

# Introduction to AI

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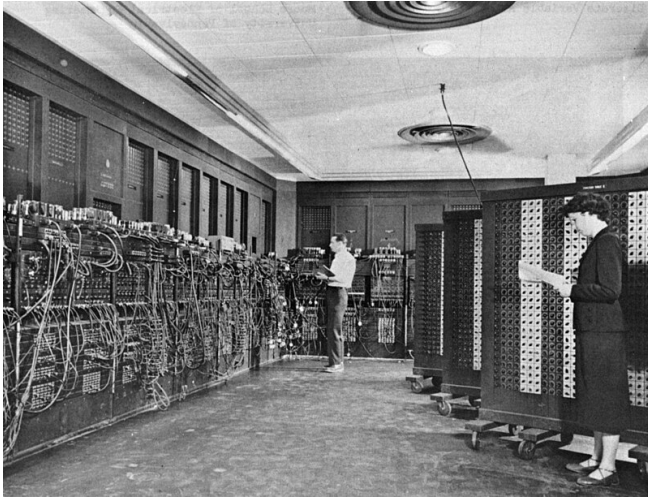
Website: <https://www.csccm.in/>

# *Goal*

- A brief introduction to the philosophy of AI
- The history of AI
- What is AI?
- Supervised learning vs unsupervised learning vs reinforcement learning

# History of AI

1946: ENIAC heralds the dawn of Computing



1950: Turing asks the question



I propose to consider the question:  
“Can machines think?”

-- Alan Turing, 1950

1956: A new field is born

- We propose that a 2-month, 10-man study of AI be carried out during the summer of 1956 in Dartmouth College in Hanover, New Hampshire.
  - Dartmouth AI Project Proposal; McCarthy et al. (Aug 31, 1955)

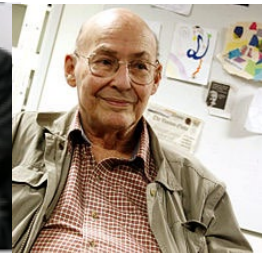
J McCarthy



C. E. Shannon and N.  
Rochester



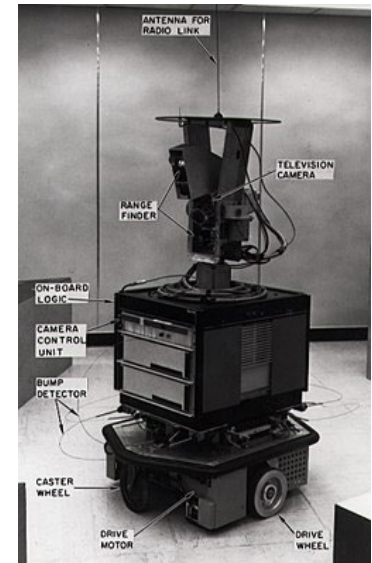
M. L. Minsky



# History of AI

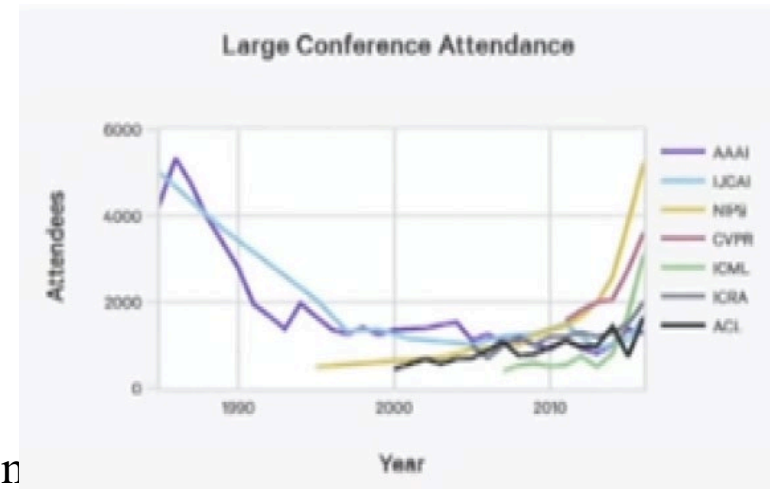
## 1950-1966

- 1950: Turing Test for Machine Intelligence
- 1956: AI born at Dartmouth College Workshop
- 1964: Eliza – the chatbot psychotherapist
- 1966: Shakey – general purpose mobile robot



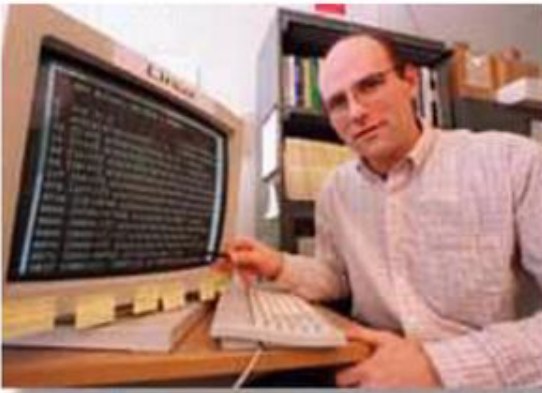
## AI Winters

- 1974 - 1980: Winter #1
  - ✓ Failure of machine translation
  - ✓ Negative results in Neural Nets
  - ✓ Poor speech understanding
- 1987 – 1993: Winter #2
  - ✓ Decline of LISP
  - ✓ Decline of specialized hardware for expert system



# History of AI

A mathematical conjecture (Robbins conjecture) unsolved for decades.  
First non-trivial mathematical theorem proved automatically.



The Robbins problem was to determine whether one particular set of rules is powerful enough to capture all of the laws of Boolean algebra. One way to state the Robbins problem in mathematical terms is:

Can the equation  $\text{not}(\text{not}(P))=P$  be derived from the following three equations?

- [1]  $P \text{ or } Q = Q \text{ or } P$ ,
- [2]  $(P \text{ or } Q) \text{ or } R = P \text{ or } (Q \text{ or } R)$ ,
- [3]  $\text{not}(\text{not}(P \text{ or } Q) \text{ or } \text{not}(P \text{ or } \text{not}(Q))) = P$ .

***[An Argonne lab program] has come up with a major mathematical proof that would have been called creative if a human had thought of it.***

***New York Times, December, 1996***

# History of AI

1996: Deep Blue ends human supremacy in chess



Deep Blue had Kasparov in deep thought  
(CNN)

vs.



The cunning Deep Blue (CNN)

I could feel human-level intelligence across the room

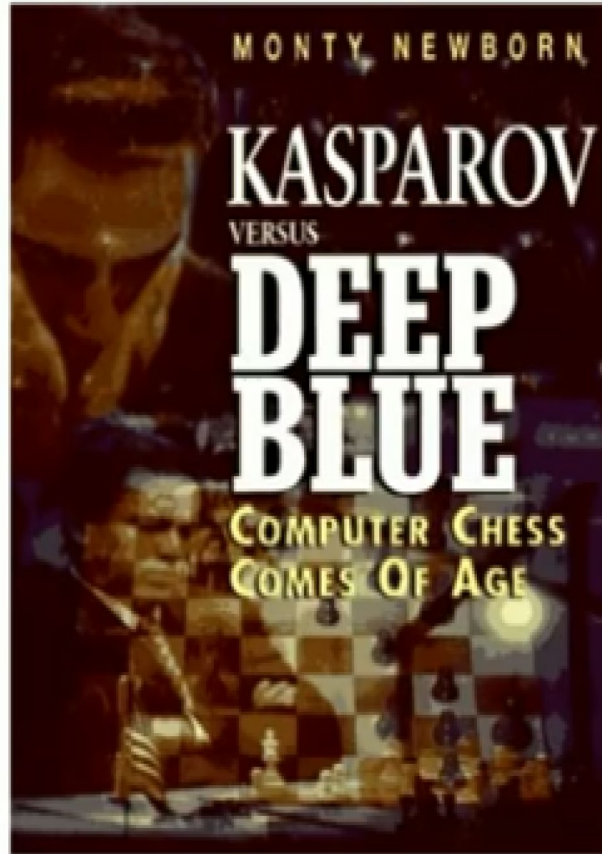
-Gary Kasparov, World Chess Champion (Human)



# *History of AI*

Does Deep Blue  
really think?

If it works, its not AI

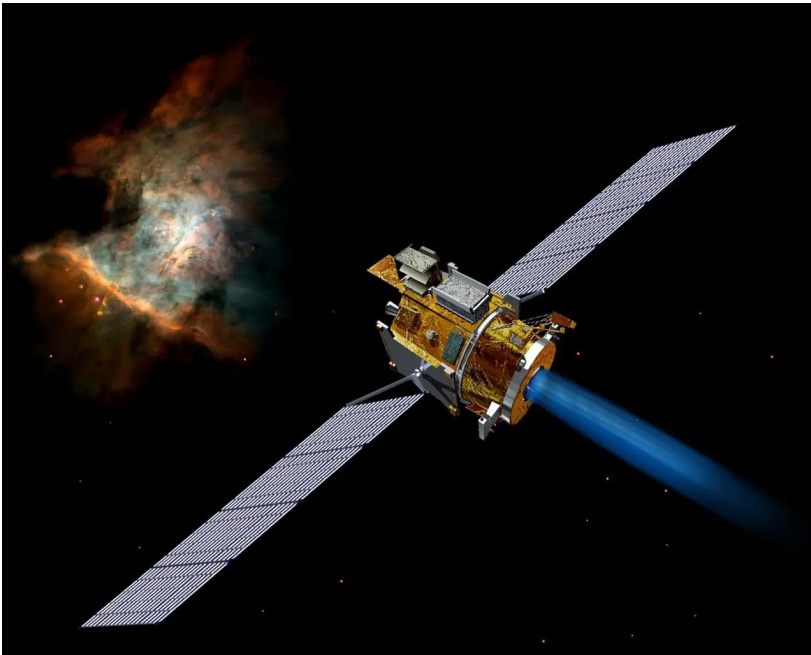


Saying Deep Blue does  
not really thins about  
AI is like saying an  
airplane does not really  
fly because it does not  
flap its wings

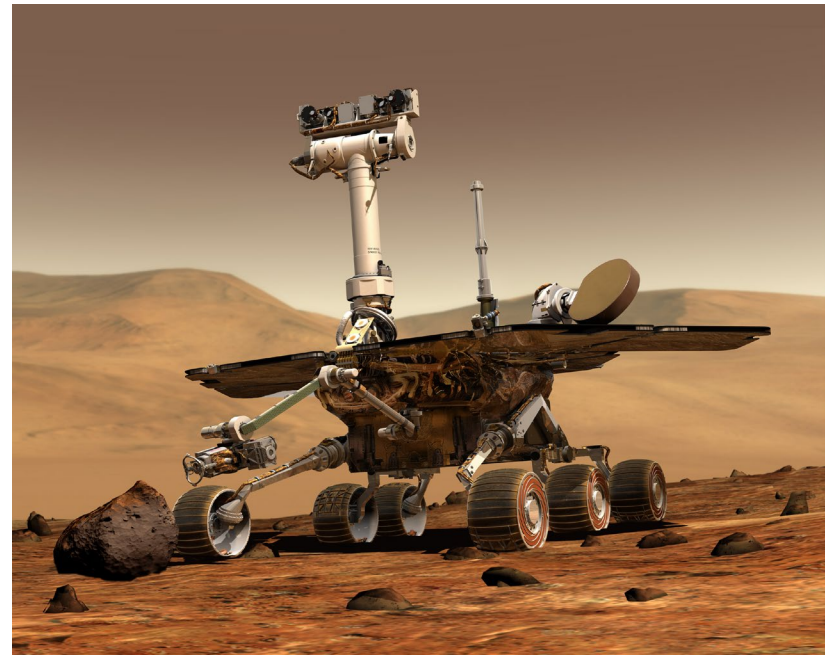
- Drew McDermott

# *History of AI - NASA*

1999: Remote Agent takes Deep Space 1 on a galactic ride



2004 and 2009: Mars Rover





# *History of AI*

2005: Stanley and 3 other cars drive themselves over a 132 miles mountain road



2010: IBM's Watson



# *What is intelligence?*

- Dictionary definition: capacity for learning, reasoning, understanding, and similar form of mental activity
- Ability to perceive and act in the world
- Reasoning: Provide theorems, medical diagnosis
- Planning: Take decisions
- Learning and adaptation: recommendation system,

# *Intelligence vs. human*

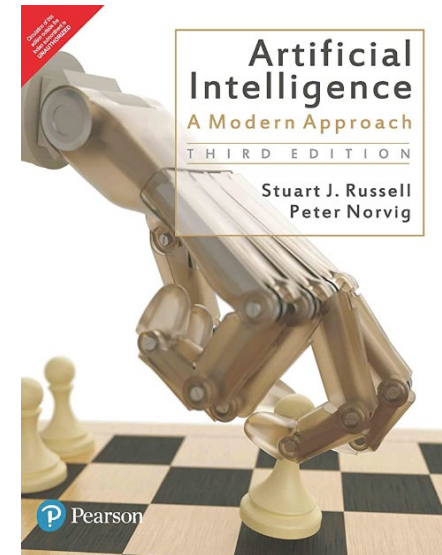
- Are humans intelligent?
  - Replicating humans is the hallmark of intelligence
- Are humans always intelligent?
- Can non-human behavior be intelligent.
- Initial development of AI system in any field is often directed towards making a system behave like human.

# What is AI?

Some early definitions, divided into four classes

	Comparison with human performance	Comparison with ideal performance
Thought processes and reasoning	<b>Thinking Humanly</b> “The exciting new effort to make computers think . . . <i>machines with minds</i> , in the full and literal sense.” (Haugeland, 1985) “[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning . . .” (Bellman, 1978)	<b>Thinking Rationally</b> “The study of mental faculties through the use of computational models.” (Charniak and McDermott, 1985) “The study of the computations that make it possible to perceive, reason, and act.” (Winston, 1992)
	<b>Acting Humanly</b> “The art of creating machines that perform functions that require intelligence when performed by people.” (Kurzweil, 1990) “The study of how to make computers do things at which, at the moment, people are better.” (Rich and Knight, 1991)	<b>Acting Rationally</b> “Computational Intelligence is the study of the design of intelligent agents.” (Poole <i>et al.</i> , 1998) “AI . . . is concerned with intelligent behavior in artifacts.” (Nilsson, 1998)

**Figure 1.1** Some definitions of artificial intelligence, organized into four categories.



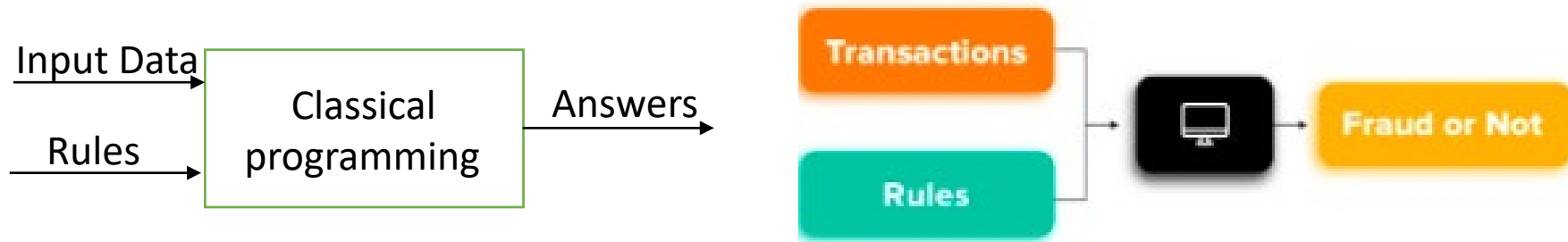
# *Acting → Thinking*

## Weak AI hypothesis vs. Strong AI hypothesis

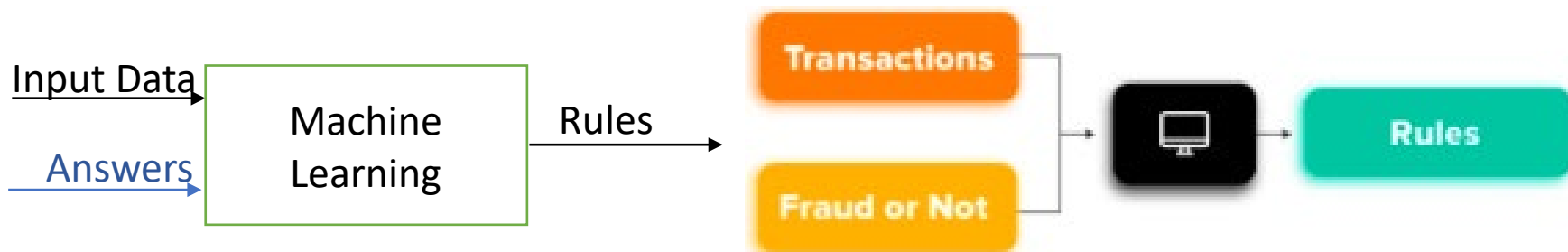
- Weak Hyp: machines could act as if they are intelligent
- Strong Hyp: machines that act intelligent have to think intelligently too

# *Machine learning vs. classical programming?*

- **Classical programming:** Program/code the rules for every task

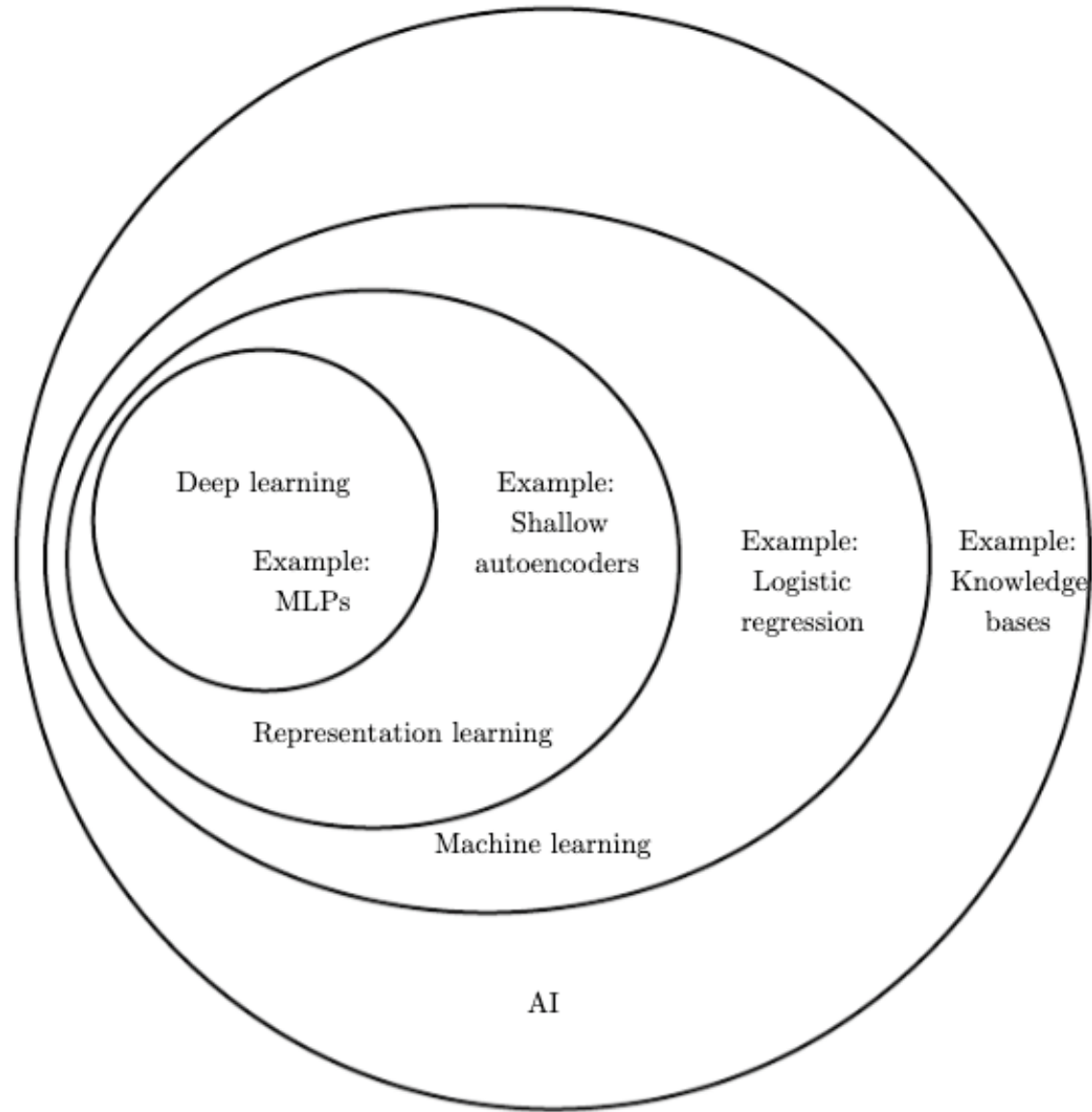


- **Machine learning approach:** an algorithm automatically learn rules from data, or from experience





# *AI vs. ML vs. DL*



# *Different types of ML algorithms*

## **Supervised**

Teacher provides answer



- Labelled data
- Direct feedback
- Predict outcome

- Classification
- Regression

## **Unsupervised**

No teacher, find patterns!

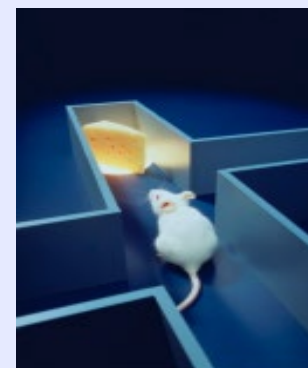


- No labels
- No feedback
- Find hidden structure

- Clustering
- ROM

## **Reinforcement**

Teacher provides rewards



- Decision process
- Rewards
- Learn series of actions

- Gaming
- Control

# Supervised learning

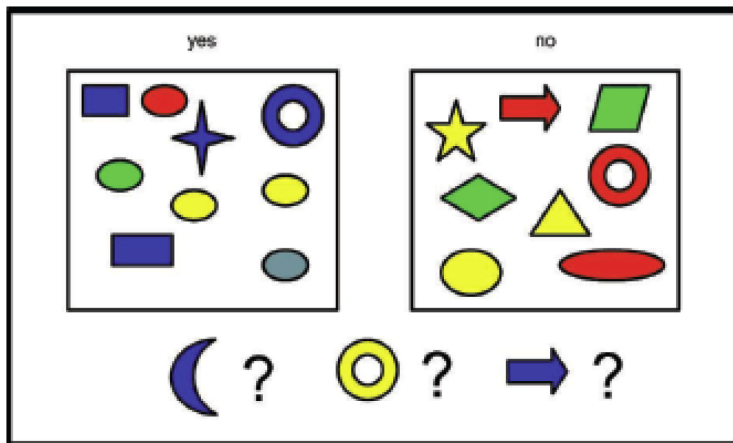
- Machine learning is divided into two types . In the supervised learning approach , the goal is to learn a mapping from inputs  $\mathbf{x}$  to output  $y$ , given a labelled set of data,  $\mathcal{D} = (\mathbf{x}_i, y_i), i = 1, \dots, N$ .
- $\mathcal{D}$  is called the training set and  $N$  is the number of training samples.
- $\mathbf{x}_i$  is a  $D$ -dimensional vector of inputs (e.g., features, attributes or covariates).
- $y_i$  is the output and, in principle, can be anything.
- If  $y_i$  is categorical (discrete values) (e.g., cat vs elephant), then the problem is a classification problem.
- If  $y_i$  is real-valued (continuous values) (e.g., price of a commodity), then the problem is a regression problem.

# *Unsupervised learning*

- In the **unsupervised learning** approach , we have input data,  $\mathcal{D} = (\mathbf{x}_i), i = 1, \dots, N$ , and the objective is to find pattern in the data (**knowledge discovery**).
- We work with un-labelled data; in other words, **we are not told what kind of pattern to look for**.
- This is a more **realistic scenario** (from AI-point of view) and is more challenging.

# Supervised learning - classification

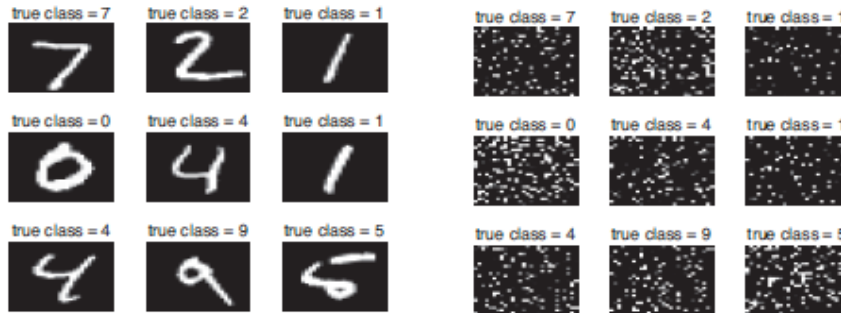
- We learn a mapping from inputs  $\mathbf{x}$  to output  $y$  where
$$y_i \in \{1, 2, \dots, C\}$$
- If  $C = 2$ , it is a **binary classification**.
- If  $C \geq 3$ , it is a **multi-class classification**.
- If class labels are not mutually exclusive (tall and strong), we call it **multi-label classification**.
- The objective is in **generalization**; i.e., given a new  $\mathbf{x}^*$ , find  $y^*$ .
- Left : Training examples of colored shapes, along with 3 unlabeled test cases.
- Right: : Training data as an  $N \times D$  **design matrix**.  $i$  –th row represent the feature vector  $\mathbf{x}_i$ . The last column is the label  $y_i$



D features (attributes)			Label
Color	Shape	Size (cm)	
Blue	Square	10	
Red	Ellipse	2.4	
Red	Ellipse	20.7	0

# Image Classification & Handwriting Recognition

- Consider the problem of classifying images directly with no preprocessing. We want to classify the image as a whole, e.g., is it an indoors or outdoors scene?



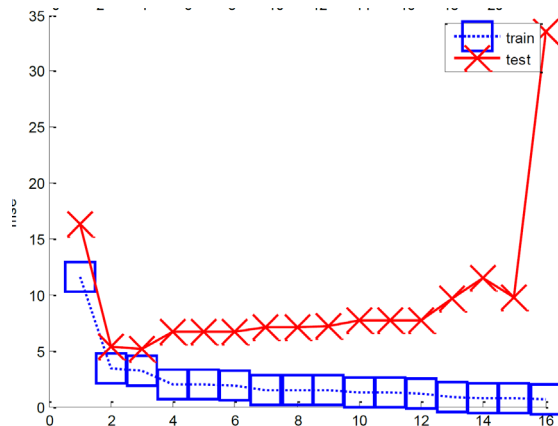
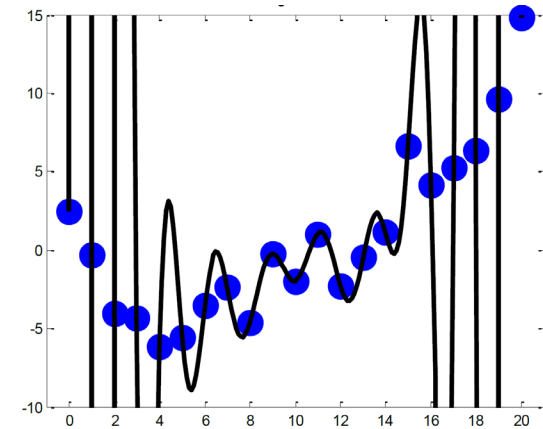
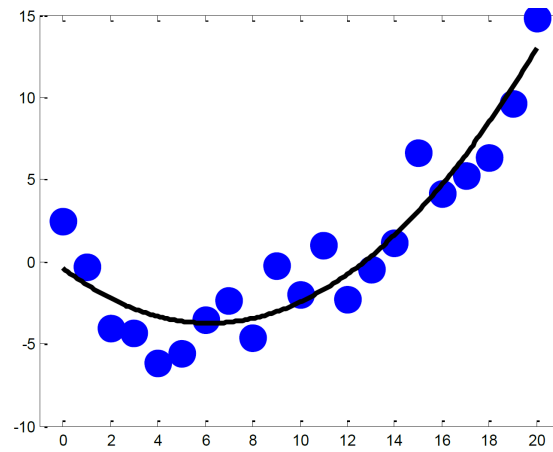
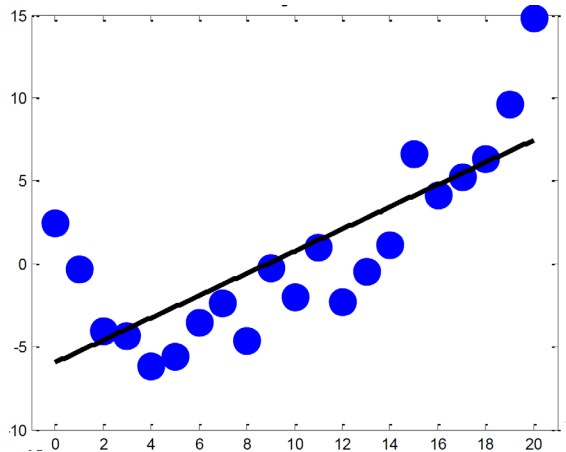
Run shuffledDigitsDemo from [PMTK](#)

- In *handwriting recognition* (dataset [MNIST](#)), the images are size  $28 \times 28$  and have grayscale values in the range 0:255
- Most generic classification methods ignore any structure in the input features including spatial layout.
- They can as easily handle data that looks like on the figure on the right (same data but with randomly permuted order of features).
- General methods are important but ignore useful source of information .



# Supervised Learning: Regression

- Consider a real-valued input  $x_i \in \mathbb{R}$ , and a single real-valued response  $y_i \in \mathbb{R}$ .
- We fit a polynomial of order 1, 2 and 20.



- Many applications with high dimensional input data.
- Issues of model selection are essential (overfitting, etc.)

linRegPolyVsDegree from [PMTK](#)

# Unsupervised Vs. Supervised Learning

- There are two differences from the supervised case.
  - Supervised learning is **conditional density estimation**,  $p(y_i|\mathbf{x}; \boldsymbol{\theta})$ 
    - $y_i$  is usually a single variable (class label) we are trying to predict. Thus, for most supervised learning problems, we can use univariate probability models.
  - Unsupervised learning is **unconditional density estimation**,  $p(\mathbf{x}_i|\boldsymbol{\theta})$ 
    - $\mathbf{x}_i$  are vectors of features and hence we need to create multivariate probability distribution.
- Cheeseman, P., J. Kelly, M. Self, J. Stutz, W. Taylor, and D. Freeman (1988). [Autoclass: A Bayesian classification system](#). In *Proc. of the Fifth Intl. Workshop on Machine Learning*.
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