

# Introduction to Machine Learning

## CSE474/574: Lecture 2

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# Outline

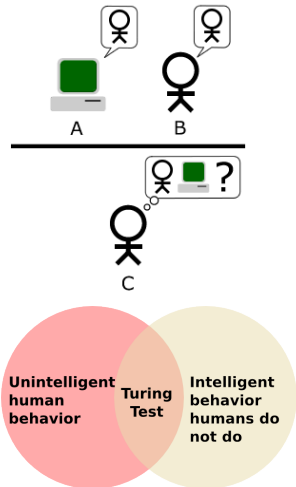
- 1 Turing's Test
- 2 Machine Intelligence
- 3 Definition of Machine Learning
  - Why Machine Learning?
  - Running Example
- 4 Concept Learning
  - Example – Finding Malignant Tumors
  - Notation
  - Representing a Possible Concept - Hypothesis
  - Hypothesis Space

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# Turing's Test [1]

- Can machines think?
- Simple version - Can machines imitate humans?
- E.g., ELIZA
  - <http://www.manifestation.com/neurotoys/eliza.php3>
- Difference between “human behavior” and “intelligent behavior”.



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# What makes a machine **intelligent**?

- ① Talk. See. Hear.
  - Natural Language Processing, Computer Vision, Speech Recognition
- ② Store. Access. Represent. (*Knowledge*)
  - Ontologies. Semantic Networks. Information Retrieval.
- ③ Reason.
  - Mathematical Logic. Bayesian Inference.
- ④ **Learn.**
  - Improve with Experience
    - Machine Learning

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# What is Machine Learning?

- Computers learn without being **explicitly programmed**.
  - Arthur Samuel (1959)
- A computer program learns from experience  $E$  with respect to some task  $T$ , if its performance  $P$  while performing task  $T$  improves over  $E$ .
  - Tom Mitchell (1989)

# Why Machine Learning?

- Machines that know everything from the beginning?
  - Too bulky. Creator already knows everything. Fails with *new* experiences.
- Machines that *learn*?
  - Compact. Learn what is *necessary*.
  - Adapt.
  - Assumption: Future experiences are not too different from past experiences.
    - Have (structural) relationship.



# Running Example - A Robotic Furniture Sorter

- Our future overlords (Kiva)
  - <https://youtube.googleapis.com/v/6KRjuuEVEZs>

# Make Kiva Learn

- Distinguish between **tables** and **chairs**.
- How do you represent the input?
- Distinguishing features.
  - *has back rest?*
- Good features should be:
  - Computable. Distinguishing. Representative.
  - *is a chair?*
  - *has four legs?*
  - *is white?*

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# Concept Learning

- Infer a boolean-valued function  $c : x \rightarrow \{\text{true}, \text{false}\}$
- *Input*: Attributes for input  $x$
- *Output*: true if input belongs to concept, else false
- Go from specific to general (*Inductive Learning*).

# Finding Malignant Tumors from MRI Scans

## Attributes

- 1 **Shape** circular, oval
- 2 **Size** large, small
- 3 **Color** light, dark
- 4 **Surface** smooth, irregular
- 5 **Thickness** thin, thick

## Concept

Malignant tumor.



# Notation

- $X$  - Set of all possible instances.
  - What is  $|X|$ ?
- Example: {circular, small, dark, smooth, thin}
- $D$  - Training data set.
  - $D = \{\langle x, c(x) \rangle : x \in X, c(x) \in \{0, 1\}\}$
- Typically,  $|D| \ll |X|$



# Representing a Concept - Hypothesis

- A conjunction over a subset of attributes
  - A malignant tumor is: *circular* **and** *dark* **and** *thick*
  - {circular,?,dark,?,thick}
- Target concept  $c$  is unknown
  - Value of  $c$  over the training examples is known

# Approximating Target Concept Through Hypothesis

- **Hypothesis:** a potential concept
- Example: {circular,?, ?, ?, ?}
- **Hypothesis Space ( $\mathcal{H}$ ):** Set of *all hypotheses*
  - What is  $|\mathcal{H}|$ ?
- Special hypotheses:
  - Accept *everything*, {?, ?, ?, ?, ?}
  - Accept *nothing*, { $\emptyset$ ,  $\emptyset$ ,  $\emptyset$ ,  $\emptyset$ ,  $\emptyset$ }

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# References



A. M. Turing.

Computing machinery and intelligence.

*Mind*, 59:433–460, 1950.