Introduction to Data Science

Decision Trees

Arijit Mondal

Dept. of Computer Science & Engineering

Indian Institute of Technology Patna

arijit@iitp.ac.in

Learning

- An agent is learning if it improves its performance on future tasks after making observation about the world
- Why would an agent learn?
  - Designers cannot anticipate all possible situations
  - Designers cannot anticipate all changes over time
  - Sometime, people have no idea how to program a solution
- Inductive learning - Learning a general function or rule from specific input-output pairs
- Analytical / deductive learning - Going from a known general rule to a new rule that is logically entailed

Paradigms of learning

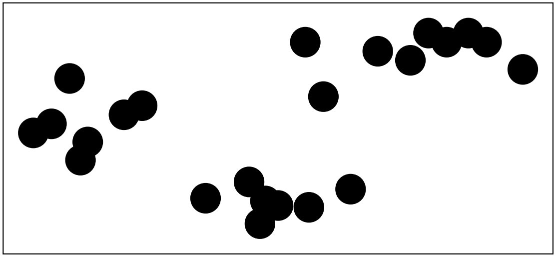
- These are based on the types of feedback
- Supervised learning
  - Both inputs and outputs are given
  - The outputs are typically provided by a friendly teacher
- Reinforcement learning
  - The agent receives some evaluation of its actions (such as a fine for stealing bananas), but is not told the correct action (such as how to buy bananas)
- Unsupervised learning
  - The agent can learn relationships among its percepts, and the trend with time

Supervised learning

- A set of labeled examples $\langle x_1, x_2, \ldots, x_n, y \rangle$
  - x_i are input variables
  - y output variable
- Need to find a function $f: X_1 \times X_2 \times \ldots X_n \to Y$
- Goal is to minimize error/loss function
  - Like to minimize over all dataset
  - We have limited dataset

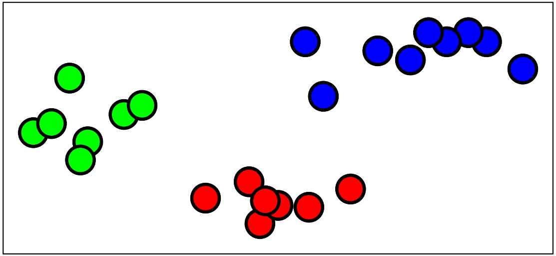
Unsupervised learning

- Learns useful properties of the structure of data set
- Unlabeled data
  - Tries to learn entire probability distribution that generated the dataset
  - Examples
    - Clustering, dimensionality reduction



Unsupervised learning

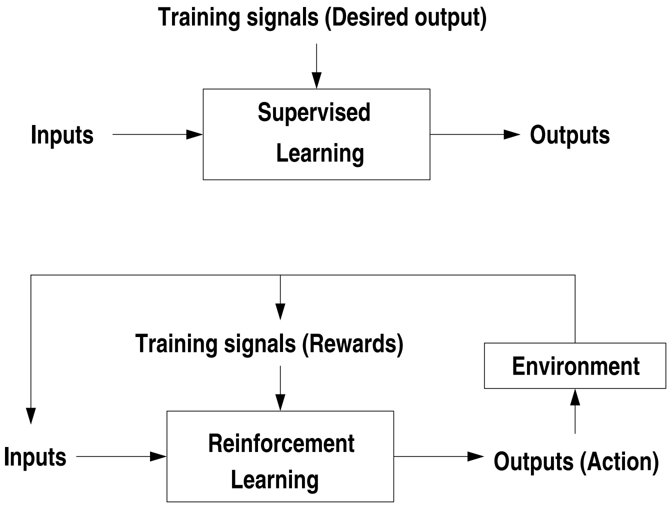
- Learns useful properties of the structure of data set
- Unlabeled data
  - Tries to learn entire probability distribution that generated the dataset
  - Examples
    - Clustering, dimensionality reduction



Reinforcement learning

- Set of actions that the learner will make in order to maximize its profit
- Action may not only affect the next situation but also subsequent situation
  - Trial and error search
  - Delayed reward
- A learning agent is interacting with environment to achieve a goal
- Agent needs to have idea of state so that it can take right action
- Three key aspects – **observation, action, goal**

Reinforcement vs supervised learning



Decision trees

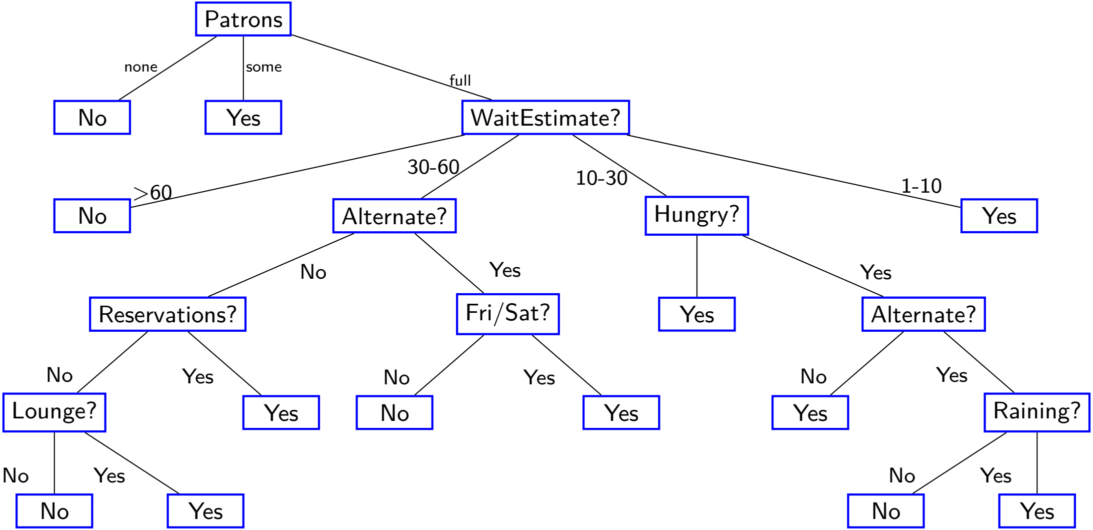
- A decision tree takes as input an object or situation described by a set of properties, and outputs a yes/no "decision"
- A list of variables which potentially affect the decision on whether to wait for a table at a restaurant.
  - Alternate: whether there is a suitable alternative restaurant
  - Lounge: whether the restaurant has a lounge for waiting customers
  - Fri/Sat: true on Fridays and Saturdays
  - Hungry: whether we are hungry
  - Patrons: how many people are in it (None, Some, Full)
  - Price: the restaurant's rating (*, **, ***)
  - Raining: whether it is raining outside
  - Reservation: whether we made a reservation
  - Type: the kind of restaurant (Indian, Chinese, Thai, Fastfood)
  - WaitEstimate: 0-10 mins, 10-30, 30-60, $>$60.

Observations

Example	Input Attributes										Goal
	Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*	*WillWait*
$\mathbf{x}_1$	*Yes*	*No*	*No*	*Yes*	*Some*	*$$$*	*No*	*Yes*	*French*	*0–10*	$_1$ = *Yes*
$\mathbf{x}_2$	*Yes*	*No*	*No*	*Yes*	*Full*	*$*	*No*	*No*	*Thai*	*30–60*	$_2$ = *No*
$\mathbf{x}_3$	*No*	*Yes*	*No*	*No*	*Some*	*$*	*No*	*No*	*Burger*	*0–10*	$_3$ = *Yes*
$\mathbf{x}_4$	*Yes*	*No*	*Yes*	*Yes*	*Full*	*$*	*Yes*	*No*	*Thai*	*10–30*	$_4$ = *Yes*
$\mathbf{x}_5$	*Yes*	*No*	*Yes*	*No*	*Full*	*$$$*	*No*	*Yes*	*French*	*>60*	$_5$ = *No*
$\mathbf{x}_6$	*No*	*Yes*	*No*	*Yes*	*Some*	*$$*	*Yes*	*Yes*	*Italian*	*0–10*	$_6$ = *Yes*
$\mathbf{x}_7$	*No*	*Yes*	*No*	*No*	*None*	*$*	*Yes*	*No*	*Burger*	*0–10*	$_7$ = *No*
$\mathbf{x}_8$	*No*	*No*	*No*	*Yes*	*Some*	*$$*	*Yes*	*Yes*	*Thai*	*0–10*	$_8$ = *Yes*
$\mathbf{x}_9$	*No*	*Yes*	*Yes*	*No*	*Full*	*$*	*Yes*	*No*	*Burger*	*>60*	$_9$ = *No*
$\mathbf{x}_{10}$	*Yes*	*Yes*	*Yes*	*Yes*	*Full*	*$$$*	*No*	*Yes*	*Italian*	*10–30*	$_{10}$ = *No*
$\mathbf{x}_{11}$	*No*	*No*	*No*	*No*	*None*	*$*	*No*	*No*	*Thai*	*0–10*	$_{11}$ = *No*
$\mathbf{x}_{12}$	*Yes*	*Yes*	*Yes*	*Yes*	*Full*	*$*	*No*	*No*	*Burger*	*30–60*	$_{12}$ = *Yes*

Image source: AI by Russel & Norvig

Sample decision tree



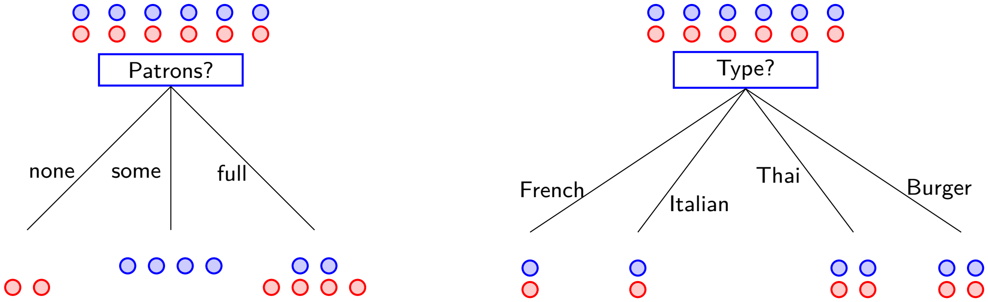
Decision Tree Learning

- Aim: find a small tree consistent with the training examples
- Idea: (recursively) choose "most significant" attribute as root of (sub) tree

1. pick an attribute to split at a non-terminal node
2. split examples into groups based on attribute value
3. for each group:
   A. if no examples - return majority from parent
   B. else if all examples in same class - return class
   C. else loop to step 1

Choosing an attribute

Idea: A good attribute splits the examples into subsets that are (ideally) "all positive" or "all negative"



Attribute selection

- Information content (Entropy): $I(P(v_1),\ldots,P(v_n)) = \sum_{j=1}^{n} -P(v_j)\log_2 P(v_j)$
- For a training set containing p positive examples and n negative examples:

$$I\left(\frac{p}{p+n},\frac{n}{p+n}\right) = -\frac{p}{p+n}\log_2\frac{p}{p+n} - \frac{n}{p+n}\log_2\frac{n}{p+n}$$

- A chosen attribute A divides the training set E into subsets $E_1,\ldots,E_v$ according to their values for A_i where A has v distinct values

$$\text{remainder}(A) = \sum_{i=1}^{v}\frac{p_i+n_i}{p+n} I\left(\frac{p_i}{p_i+n_i},\frac{n_i}{p_i+n_i}\right)$$

- Information gain (IG) or reduction in entropy $IG(A) = I\left(\frac{p}{p+n},\frac{n}{p+n}\right) - \text{remainder}(A)$
- Choose the attribute with the largest IG

Information gain: example

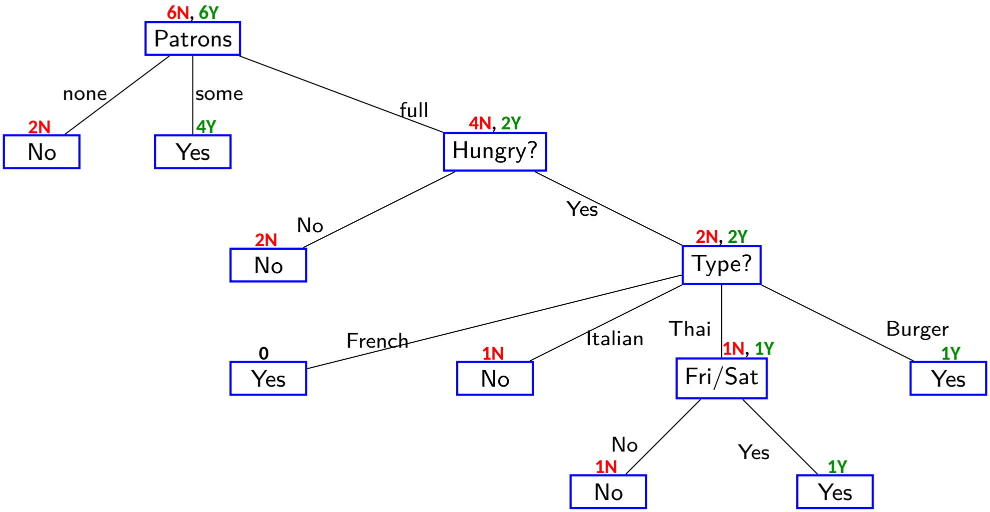
- For the training set $p = n = 6$, $I(\frac{6}{12}, \frac{6}{12}) = 1$ bit

  $IG(Patrons) = 1 - [\frac{2}{12}I(0,1) + \frac{4}{12}I(1,0) + \frac{6}{12}I(\frac{2}{6}, \frac{4}{6})] = 0.0541$

  $IG(Type) = 1 - [\frac{2}{12}I(\frac{1}{2}, \frac{1}{2}) + \frac{2}{12}I(\frac{1}{2}, \frac{1}{2}) + \frac{4}{12}I(\frac{2}{4}, \frac{2}{4}) + \frac{4}{12}I(\frac{2}{4}, \frac{2}{4})] = 0$

- Patrons will be selected

Final decision tree



A good tree

- Not too small: need to handle important but possibly subtle distinctions in data
- Not too big:
  - Computational efficiency (avoid redundant, spurious attributes)
  - Avoid over-fitting training examples