

**DEPARTMENT OF COMPUTER SCIENCE  
INSTITUTE OF MANAGEMENT AND RESEARCH, JALGAON**

Name Gradilabar Hitesh Digambar  
 Expt. Title Implement the find-s Inductive learning alg<sup>m</sup>  
 Class ET.MCA Batch \_\_\_\_\_ Performed on \_\_\_\_\_  
 Roll No. 38 Expt. No. 01 Submitted on \_\_\_\_\_  
 Remarks \_\_\_\_\_ Returned on \_\_\_\_\_

**\* Find s Algorithm:-**

The find s algorithm is a basic concept learning algorithm in machine learning. The find-s algorithm finds the most specific hypothesis that fits all the positive examples. We have to note here that the algorithm considers only those positive training examples.

**Algorithm :-**

Step 1:- Initialize  $h$  to the most specific hypothesis in  $H$

Step 2:- for each positive training instance  $x$   
 for each attribute constraint  $a_i$  in  $h$  If the constraint  $a_i$  is satisfied by  $x$  then do nothing.

Else replace  $a_i$  in  $h$  by the next more general constraint that is satisfied by  $x$   
 Step 3:- Output hypothesis  $h$ .

| Example | Color  | Toughness | Fungus | Appearance | Poisonous |
|---------|--------|-----------|--------|------------|-----------|
| 1       | Green  | Hard      | No     | Wrinkled   | Yes       |
| 2       | Green  | Hard      | Yes    | Smooth     | No        |
| 3       | Brown  | Soft      | No     | Wrinkled   | No        |
| 4       | Orange | Hard      | No     | Wrinkled   | Yes       |
| 5       | Green  | Soft      | Yes    | Smooth     | Yes       |

Complete for :

Algorithm

Chart

Program Listing

Results

Comments

First we consider the hypothesis to be a more specific hypothesis Hence our hypothesis would be  
 $h = \{ \phi, \phi, \phi, \phi, \phi, \phi, \phi \}$

Consider example 1:-

$h = \{ \text{Green, Hard, No, Wrinkled} \}$

Consider example 2:-

$h = \{ \text{Green, Hard, No, Wrinkled} \}$

Consider example 3:-

$h = \{ \text{Green, Hard, No, wrinkled} \}$

Have we seen that above 2 examples have a negative outcome Hence we neglect this example & our hypothesis remains the same.

Consider Example 4:-

$h = \{ ?, \text{Hard, No, Wrinkled} \}$

Consider example 5:-

$h = \{ ?, ?, ?, ? \}$

Hence for the given data find final hypothesis would be:

Final Hypothesis :  $h = \{ ?, ?, ?, ? \}$



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Name Gadilohar Hitesh Digambar  
Expt. Title Implement the Candidate-Elimination Inductive Learning algorithm  
Class IT-MCA Batch \_\_\_\_\_ Performed on \_\_\_\_\_  
Roll No. 38 Expt. No. 02 Submitted on \_\_\_\_\_  
Remarks \_\_\_\_\_ Returned on \_\_\_\_\_

\* Candidate-Elimination Algorithm:-

The Candidate elimination algorithm incrementally builds the version Space given a Hypothesis Space  $H$  & a Set  $E$  of examples.

Algorithm :-

Step 1:- Load Data Set.

Step 2:- Initialize General Hypothesis & Specific Hypothesis.

Step 3:- for each training example.

Step 4:- If example is positive example.

if attribute value == hypothesis-value:

Do nothing.

else:-

replace attribute value with '?'

(Basically generalizing it)

Step 5:- if example is ~~negative~~ example make generalizing hypothesis more Specific.

Example:-

Consider the dataset given below:

| Sky   | Temperature | Humid  | wind   | Water | forest | Output |
|-------|-------------|--------|--------|-------|--------|--------|
| 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    |

Initially :-

$G = [ [?, ?, ?, ?, ?, ?], [?, ?, ?, ?, ?, ?], [?, ?, ?, ?], [?, ?, ?, ?, ?], [?, ?, ?, ?, ?], [?, ?, ?] ]$

$S = [ \text{Null}, \text{Null}, \text{Null}, \text{Null}, \text{Null}, \text{Null} ]$

for instance 1:-  $\langle \text{'Sunny'}, \text{'Warm'}, \text{'Normal'}, \text{'Strong'}, \text{'Warm'} \rangle$   
 $\neq$  positive Output.

$G_1 = G$

$S_1 = [ \text{'Sunny'}, \text{'warm'}, \text{'normal'}, \text{'strong'}, \text{'warm'}, \text{'Same'} ]$

for instance 2:-

$\langle \text{'Sunny'}, \text{'warm'}, ?, \text{'Strong'}, \text{'Warm'}, \text{'Same'} \rangle$

for instance 3:-

$\langle \text{'rainy'}, \text{'Cold'}, \text{'high'}, \text{'Strong'}, \text{'Warm'}, \text{'Change'} \rangle \neq$

$G_3 = [ [ \text{'Sunny'}, ?, ?, ?, ?, ? ], [ ?, \text{'warm'}, ?, ?, ?, ? ], [ ?, ?, ?, ?, ? ], [ ?, ?, ?, ?, ? ], [ ?, ?, ?, ?, ? ], [ ?, ?, ? ] ]$

Output  $[ [?, ?, ?, ?, ?, ?], [?, ?, ?, ?, ?, ?], [?, ?, ?, ?, ?], [?, ?, ?, ?, ?], [?, ?, ?, ?, ?], [?, ?, ?] ]$

$S_3 = S_2$

for instance 4:-  $\langle \text{'Sunny'}, \text{'Warm'}, \text{'high'}, \text{'Strong'}, \text{'cool'} \rangle$

$G_4 = G_3$

$S_4 = [ \text{'Sunny'}, \text{'Warm'}, ?, \text{'Strong'}, ?, ? ]$

At last, by Synchronizing the  $G_4$  &  $S_4$  algorithm,  
 Output:-

$G = [ [ \text{'Sunny'}, ?, ?, ?, ?, ? ], [ ?, \text{'Warm'}, ?, ?, ?, ? ], [ ?, ?, ?, ?, ? ], [ ?, ?, ?, ?, ? ], [ ?, ?, ?, ?, ? ], [ ?, ?, ? ] ]$

$S = [ \text{'Sunny'}, \text{'Warm'}, ?, \text{'Strong'}, ?, ? ]$



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Name Gadilohar Hitesh Digambar  
Expt. Title Write a program to implement Decision tree using python programming  
Class ET. MCN Batch \_\_\_\_\_ Performed on \_\_\_\_\_  
Roll No. 38 Expt. No. 03 Submitted on \_\_\_\_\_  
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\* What is decision trees?

Decision tree is a Supervised learning technique that can be used for both classification & regression problems, but mostly it is preferred for solving classification problem. It is a tree structure classifier, where internal nodes represent the feature of a dataset, branches represent the decision rules & each leaf node represent the outcome.

It is a graphical represent of for getting all the possible solution to problem/decision based on given conditions. This works surprisingly well in most of class.

\* ID3 Algorithm:-

- If all examples have same label:-
  - return a leaf with that label
- Else if there are no feature left to test:-
  - return a leaf with the most common label
- Else:-
  - choose the feature  $F$  that maximise the information on gain of  $S$  to be the next node using equation  $IG(S, F)$
  - add branch from the node for each possible value  $f$  in  $P$ .

- for each Branch:-

- \* Calculate  $S_f$  by removing  $\hat{f}$  from the Set of
- \* recursively call the algorithm with  $S_f$  to compute the gain relative to the Current Set of examples

\* formula of Information Gain :-

1) Entropy :-  $-p \log_2 p - q \log_2 q$

- To build a decision tree, we can need to calculate two types of entropy using frequency tables:

i) Entropy Using the frequency table of one

$$E(S) = \sum_{i=1}^c -P_i \log_2 P_i$$

ii) Entropy Using the frequency table of two attributes

$$E(T, X) = \sum_{c \in X} P(c) \cdot E(c)$$

$$2) \text{ Gini} = 1 - \sum_{i=1}^n (P_i)^2$$

$$3) \text{ Information Gain} = 1 - \text{Entropy}$$



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Name Gradilohar Hitesh Digambar  
Expt. Title White Diagram to Calculate popular Attribute  
Class MCA 1 Batch B1 Performed on \_\_\_\_\_  
Roll No. 38 Expt. No. 04 Submitted on \_\_\_\_\_  
Remarks \_\_\_\_\_ Returned on \_\_\_\_\_

### Attribute Selection Measure: (ASM)

The best attribute or feature is selected using the attribute selection measure (ASM) the attribute selection is the root node decision.

ASM is a technique used for the selecting best attribute for discrimination among tuples. It gives rank to each attribute & the best attribute is selected as splitting criterion.

The most popular methods of selection are:-

#### 1) Information Gain:-

Information gain is a decision in decrease in entropy. Decision tree uses the use of information gain & entropy to determine which feature to split into nodes to get closer to predicting the target & also to determine when to stop splitting.

$$\text{Information Gain} = \text{Entropy}(S) - [\text{weighted Avg}]$$

\* Entropy (each feature).

#### 2) Gini Index:-

Gini index is a measure of impurity or probability used while creating a decision tree in the CART index can be calculated using the below formulae.

$$\text{Gini index} = 1 - \sum p_i^2$$

complete for:

Algorithm

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Name Gadilohar Hitash Digambar  
Expt. Title \_\_\_\_\_  
Class E.Y. MCA Batch \_\_\_\_\_ Performed on \_\_\_\_\_  
Roll No. 38 Expt. No. 05 Submitted on \_\_\_\_\_  
Remarks \_\_\_\_\_ Returned on \_\_\_\_\_

\* K-Nearest Neighbour (KNN) Algorithm:-

K-Nearest Neighbour is one of the simple machine learning algorithm based on Supervised learning technique. KNN algorithm store all the available data & classification a new data point based on the similarity. This mean when new data appears, then it can be easily classified into a well suit category by using K-NN algorithm.

K-NN is a non-parametric algorithm which means it does not make any assumption on underlying data. It is a lazy learning algorithm where all computation is deferred until classification.

\* Algorithm:-

- The KNN Classification is performed using the following four steps
- Compute the distance metric bet<sup>n</sup> the test data point & all the labeled data point.
- Order the labeled data point in the increasing order of the distance metric.
- Select the top  $k$  labeled data point & look at the class labels.
- Find the class label that the majority of these labeled data points have & assign it to the test data point.



\* Distance Calculation formula :-

1) Euclidean Distance :-

It is generally used to find the distance between real-valued vectors.

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

2) Manhattan Distance :-

This is simple way or technique to calculate distance between two points often called Taxicab distance or city block distance.

$$\text{Manhattan Distance} = \sum_{i=1}^N |x_{1i} - x_{2i}|$$

3) Hamming distance :-

The hamming distance is mostly used in processing or having the boolean vector. Boolean means the data is in the form of binary 0 and 1.

$$\text{Hamming distance}(x_1, x_2) = \dots$$

4) Minkowski Distance :-

Minkowski distance is a generalization form of the euclidean & manhattan distance.

$$\|x_1 - x_2\| = \left( \sum_{i=1}^n |x_{1i} - x_{2i}|^p \right)^{1/p}$$