CSDS 440: Machine Learning

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Office hours T 11:15-11:45/2:15-2:45 or by appointment

Announcements

- Groups

Today

- Intro to machine Learning

What is “machine learning”?

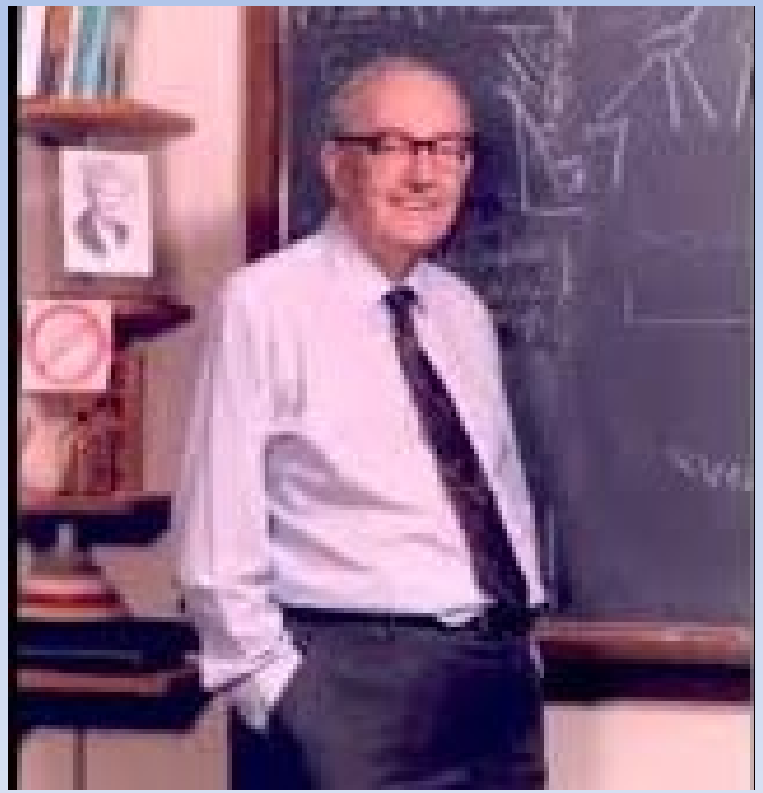
- “Machine”=autonomous system
  - No (or limited) human intervention
  - Robots, software agents, etc.

What is “Learning”?

“Learning denotes changes in the system that enable the system to do the same task more effectively the next time.”

—Herbert Simon (1916-2001)

- Also, how to do *related* tasks more effectively



A Specification for a Learning System

- Given: Learning task goal, task examples *E,* performance measure *P*

- Do: Produce a concept that is good with respect to *P* on *all* examples of the task
  - Measured by proxy on *E*

Example

- Learning Task: Learn to play chess
- Performance measure?
  - Games won/lost
- Examples?
  - Games played (sequences of moves till win/loss)
- Concept?
  - Some function mapping current state of game to suitable moves to play

Idea

- If the learning system plays/sees enough games,
- And it produces a mapping from game state to moves (concept),
- And this concept does well with respect to the measure of “number of games won”,
- Then the system has “learned to play chess”

Other Examples

- Learn to recognize lions
  - *E*: animals, annotated “lion” or “not-lion”
  - *P*: fraction of animals correctly recognized as lion/not-lion
- Learn to drive
  - *E*: sequence of road/traffic conditions and correct vehicle operation
  - *P*: distance traveled without accident

Two Phases of Learning

- "Learning" or "Training" phase
  - Reason about the examples *E*
  - Formulate a concept that does well w.r.t. *P* on *E*
  - Could also use any prior knowledge

- "Evaluation" or "Testing" phase
  - Use learned concept on future, novel examples

Online and Batch (Offline) Learning

- Batch/Offline Learning: one learning phase, with a large set of examples, followed by a testing phase

- Online learning: Examples arrive one at a time (or in small groups); learning and evaluation phases are iterated

Inductive Generalization

- In all learning problems, need to reason from specific examples to a general case
  - Memorization ≠ Learning

- Other kinds of reasoning
  - deduction (general to specific)
  - abduction (most likely cause)

Target Concept

- The unknown underlying concept that solves the learning task
  - E.g., “has-fur” and “long-teeth” and “looks-scary” $\rightarrow$ “lion”

- Typically, *P* will be a measure of difference between the learner’s concept and the target concept, with respect to *E*

Hypothesis Space

- Defines the space of general concepts the learning system will consider
  - E.g., all possible conjunctions of animal properties
  - “has-fur” and “long-teeth” and “looks-scary”, “has-fur” and “long-teeth” and NOT-“looks-scary” , “has-fur” and NOT-“long-teeth” and “looks-scary” ….
- Ideally, target concept is a member of this space
  - What if it isn’t?
    - Maybe we should include *all possible* hypotheses?

No “Tabula Rasa” Learning

- A space that includes all possible hypotheses also
  - Contains many overly complex concepts
  - Contains the concept that memorizes *E*
    - Indistinguishable from target by any *P* (w.r.t. *E*)
  - *May be* too big to search feasibly

- For effective inductive generalization
  - **Must** restrict hypothesis space
  - while still (hopefully) keeping the target concept in it

Inductive Bias

- The set of assumptions used by a learning system to restrict its hypothesis space
- The more assumptions made, the “stronger” the bias
- Can quantify this (later)

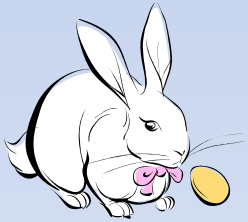
Supervised Learning

- Examples *E* are annotated with target concept's output by a teacher/oracle
- Learning system must find a concept that matches annotations (*P*)
- Example: learn to recognize animals

Supervised Learning

tiger

cow



elephant

starfish

Note: Annotation received by learner does not need to be correct!!

Other Learning Paradigms

- Unsupervised Learning
- Semi-supervised Learning
- Active Learning
- Transductive Learning
- Transfer Learning
- Structured Prediction
- Reinforcement Learning
- Preference Learning (Ranking)
- “Few-shot” learning

Example Representation

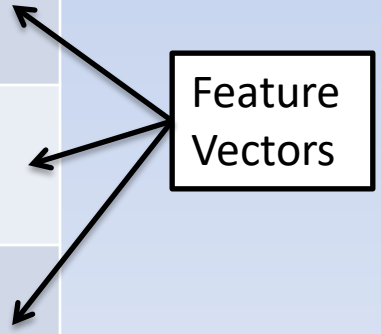
- What is the *internal representation* of an example in a learning system?

- Representation choice affects reasoning and the choice of hypothesis space, and the cost of learning

Feature Vector Representation

- Examples are attribute-value pairs (note "feature"=="attribute")
- Number of attributes are fixed
- Can be written as an n-by-m matrix

	Attribute$_1$	**Attribute$_2$**	**Attribute$_3$**
Example$_1$	Value$_{11}$	Value$_{12}$	Value$_{13}$
Example$_2$	Value$_{21}$	Value$_{22}$	Value$_{23}$
Example$_3$	Value$_{31}$	Value$_{32}$	Value$_{33}$



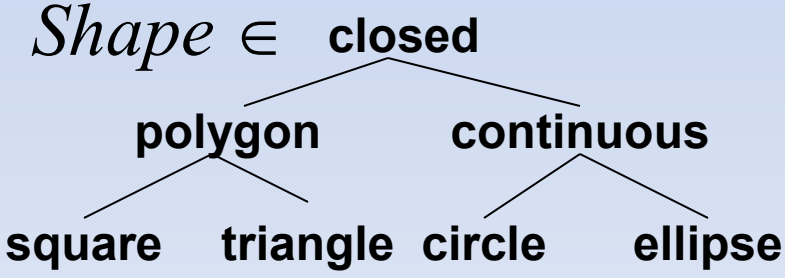
Example

	Has-fur?	Long-Teeth?	Scary?
$Animal_1$	Yes	No	No
$Animal_2$	No	Yes	Yes
$Animal_3$	Yes	Yes	Yes

Types of Features

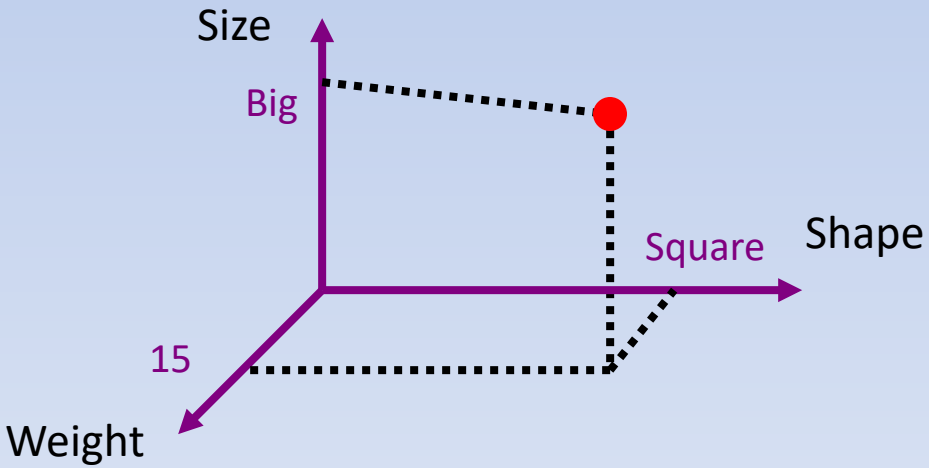
- Discrete, Nominal
- Continuous
- Discrete, Ordered
- Hierarchical

- *Color ∈ (red, blue, green)*
- *Height*
- *Size ∈ (small, medium, large)*
- *Shape ∈*



Feature Space

- We can think of examples embedded in an n dimensional vector space



Other Example Representations

- Relational representation
- Multiple-instance representation
- Sequential representation
- Multi-view representation

The Binary Classification Problem

- Simplest supervised learning problem

- Target concept assigns one of two labels ("*positive*" or "*negative*") to all examples---the class label

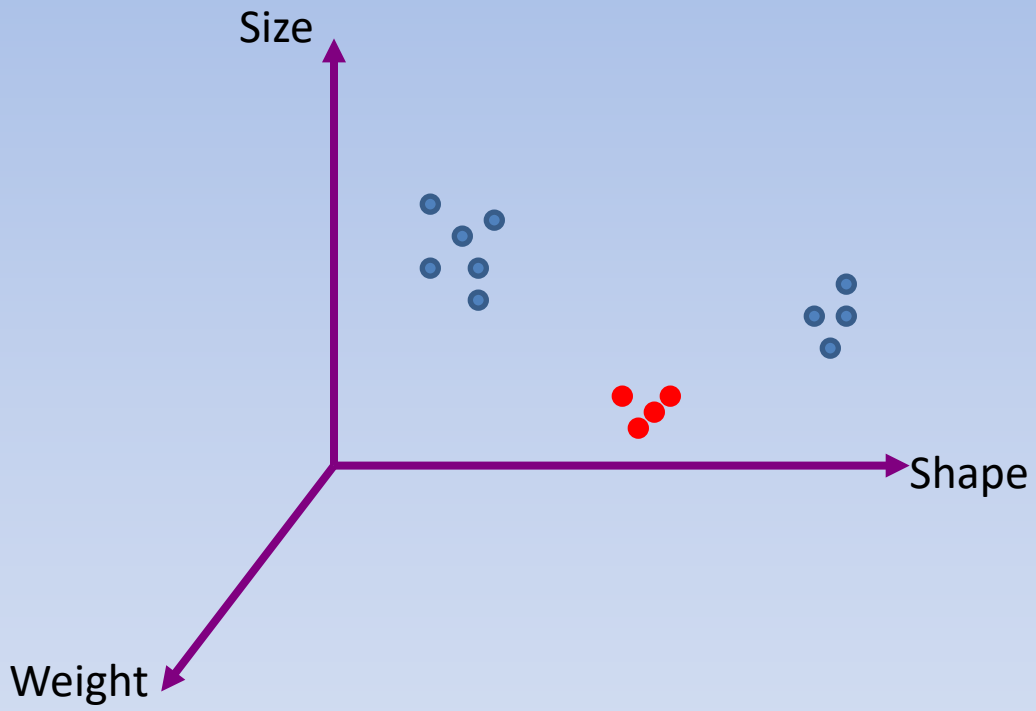
- Can extend to "multiclass", "regression", "multi-label" problems

Example

	X			Y
	Has-fur?	**Long-Teeth?**	**Scary?**	***Lion?***
Animal$_1$	Yes	No (x_{ij})	No	No
Animal$_2$	No	Yes	Yes	No
Animal$_3$	Yes	Yes	Yes	Yes

(x_i, y_i)

Example in Feature Space



The Learning Problem

- Given: A binary classification problem

- Do: Produce a "classifier" (concept) that assigns a label to a new example

Binary Classifier Concept Geometry

- (Union of) N-dimensional volume(s) in feature space (possibly a disjoint collection)