

29.10.19

Concept learning:

The problem of searching through a predefined space of potential hypotheses for the hypothesis that best fits the training examples.

Example:

If some instance x satisfies all the constraints of hypothesis h , then h classifies x as a positive example, $h(x) = 1$. If the hypothesis that Aldo enjoys his favorite sport only on cold days with high humidity is presented by the expression

$$(?, \text{cold}, \text{High}, ?, ?, ?)$$

The most general hypothesis, that every day is a positive example, is presented by $(?, ?, ?, ?, ?, ?)$

And the most specific possible hypothesis that no day is positive example is represented by ($\emptyset, \emptyset, \emptyset, \emptyset, \emptyset, \emptyset$)

Indicate by a "?" that any value is acceptable or for this attribute.

Indicate by a "∅" that no value is acceptable.

Sky	Air Temp	Humid	Wind	Water	Forecast
?	Cold	High	?	?	?

The set of items over which the concept is defined is called the set of instances, which is denoted by "X".

X in this case is the set of all possible buys represented by the attributes - Sky, AirTemp, Humidity, Wind, Water and forecast.

The concept or function to be learned is called the target concept, is denoted by "c".

It can be seen as a boolean valued function defined over "X"

$$c: X \rightarrow \{0, 1\}$$

The target concept corresponds to the value of the attribute EnjoySport

$$c(x) = 1$$

if EnjoySport = Yes

$$c(x) = 0$$

if EnjoySport = No

H is be used to denote the set of all possible hypothesis that the learner may consider regarding the identity of the target concept.

The goal of a learner is to find a hypothesis h which can

identify all objects in X .

$$h(n) = c(n) \quad \text{for all } n \in X$$

The symbol D use to denote the set of available training examples.

Prototypical concept learning task:

Given:

Instance X : Possible days, each describe by the attributes sky, AirTemp, Humidity, Wind, Water, forecast.

Target concept
EnjoySport : $X \rightarrow \{0, 1\}$

Hypotheses H :

Each hypothesis is described by a conjunction of the attributes given before. The constraints may be "?" or a specific value.

$$n \rightarrow ?, \text{cold}, \text{High}, ?, ?, ?, ?$$

→ Training examples D : positive and negative examples of the target function.

Determine:

A hypothesis h in H with
$$h(n) = c(n) \text{ for all } n \in X$$

General to specific ordering of hypothesis:

Many machine learning algorithms rely on the concept of General-to-Specific ordering of hypothesis.

$$h_1 = (\text{true}, \text{true}, ?, ?, ?, ?)$$

$$h_2 = (\text{true}, ?, ?, ?, ?, ?)$$

Any instance classified by h_1 will also be classified by h_2 . So we can say that h_2 is more general than h_1 .

Consider the given attributes
 $h_1 = (\text{sunny}, ?, ?, \text{strong}, ?, ?)$
 $h_2 = (\text{sunny}, ?, ?, ?, ?, ?, ?)$

using this concept we can find a general hypothesis that can be defined over entire data set X .

Find-S

To find out a single hypothesis defined on X we can use the concept of more-general-than partial ordering. It finds the most specific hypothesis and it considers only the positive example. And it will eliminate all the negative examples.

Find-S algorithm's limitations can be removed by candidate elimination algorithm.

Find-s Algorithm:

1. Initialize h to the most specific hypothesis in H .

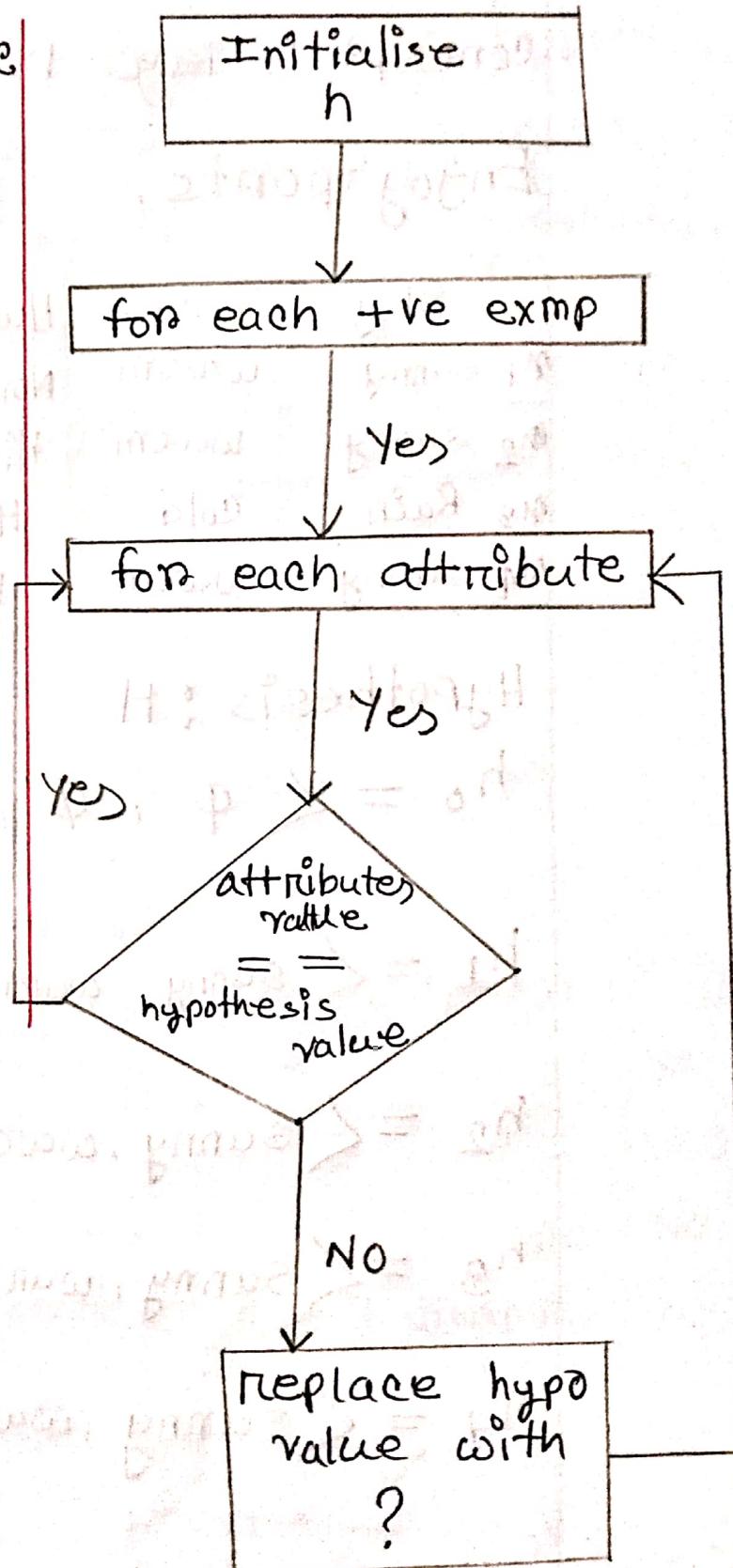
2. For each positive instance x ,

— For each attribute a_i in h
* if the constraint a_i in h is satisfied by x ,

* Then do nothing

* Else replace that by "?"

3. Output hypothesis h .



④ Hypothesis space search by Find-s

Dataset :

concept — ~~Reg~~: Days on which Person Enjoy Sports.

	Sky	Temp.	Humidity	Wind	water	forecast	Enjoy
m ₁	sunny	warm	Normal	strong	warm	same	Yes
m ₂	sunny	warm	High	strong	warm	same	Yes
m ₃	Rain	cold	High	strong	warm	Change	No
m ₄	Sunny	warm	High	strong	cool	Change	Yes

Hypothesis : H

$$h_0 = \langle \phi, \phi, \phi, \phi, \phi, \phi \rangle$$

$$h_1 = \langle \text{sunny, warm, normal, strong, warm, same} \rangle$$

$$h_2 = \langle \text{sunny, warm, ?, ?, strong, warm, same} \rangle$$

$$h_3 = \langle \text{sunny, warm, ?, strong, warm, same} \rangle$$

$$h_4 = \langle \text{sunny, warm, ?, strong, ?, ?, ?} \rangle$$

So this is the hypothesis depends on the dataset.

Version Space

The candidate elimination algorithm represents the set of all hypothesis consistent with the training examples.

The subset of all hypothesis is called the version space with respect to the hypothesis space H , and the training examples D , denoted by $VS_{H,D}$.

Example of Version Space:

Sky	Temp	Humid	Wind	Water	Forecast	Enjoy Spt
Sunny	warm	Normal	strong	warm	same	yes
Sunny	warm	High	strong	warm	same	yes
Rainy	cold	High	strong	warm	change	No
Sunny	warm	High	strong	cool	change	yes

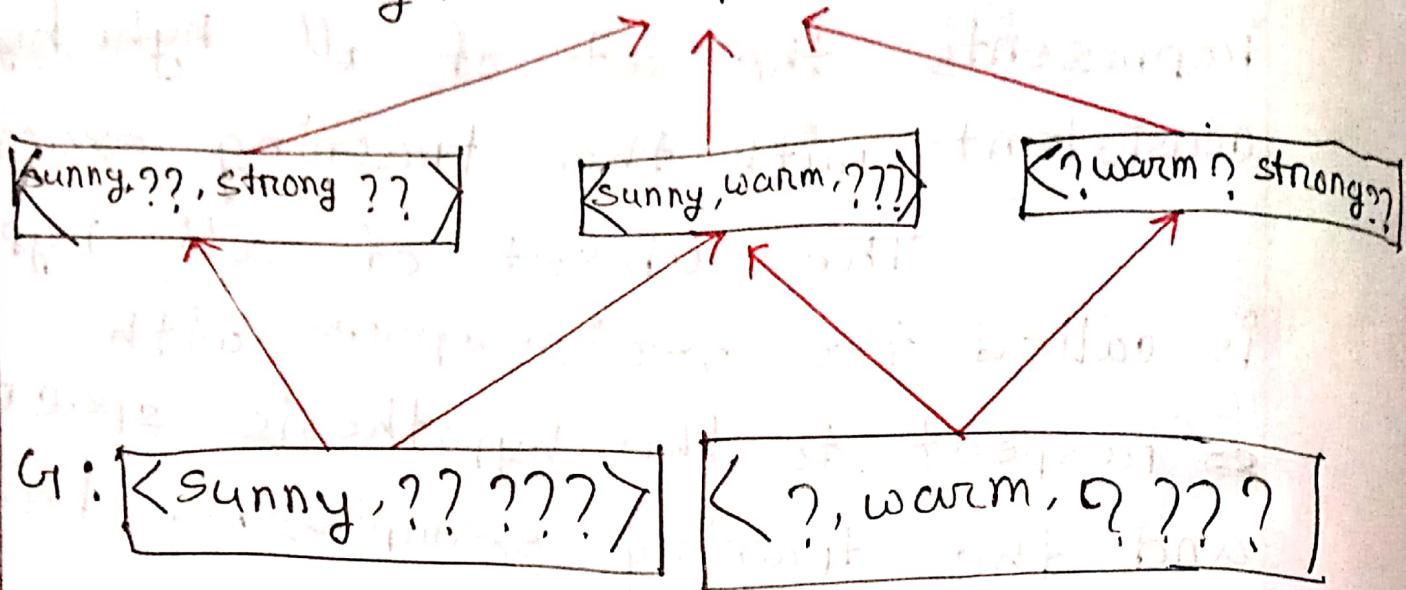
① $s: \langle \text{sunny}, \text{warm}, ?, ?, \text{strong}, ?, ?, ? \rangle$

$\langle \text{sunny}, ?, ?, \text{strong} ? ? \rangle$ $\langle \text{sunny}, \text{warm}, ?, ?, ?, ? \rangle$ $\langle ?, \text{warm}, ?, ?, \text{strong}, ?, ? \rangle$

$g: \langle \text{sunny} ?, ?, ?, ?, ?, ?, ? \rangle, \langle ?, \text{warm}, ?, ?, ?, ?, ? \rangle$

Step 2:

$S: \langle \text{sunny}, \text{warm}, ?, \text{strong} ?, ?, ? \rangle$



General boundary: General boundary "G" of version space V_{SHD} , is the set of its maximally general members that are consistent with the given training set.

Specific boundary: Specific boundary "S" of version space V_{SHD} , is the set of its maximally specific members that are consistent with the given training set.

Every member of the inversion space lies between these boundaries.

• Candidate Elimination Alg.

The candidate Elimination algo is used for remove the limitations of Find-s algo.

Example trace:

Sky	Temp	Humidity	Wind	water	forecast	Enjoy
Sunny	warm	Normal	strong	warm	same	+ve
Sunny	warm	High	strong	warm	same	+ve
Rain	cold	High	strong	warm	change	-ve
Sunny	warm	High	strong	cool	change	+ve

step 1:

$$S_0: \langle \emptyset, \emptyset, \emptyset, \emptyset, \emptyset, \emptyset \rangle$$

$$G_0: \langle ?, ?, ?, ?, ?, ? \rangle$$

step 2:

$$S_1: \langle \text{sunny}, \text{warm}, \text{Normal}, \text{strong}, \text{warm}, \text{same} \rangle$$

~~Do do~~

$$G_1: \langle ?, ?, ?, ?, ?, ? \rangle$$

Training example:

n₁ -

$$\langle \text{sunny}, \text{warm}, \text{Normal}, \text{strong}, \text{warm}, \text{same} \rangle$$

ye)

Step 3:

S1: < sunny, warm, normal, strong, warm, same >



S2: < sunny, warm, ?, strong, warm, same >

G2: < ? ? ? ? ? ? >

G2: < ? ? ? ? ? ? >

~~Step 4~~

Training example: < ? ? ? ? ? ? > : yes.

x2: < sunny, warm, High, strong, warm, same, > yes.

Step 4:

S₂: < sunny warm ? strong warm same >
↓ ↓ ↓

S₃: < sunny warm ? strong warm same >

G₃: {sunny?????} <? warm????> <????? same>

G₂: < ? ? ? ? ? >

Training example:

n₃: < Rainy cold High strong warm change >

No

DEAD

DEAD</

Step 5 :

S3: <sunny warm & strong warm same>

1

11

S4: < sunny? warm? strong? ? >

2

10

~~1999 brother band > 1999 after 99 page~~

G12: {<sunny ? ? ? ? ?> <? warm ? ? ? ? ?>}

1

1

43 : {<sunny?????><?warm?????><????? same>}

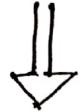
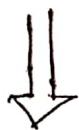
Training example:

m_4 : <sunny warm High strong cool, change>

yes

Step 5: resulting version space

S: < sunny ? warm ? strong ? ? >



< sunny ?? warm ??? > < sunny ?? strong ?? >

< ? warm ? strong ? >



G: < sunny ?????? > < ? warm????? >

Limitations of Find-s Alg:

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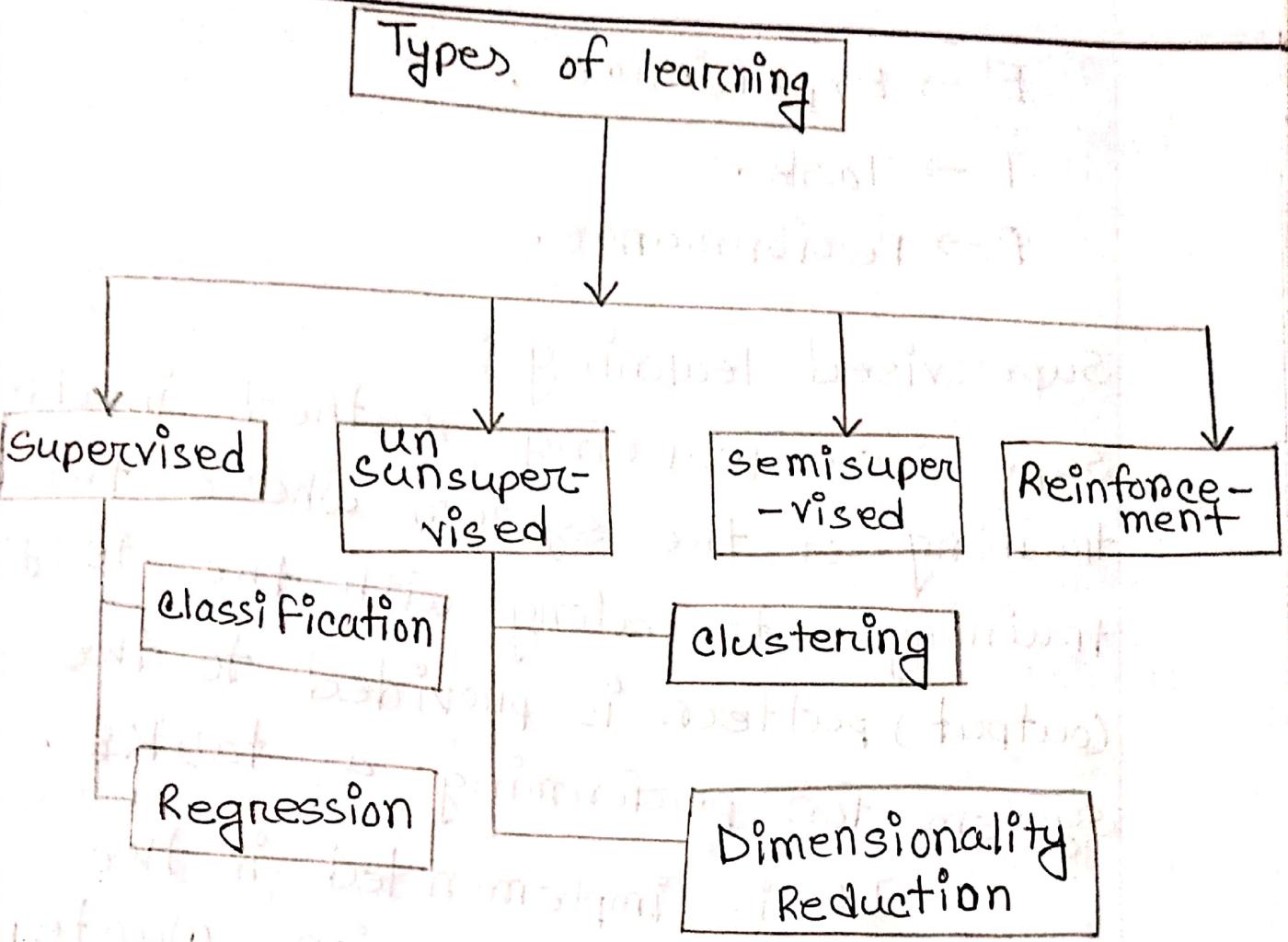
what is machine learning?

Machine learning is an application of AI that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. It can access data and use it learn for themselves.

ML is to allow computer systems to learn from experience, ~~without~~ being

Machine learning algorithms are three types of categorized:

1. Supervised learning.
2. Un-supervised learning.
3. Reinforcement learning.
4. Semi-supervised learning.



Machine learning:

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P , if it improves with respect to P in T , as measured by E .

E → Experience.

T → Task.

P → Performance.

Supervised learning :

Supervised learning method involves the training of the system where the training sets along with the target (output) pattern is provided to the system for performing a task.

It is implemented in the machine learning regression, clustering and neural networks.

Unsupervised learning :

Unsupervised learning model does not involve the target output which means no training is provided to the system. The system has to learn by its own through determining and adapting according to the structural

Characteristics in the input patterns.
It draw conclusions on unlabeled data.

Reinforcement learning;

Reinforcement learning is also an area of machine learning based on the concept of behavioral psychology that works on interacting directly with an environment.

Reinforcement learning tasks on exploitation vs exploration.

Difference between supervised and un-supervised learning:

Supervised	un-supervised
1. Supervised learning technique deals with the labelled data.	1. Un-supervised learning technique deals with unlabelled data.
2. The output data patterns are known to the system.	2. The output data patterns are just based on the collection of perceptions.
3. Supervised learning concept is less complex.	3. Un-supervised learning method is more complicated.
4. The supervised learning can conduct offline analysis	4. The un-supervised learning employs real-time analysis.
5. Classification and Regression	5. Un-supervised learning includes

are the types of problems solved under supervised learning method

clustering and associative rule mining problems.

6. The outcome of the supervised learning technique is more accurate and reliable.

6. Unsupervised learning generates moderate but reliable results.

Difference between supervised and Reinforcement learning.

Supervised

1. Supervised learning technique deals with labeled data.

2. It highly supervised

Reinforcement

1. It works on interacting with the environment

2. Less supervised and depends on the learning agent.

Supervised

3. Many algorithms are exist in using this learning.

4. Assets are depreciable

5. Runs on any platform or with any applications.

Reinforcement

3. Neither supervised nor un-supervised algorithms are used.

4. Liabilities are non-depreciable.

5. Run with any hardware or software devices.

Difference between classification and Regression:

Classification

1. Classification is the process of finding a model which helps in separating the data into multiple classes.

Regression

1. Regression is the process of finding a model for distinguishing the data into continuous real values instead of using classes.

Classification

Regression

2. Nature of the predicted data is unordered.

2. Nature of the predicted data is ordered.

3. Mapping function is used for mapping of values to predefined classes.

3. Mapping function is used for mapping of values to continuous output.

4. Involves prediction of discrete values.

4. Involves prediction of continuous values

5. Method of calculation by measuring accuracy

5. Method of calculation by measurement of root mean square errors

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Formal Def. of Reinforcement:

Reinforcement learning refers to goal-oriented algorithms, which learn how to attain a complex objective or maximize along a particular dimension over many steps. This learning can be understood using the following concepts.

- Agents

- Action (A)

- Discount factor

- Environment

- State (s)

- Reward (R)

- Policy (π)

- Value (v)

- Q-value or action value (Q)

- Trajectory.

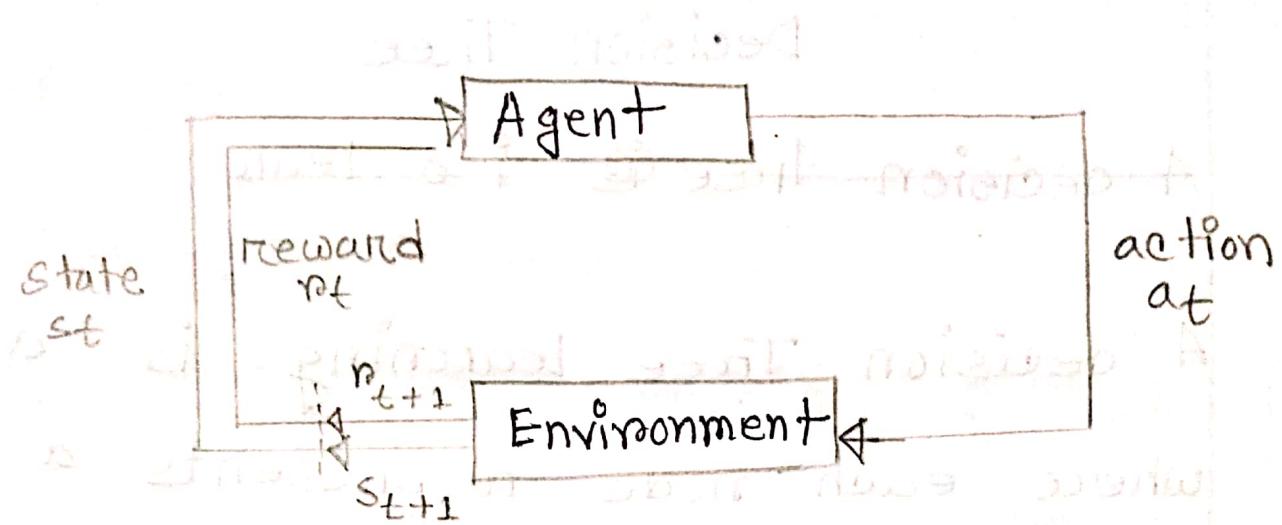


fig: Reinforcement. text

- first example to explain what agent
- part of reinforcement learning
- first step - learn policy
- second step - learn value function

Implements Tabular reinforcement learning

Learned function approximations

Generalized additive models

Deep continuous function approximation

Monte Carlo methods

03.11.19

Decision Tree

A decision tree is a learn

A decision Tree learning is a tree where each node represents a feature (attribute), each link (branch) represents a decision and each leaf represents an outcome.

There are couple of algorithms to build a decision tree — such as — Assistant
— C4.5
— CART (classification and regression trees)
— ID3 (Iterative Dichotomiser 3)

ID3 :

ID3 is an algorithm used to generate a decision tree from a

dataset. ID3 is a precursor of C4.5 algorithm.

Weather Dataset:

Day	outlook	Temp.	Humidity	Wind	Play
D 1	sunny	Hot	High	weak	No
D 2	sunny	Hot	High	strong	No
D 3	overcast	Hot	High	weak	Yes
D 4	Rain	Mild	High	weak	Yes
D 5	Rain	Cool	Normal	weak	Yes
D 6	Rain	Cool	Normal	strong	No
D 7	overcast	Cool	Normal	strong	Yes
D 8	sunny	Mild	High	weak	No
D 9	sunny	Cool	Normal	weak	Yes
D 10	Rain	Mild	Normal	weak	Yes
D 11	sunny	Mild	Normal	strong	Yes
D 12	overcast	Mild	High	strong	Yes
D 13	overcast	Hot	Normal	weak	Yes
D 14	Rain	Mild	High	strong	No

ID3 App

Applying ID3 Algorithm

Output = entropy

information gain = total entropy

Play = 9 Yes and 5 No

Entropy_{total} = [9+, 5-]

$$= -\frac{9}{14} \log_2 \frac{9}{14} - \frac{5}{14} \log_2 \frac{5}{14}$$

$$= 0.94$$

Values [Wind] = weak (8), strong (6)

S_{total} = 9+, 5-

S_{weak} = 6+, 2-

S_{strong} = 3+, 3-

$$E_{\text{weak}} = -\frac{6}{8} \log_2 \frac{6}{8} - \frac{2}{8} \log_2 \frac{2}{8}$$
$$= 0.811$$

$$E_{\text{strong}} = -\frac{3}{6} \log_2 \frac{3}{6} - \frac{3}{6} \log_2 \frac{3}{6}$$
$$= 1$$

Information gain of wind —

$$= E_{\text{total}} - \frac{8}{14} \times E_{\text{weak}} - \frac{6}{14} E_{\text{strong}}$$

$$= .94 - \frac{8}{14} \times .811 - \frac{6}{14} \times 1$$

$$= .94 - .463 - .42$$

$$= .940 - .883$$

$$= +0.48 - 0.053$$

Values [Humidity] = High (+), Normal (-)

$$S_{\text{total}} = 9+, 5-$$

$$S_{\text{high}} = 3+, 4-$$

$$S_{\text{Normal}} = 6+, 1-$$

$$E_{\text{High}} = -\frac{3}{7} \log_2 \frac{3}{7} - \frac{4}{7} \log_2 \frac{4}{7}$$
$$= 0.985$$

$$E_{\text{Normal}} = -\frac{6}{7} \log_2 \frac{6}{7} - \frac{1}{7} \log_2 \frac{1}{7}$$
$$= .59$$

Information gain of Humidity

$$E_{\text{total}} = \frac{7}{14} \times E_{\text{High}} + \frac{7}{14} \times E_{\text{Normal}}$$

$$= 0.99 - 0.71875 \log_2 \frac{1}{P_H} - P_E =$$

$$= 0.1525 \log_2 \frac{1}{P_H} - P_E =$$

Values [Temp.] = Hot(4), Mild(6), Cool(9)

$$S_{\text{total}} = 9+, 5-$$

$$S_{\text{Hot}} = 2+, 2-$$

$$S_{\text{Mild}} = 4+, 2-$$

$$S_{\text{Cool}} = 3+, 1-$$

$$E_{\text{Hot}} = -\frac{2}{4} \log_2 \frac{2}{4} - \frac{2}{4} \log_2 \frac{2}{4}$$
$$= 1$$

$$E_{\text{Mild}} = -\frac{4}{6} \log_2 \frac{4}{6} - \frac{2}{6} \log_2 \frac{2}{6}$$
$$= 0.917$$

$$E_{\text{Cool}} = -\frac{3}{4} \log_2 \frac{3}{4} - \frac{1}{4} \log_2 \frac{1}{4}$$
$$= 0.8112$$

Gain of Temp. —

$$E_{\text{total}} = \frac{4}{14} \times E_{\text{Hot}} + \frac{6}{14} E_{\text{Mild}} + \frac{4}{14} \times E_{\text{Cool}}$$

$$= 0.94 - \frac{4}{14} \times 1 - \frac{6}{14} - 0.17 - \frac{4}{14} \times 0.8112$$

$$= 0.94 - 0.2857 - 0.393 - 0.231$$

$$= 0.0303$$

Values [outlook] = sunny (5), overcast (4)

$$b_{\text{total}} = 9 + , 5 -$$

$$b_{\text{sunny}} = 2 + , 3 -$$

$$b_{\text{overcast}} = 4 +$$

$$b_{\text{rain}} = 3 + , 2 -$$

$$E_{\text{sunny}} = -\frac{2}{5} \log_2 \frac{2}{5} - \frac{3}{5} \log_2 \frac{3}{5}$$
$$= 0.97$$

$$E_{\text{overcast}} = -\frac{4}{4} \log_2 \frac{4}{4} - \frac{0}{4} \log_2 \frac{0}{4}$$
$$= 0$$

$$E_{Rain} = -\frac{3}{5} \log_2 \frac{3}{5} - \frac{2}{5} \log_2 \frac{2}{5}$$
$$= .97$$

Gain of Outlook -

$$E_{total} = \frac{5}{14} \times E_{sunny} + \frac{4}{14} E_{overcast} + \frac{5}{14} E_{rain}$$

$$= .99 - \frac{5}{14} \times .97 - \frac{4}{14} \times 0 - \frac{5}{14} \times .97$$

$$= .94 - .35 - 0 - .35$$

$$= .94 - .70$$

$$= 0.24$$

+ E = favorable

- E = unfavorable

total also = $\sqrt{.24 \times .76} = 0.49$

50% =

std dev = $\sqrt{.24 \times .76} = 0.49$