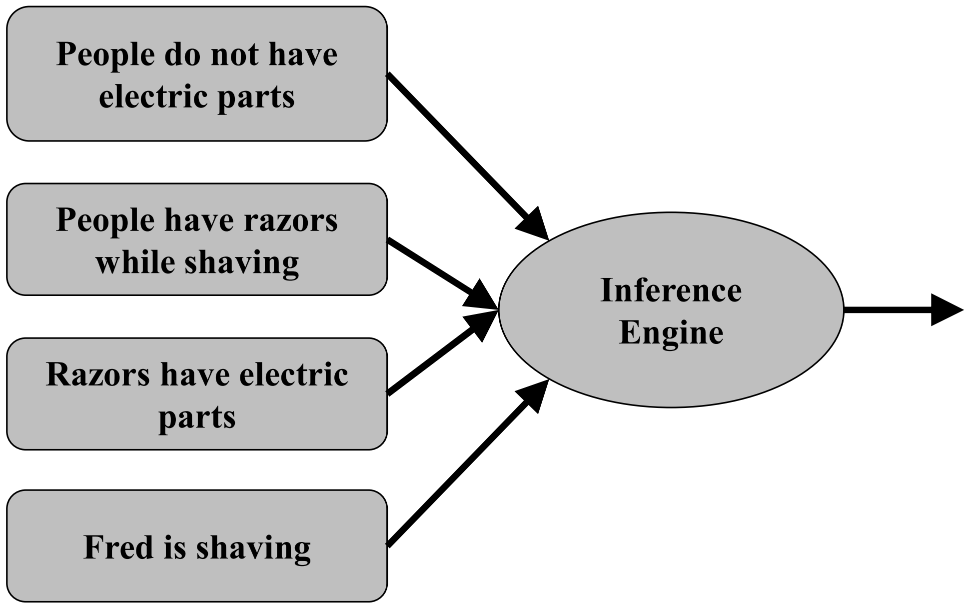
- Comprehensive ontology and knowledge base of common sense
- Cyc reasons about formal statements about the world



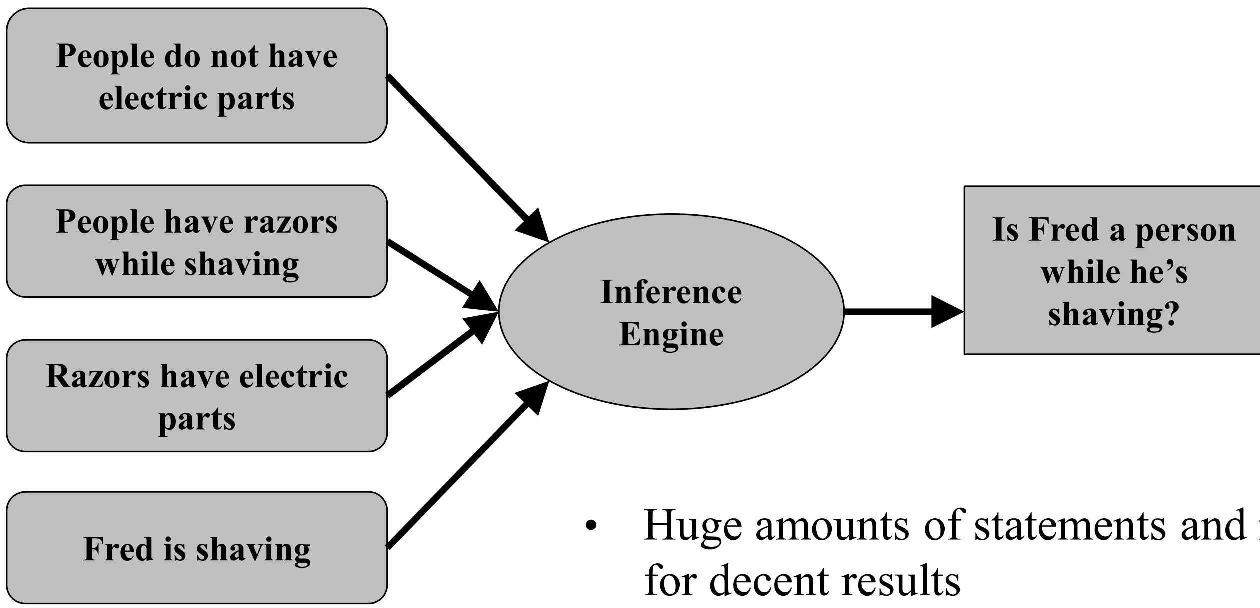
Cyc: A Simple Example



Cyc: FredWhileShaving

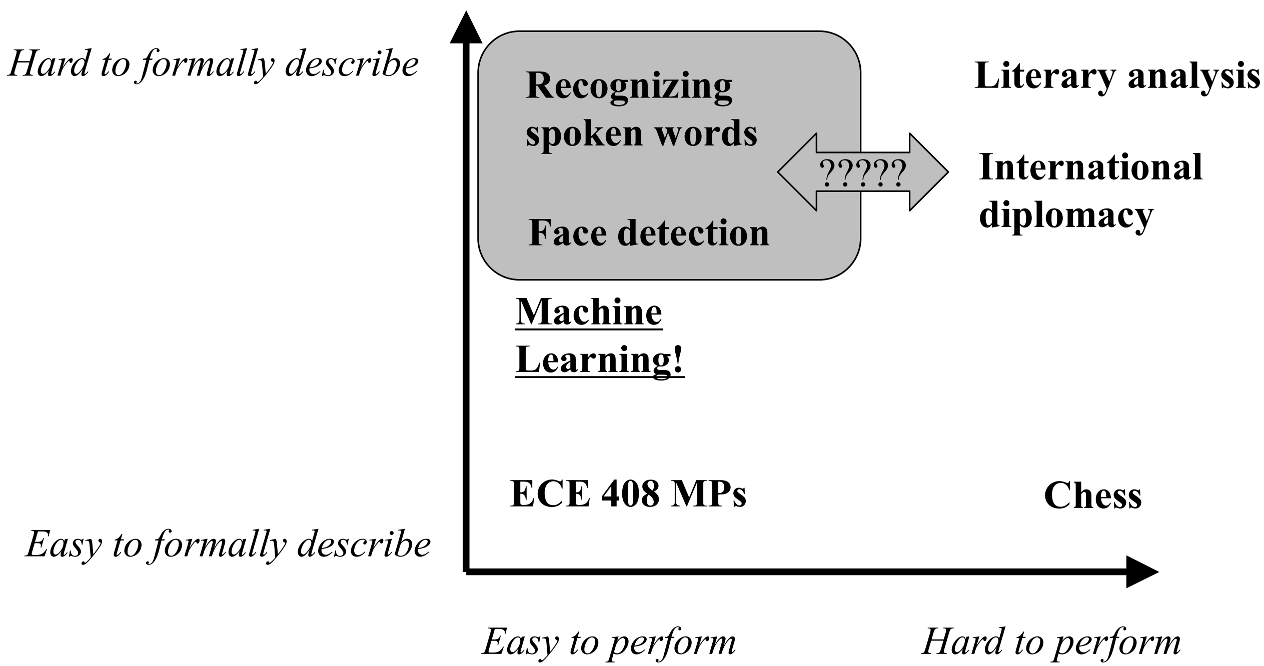


Cyc: FredWhileShaving



- Huge amounts of statements and rules for decent results
- Cannot learn new rules or statements on its own

Types of Problems



The "Machine Learning" Approach

Challenge

Hard to formalize the problem.

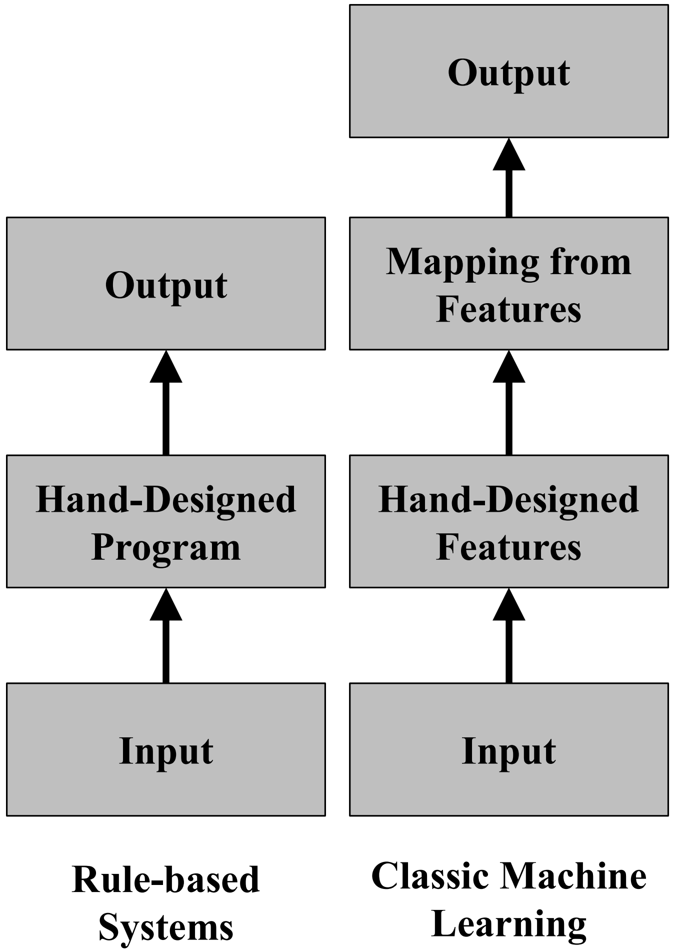
Solution

Don't formalize the problem.

Let the machine learn from experience.

Classic Machine Learning

- Humans choose features
- Learn how features are associated with outputs

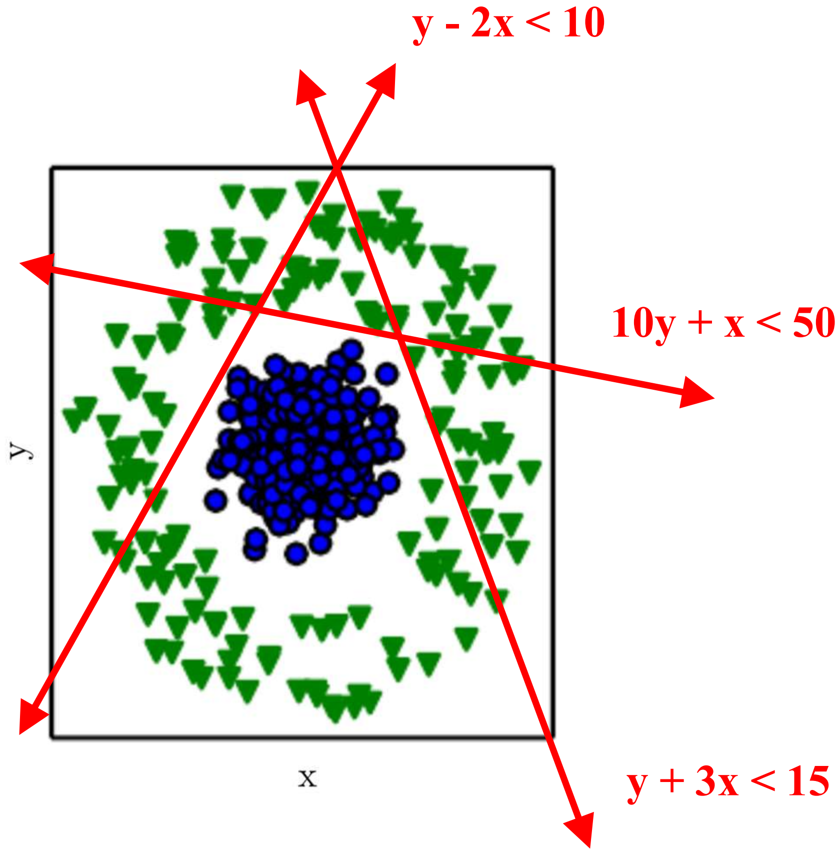


You may have heard of…

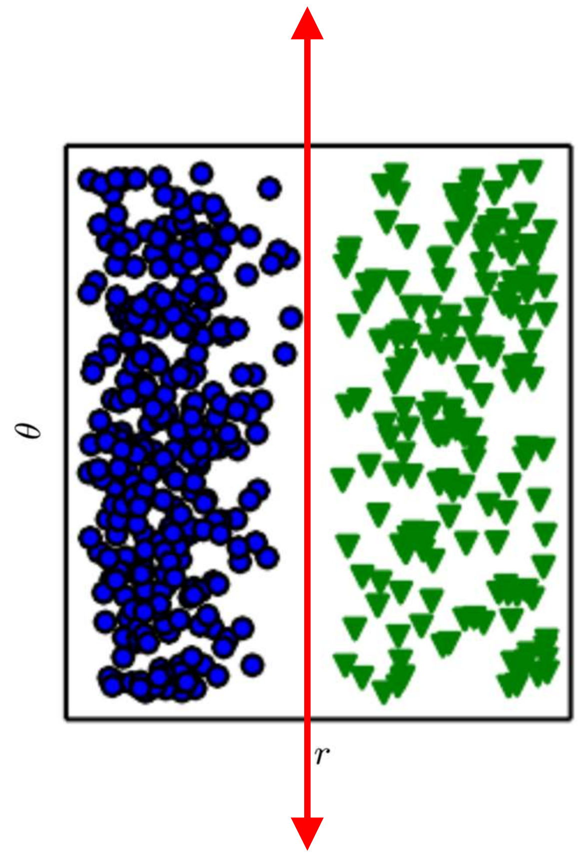
- Naïve Bayes:
  features as independent contributors to output
- Logistic Regression:
  - learn how to weight each feature's contribution to output,
  - usually through gradient descent*

*more on this topic later in these slides

Data Representation is important!

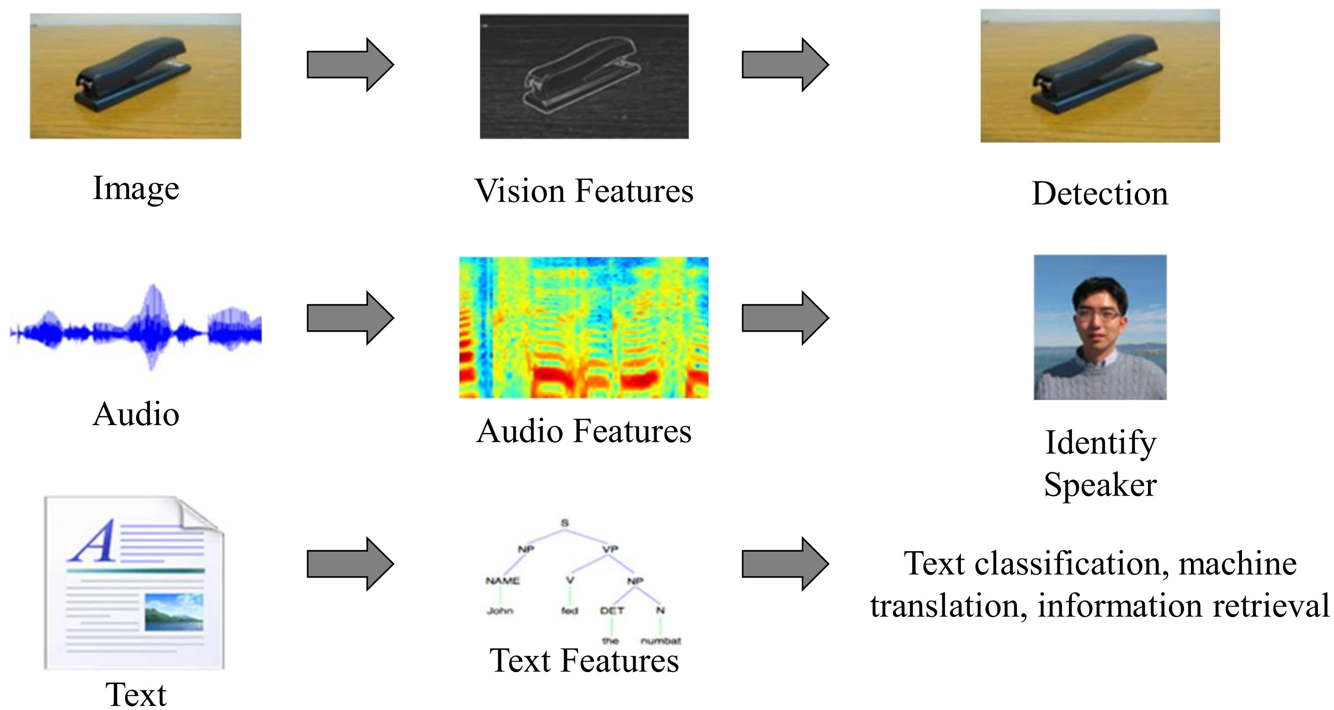


Data Representation is important!



Θ = arctan(y / x)
r = sqrt($x^2 + y^2$)

Different Features for Different Tasks



Which Data Features are Relevant

- Detecting a car in an image
- Cars have wheels ➡ presence of a wheel?
- Can we describe pixel values that make up a wheel?
  - Circle-shaped?
  - Dark around perimeter?

Which Data Features are Relevant

- Detecting a car in an image
- Cars have wheels ➡ presence of a wheel?
- Can we describe pixel values that make up a wheel?
  - Circle-shaped?
  - Dark around perimeter?
- But what about?
  - Occlusion, perspective, shadows, white-walled tires, …

Identify Factors of Variation that Explain Data

- Unobserved objects or forces that affect observed quantities
- Mental constructs that provide simplifying explanations or inferred causes
- Ex: speech
  – Age, sex, accent, words being spoken
- Ex: car
  – Position, color, angle of sun
- Many factors influence each piece of observed data

Representation Learning Approach

Challenge

Which data features are relevant?

Solution

Learn the features too!

(Looking ahead)

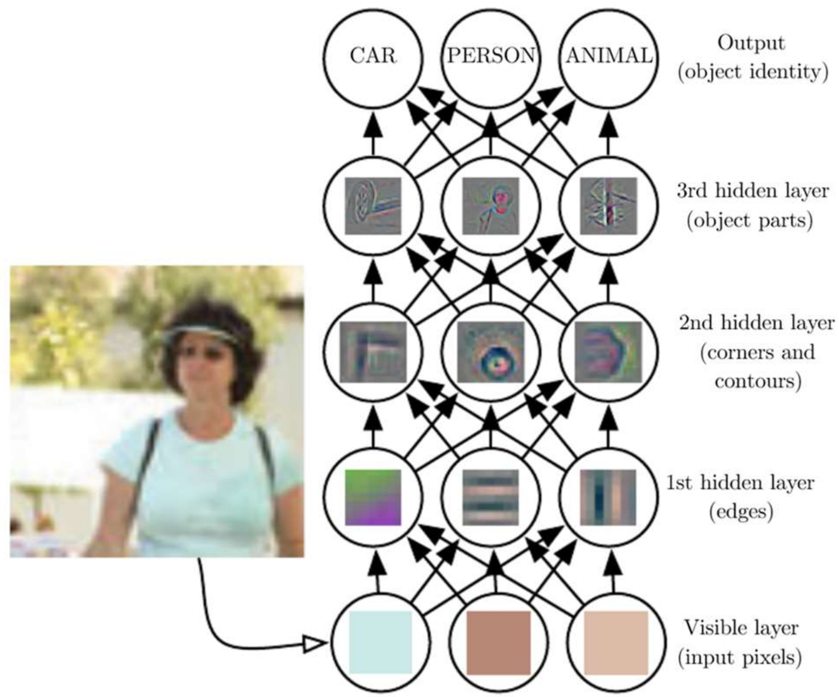
Deep Learning: a deep hierarchy of features

Machine Learning

- Ability to acquire knowledge by extracting patterns from data

Deep Learning

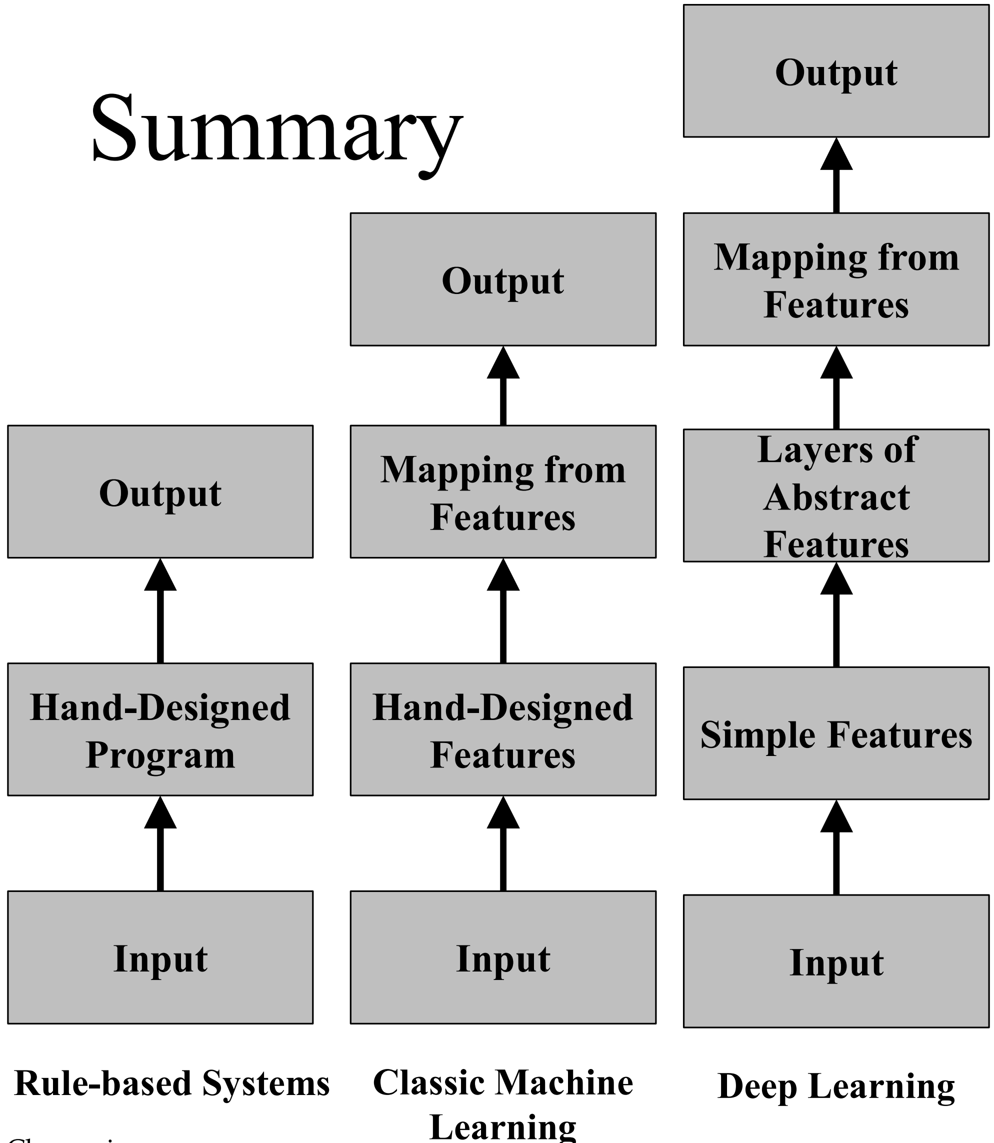
- A type of representation learning
- Representations expressed in terms of other representations



Deep Learning Approach

Challenge	**Solution**
Hard to formalize the problem?	Don’t formalize the problem
	Let the machine learn from experience
Which data features are relevant?	Hierarchy of concepts to capture simple and complicated features
	Learn the hierarchy too!

Summary


Output
Hand-Designed Program
Input
Rule-based Systems
Output
Mapping from Features
Hand-Designed Features
Input
Classic Machine Learning
Output
Mapping from Features
Layers of Abstract Features
Simple Features
Input
Deep Learning

Let's Look at Classification

In a **classification problem**, we model

- a function mapping an input vector to a set of C categories: $F : \mathbb{R}^N \rightarrow \{1, \ldots, C\}$,
- where the function F **is unknown**.

We **approximate** F **using a set of functions** f

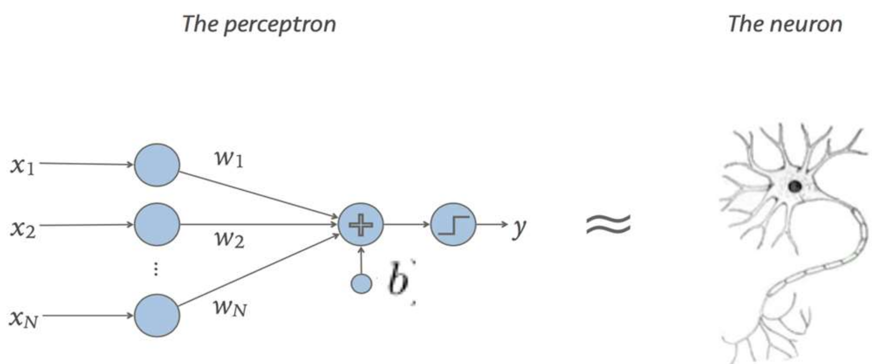
- – parametrized by a (large) set of weights, θ
- – that map from a vector of N real values* to an integer value representing a category:
- – for category i, $\mathbf{prob}(i) = f(x, \theta)$

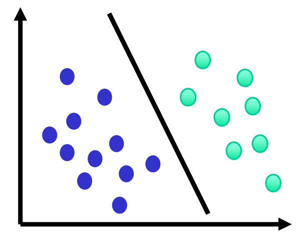
*floating-point values

Perceptron is a Simple Example

- Example: a **perceptron**

$$y = \mathrm{sign}(W \bullet x + b) \qquad \Theta = \{W, b\}$$





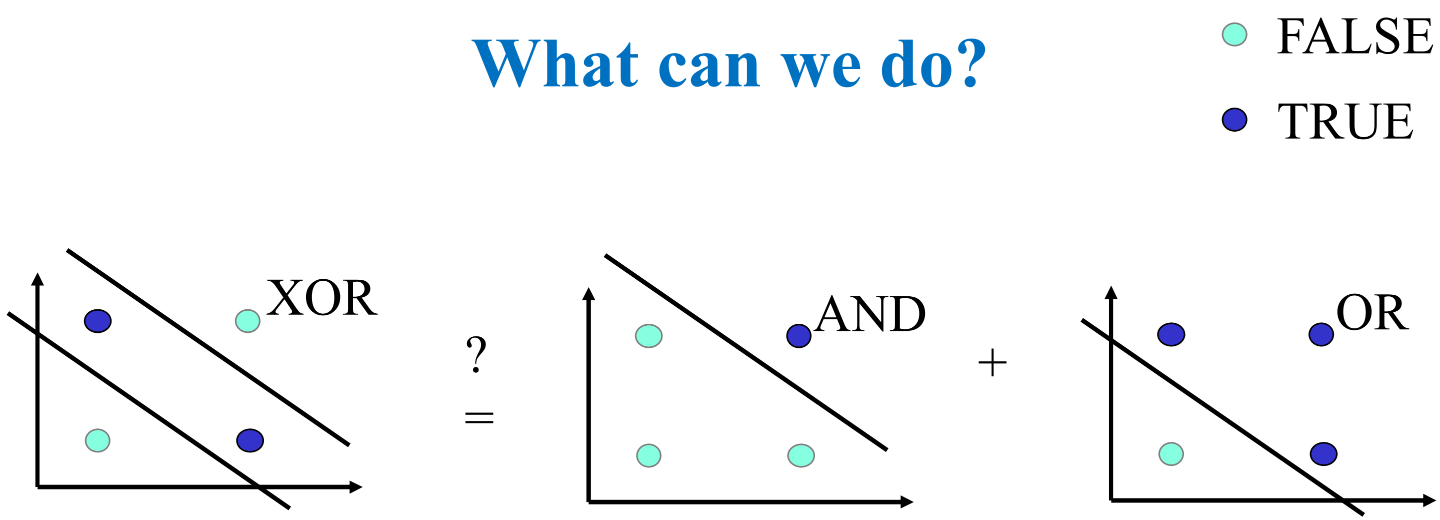
- Dot product: $y = W \bullet \boldsymbol{x}$
- Scalar addition: $+\, b$

output
input
weight
bias

One Perceptron is not Enough

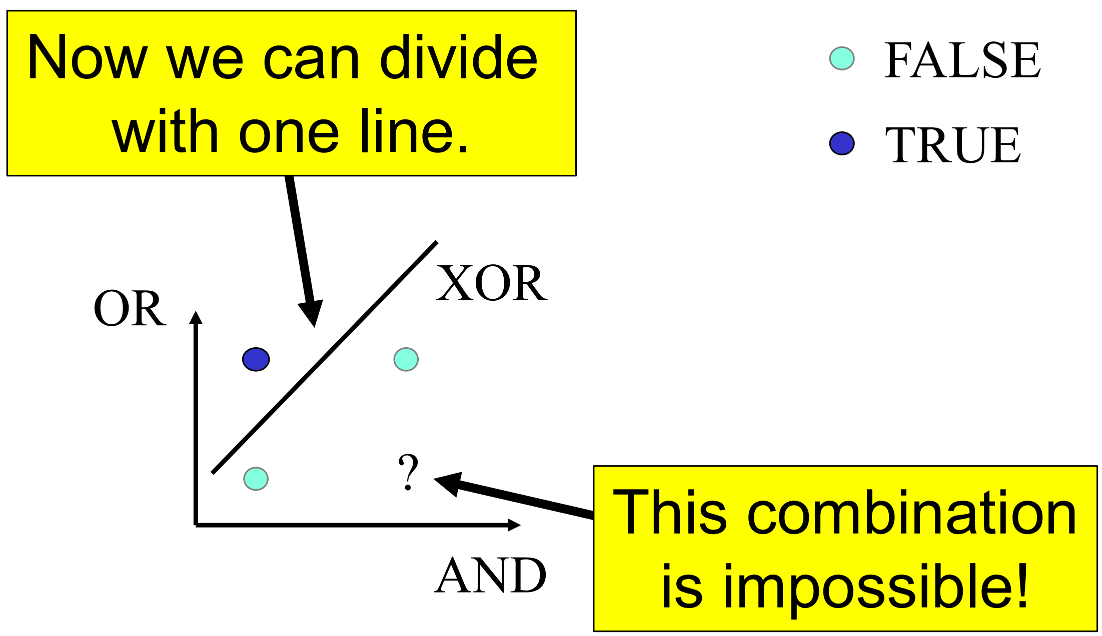
Some functions are non-linear.

What can we do?



Multiple Layers Solve More Problems

What if input dimensions are AND and OR?

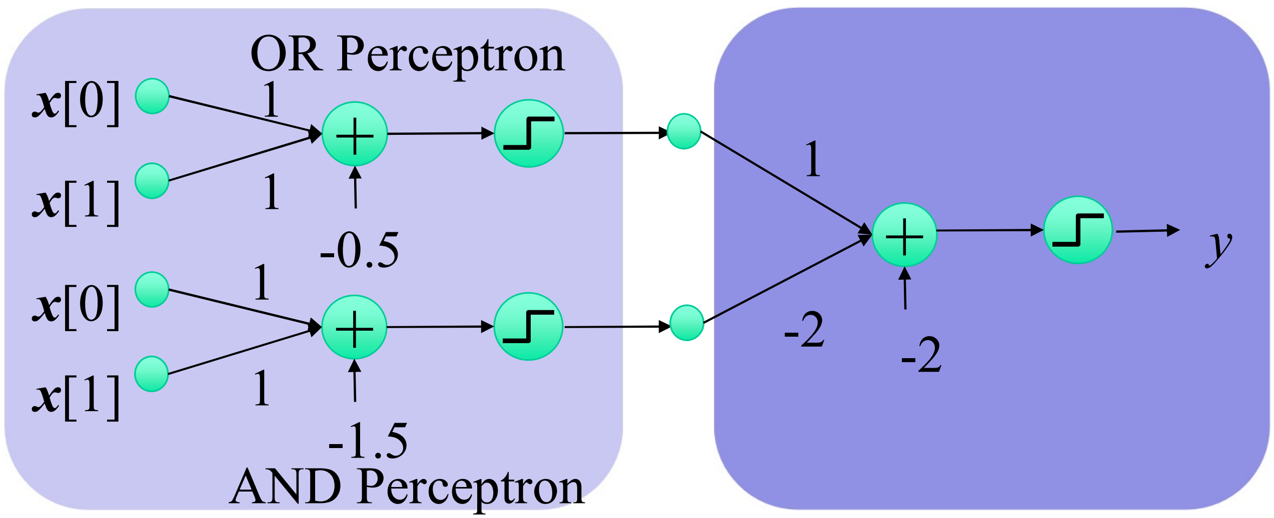


A	B	OR	AND	XOR
0	0	-1	-1	-1
0	1	1	-1	1
1	0	1	-1	1
1	1	1	1	-1

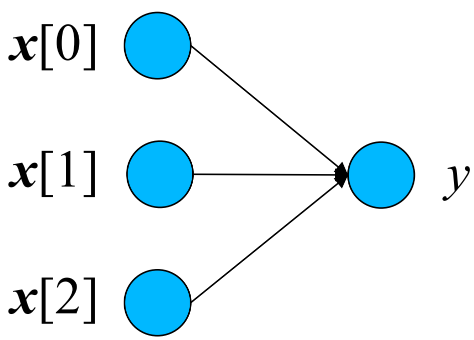
$$\text{AND} = \text{sign}(\boldsymbol{x}[0] + \boldsymbol{x}[1] - 1.5)$$

$$\text{OR} = \text{sign}(\boldsymbol{x}[0] + \boldsymbol{x}[1] - 0.5)$$

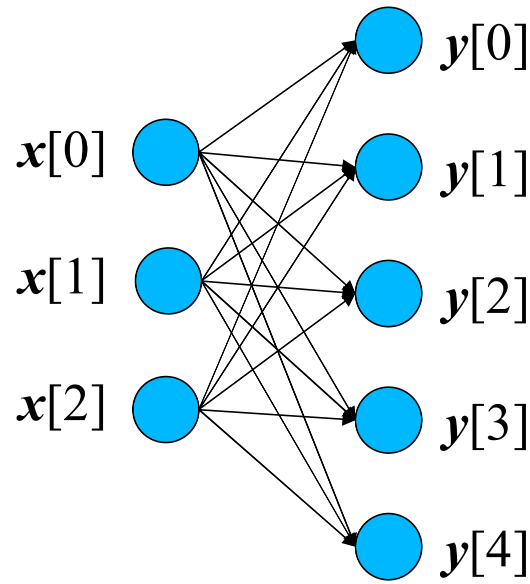
$$\text{XOR} = \text{sign}(2 * \text{OR} - \text{AND} - 2)$$



Generalize to Fully-Connected Layer

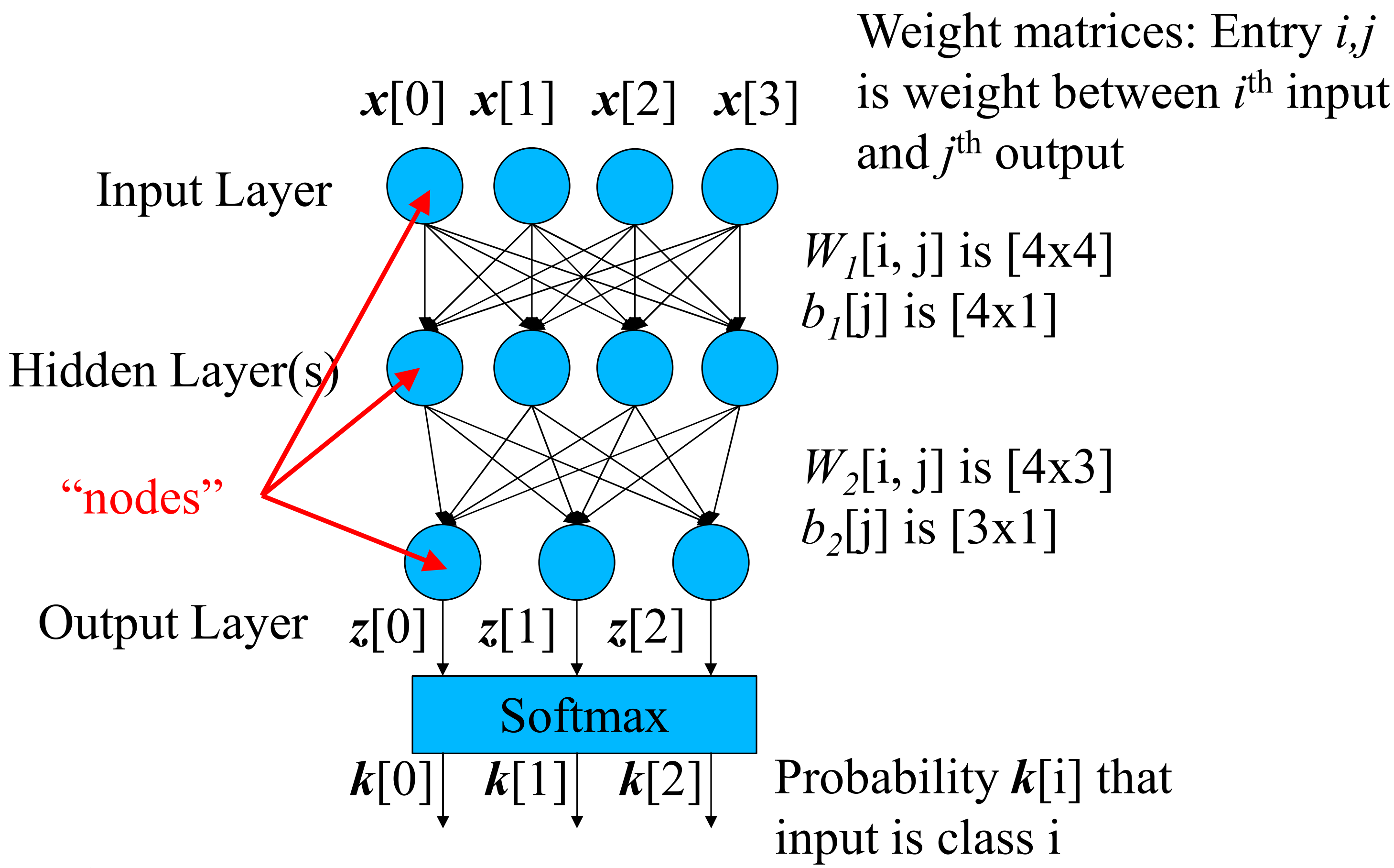


Linear Classifier:
Input vector $\boldsymbol{x} \times$ weight vector $\boldsymbol{w}$ to produce scalar output y



Fully-connected:
Input vector $\boldsymbol{x} \times$ weight <u>matrix</u> $\boldsymbol{w}$ to produce <u>vector</u> output y

Multilayer Terminology



How Can We Choose the Right Weights?

- Look at some observed data?
- Pick some random values?
- Start with something that partially works?

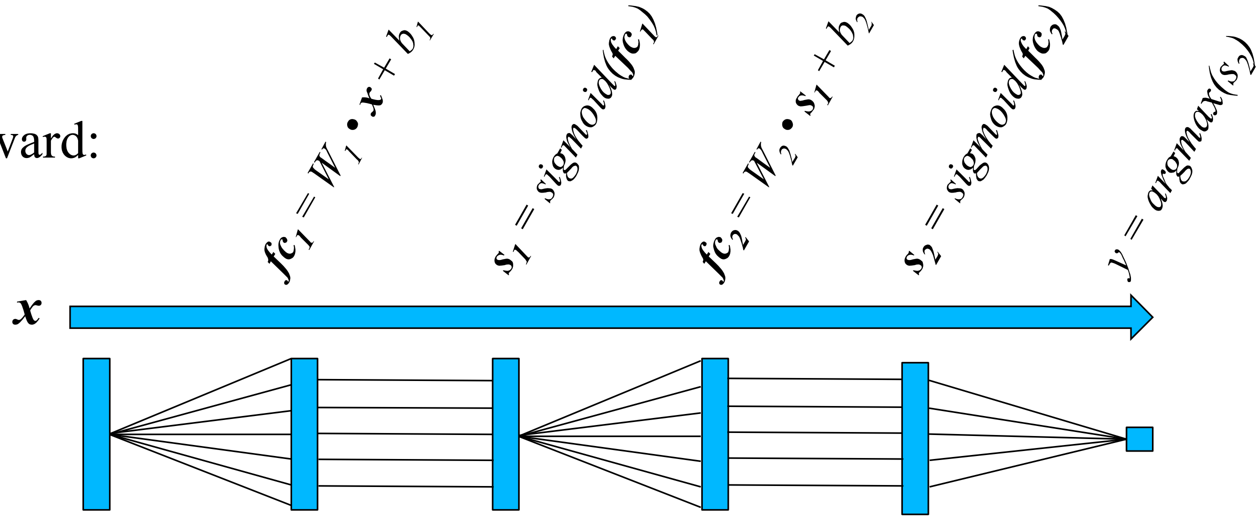
- With enough *labeled* data, we can automatically *encode* the relationship between inputs and outputs.

Forward and Backward Propagation

- Forward (inference)
  - Given parameters Θ and input $\boldsymbol{x}$, produce label y
- Backward (training)
  - Need a way to assess correctness (loss function)
  - Example: $(x - y)^2$
  - Find Θ , such that loss is minimized over all input data

Forward Propagation (Inference)

Forward:



Backward Propagation (Training)

Forward:

$fc_1 = W_1 \bullet \boldsymbol{x} + b_1$

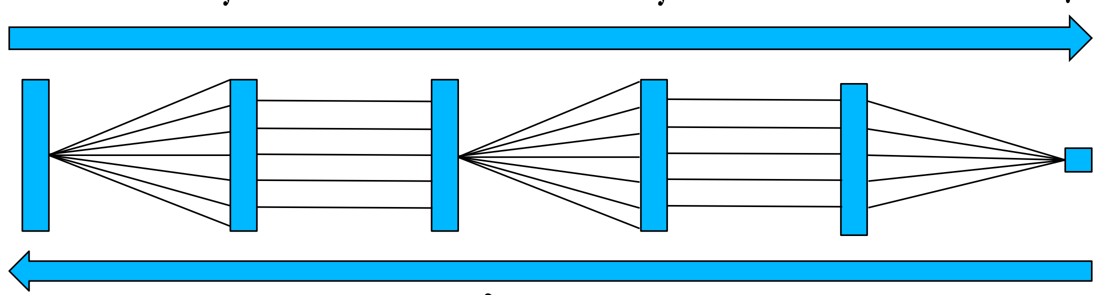
$s_1 = sigmoid(fc_1)$

$fc_2 = W_2 \bullet s_1 + b_2$

$s_2 = sigmoid(fc_2)$

$y = argmax(s_2)$

$\boldsymbol{x}$



Minimize loss over entire training set:

Need $\frac{dE}{dW}$

Backward:

$\frac{dE}{dfc_1} = \frac{dE}{ds_1}\frac{ds_1}{dfc_1}$

$\frac{dE}{ds_1} = \frac{dE}{dfc_2}\frac{dfc_2}{ds_1}$

$\frac{dE}{dfc_2} = \frac{dE}{ds_2}\frac{ds_2}{dfc_2}$

$\frac{dE}{ds_2} = \frac{dE}{dy}\frac{dy}{ds_2}$

$\frac{dE}{dy}$

QUESTIONS?