Serial No. 01

Notes

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Subject : Machine Learning
Assignment: 01

Q.1. Find the classifier (version space) by using Find-S Algorithm for the given dataset.

Data: Loan Approval Prediction

ID	AGE	Job-Status	Owns-House	Credit Rating	Class (Yes/No) Target
1	Young	False	False	Fair	NO
2	Young	False	False	Good	NO
3	Young	True	False	Good	Yes
4	Young	True	True	Fair	Yes
5	Young	False	False	Fair	NO
6	Middle	False	False	Fair	NO
7	Middle	False	False	Good	NO
8	Middle	True	True	Good	Yes
9	Middle	False	True	Excellent	Yes
10	Middle	False	True	Excellent	Yes
11	Old	False	True	Excellent	Yes
12	Old	False	True	Good	Yes
13	Old	True	False	Good	Yes
14	Old	True	False	Excellent	Yes
15	Old	False	False	Fair	NO

Solution:

Φ : No acceptance [Most specific]

? : Any acceptance [Most general]

Serial No. 02 Notes Date

Step:1 : Initialize h to the most specific hypothesis in h.

$h_0 = \langle \phi, \phi, \phi, \phi \rangle$ [∵ Target depends on ~~four~~ ~~three~~ attributes]]

Step-2: For each positive training instance (target) x

- For each attribute constraint a_i in h
  - i) If the constraint a_i is satisfied by x Then do nothing
  - ii) Else replace a_i in h by the next more general constraint that is satisfied by x.

Iteration:1 Since x_1 is negative.

Hence, $h_1 = h_0$ (Do Nothing)

Iteration-2 : Since x_2 (Target) is also negative.

Hence, $h_2 = h_1$

Iteration-3 : Since x_3 is +ve, then replace each attribute of previous hypothesis by more general constraint that is satisfied by x_3

$h_2 = \langle \phi, \phi, \phi, \phi \rangle$ [From previous iteration]

$x_3 = \langle$Young, True, False, Good$\rangle$

∴ $h_3 = \langle$Young, True, False, Good$\rangle$

Iteration-4 : Target is +ve.

$h_3 = \langle$Young, True, False, Good$\rangle$

$x_4 = \langle$Young, True, True, Fair$\rangle$

∴ $h_4 = \langle$Young, True, ?, ?$\rangle$

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Iteration-5: $h_5 = h_4$ (-ve instance)
Iteration-6: $h_6 = h_5$ (-ve instance)
Iteration-7: $h_7 = h_6$ (-ve instance)

Iteration-8:

$h_7 = \langle$ Young, True, ?, ? $\rangle$

$x_8 = \langle$ Middle, True, True, Good $\rangle$

$h_8 = \langle$?, True, ?, ? $\rangle$

Iteration-9: $x_9 = \langle$ Middle, False, True, Excellent $\rangle$

$\therefore h_9 = \langle$?, ?, ?, ? $\rangle$

Here, h_9 is the most general hypothesiss, so it satisfies all instance x. It can accept any thing.

Iteration-10: $h_{10} = h_9$
Iteration-11: $h_{11} = h_{10}$
Iteration-12: $h_{12} = h_{11}$
Iteration-13: $h_{13} = h_{12}$
Iteration-14: $h_{14} = h_{13}$
Iteration-15: $h_{15} = h_{14}$

$h_{15} = \langle$?, ?, ?, ? $\rangle$

Step-3: Output is the final hypothesis

$h = \langle$?, ?, ?, ? $\rangle$

Serial No. 04 Notes

Q.2: Apply the candidate-Elimination algorithm step by step for the following.

The concept to be learnt is Grades Good.

	Student	Grades	Hardworking	Intelligent	unlucky
1.	Peter	Good	yes	yes	NO
2.	John	Bad	NO	yes	yes
3.	Charles	Bad	yes	NO	yes
4.	Paul	Good	yes	yes	NO
5.	Henry	Good	yes	yes	NO
6.	Timothy	Bad	NO	yes	NO
7.	Edward	Bad	yes	NO	NO

Solution

Step 1: Initialize G to the set of maximally general hypotheses in H and S to the set of maximally specific hypotheses in H.

ie $G_0 \leftarrow \{(?, ?, ?, ?)\}$ G boundary

$S_0 \leftarrow \{(\phi, \phi, \phi, \phi)\}$ S-boundary

In the given problem, unlucky is a dependent variable which depends on three features Grades, Hardworking and intelligent.

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Serial No. 05

Notes

Step.2: For each traing example d, do
i) If d is a positive example
a) Remove from G any hypothesis inconsistent with d.
b) For each hypothesis s in S that is not consistent with d
- Remove s from S.
- Add to S all minimal generalization of h of S such that h is consistent with d, and some member of G is more general than h.
- Remove from S any hypothesis that is more general than another hypothesis in S.

ii) If d is a negative example
a) Remove from S any hypothesis inconsistent with d.
b) For each hypothesis g in G that is not consistent with d.
- Remove g from G.
- Add to G all minimal specializations h of g such that h is consistent with d, and some member of S is more specific than h.
- Remove from G any hypothesis that is less general than another hypothesis in G.

Soln:

$S_0 = (\phi, \phi, \phi)$

$S_1 = \langle \phi, \phi, \phi \rangle$

$S_2 = \langle \text{Bad}, \text{No}, \text{Yes} \rangle$

$S_3 = \langle \text{Bad}, ?, ? \rangle$

$S_4 = \langle \text{Bad}, ?, ? \rangle$

$S_5 = \langle \text{Bad}, ?, ? \rangle$

$S_6 = \langle \text{Bad}, ?, ? \rangle$

$S_7 = \langle \text{Bad}, ?, ? \rangle$

$G_7 = \langle \text{Bad}, \text{Yes}, \text{Yes} \rangle \langle \text{Bad}, \text{No}, \text{No} \rangle$

$G_6 = \langle \text{Bad}, \text{Yes}, ? \rangle \langle \text{Bad}, ?, \text{No} \rangle$

$G_5 = \langle \text{Bad}, ?, ? \rangle$

$G_4 = \langle \text{Bad}, ?, ? \rangle$

$G_3 = \langle \text{Bad}, ?, ? \rangle$

$G_2 = \langle \text{Bad}, ?, ? \rangle \langle ?, \text{No}, ? \rangle$

$G_1 = \langle \text{Bad}, ?, ? \rangle \langle ?, \text{No}, ? \rangle \langle ?, ?, \text{No} \rangle$

$G_0 = \langle ?, ?, ? \rangle$

Now combining S boundary and G boundary,

S: $\langle \text{Bad}, ?, ? \rangle$

$\langle \text{Bad}, \text{Yes}, ? \rangle \langle \text{Bad}, ?, \text{Yes} \rangle \langle \text{Bad}, \text{No}, ? \rangle \langle \text{Bad}, ?, \text{No} \rangle$

G: $\langle \text{Bad}, \text{Yes}, \text{Yes} \rangle \langle \text{Bad}, \text{No}, \text{No} \rangle$

Final version space for the concept to be learnt for good grade.

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Q.3. State and explain Baye's theorem in details. Explain why we need it and the cases in which we use it. Give two examples and solve them by using Bayes' theorem.

Bayes' theorem
It is a fundamental principle in probability theory that relates conditional probabilities.

Bayes' theorem is used for the calculation of a conditional probability where intuition often fails.

Conditional Probability:
A conditional probability is defined as the probability of one event given the occurrence of another event.

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

where
- $P(A|B)$ is the conditional probability of event A occuring given that the event B has occurred.
- $P(B|A)$ is the conditional probability of event B occuring given that event A has occurred.
- $P(A)$: Probability of event A.
- $P(B)$: Probability of event B.

Example: 1) • Dangerous fires are rare (1%)
• But smoke is fairly common (10%) due to barbecues,
• And 90% dangerous fires make smoke

What is the probability of dangerous Fire when there is smoke?

Solution:

$$P(\text{Fire}|\text{smoke}) = P(\text{Fire})\,P(\text{smoke}|\text{Fire}) / P(\text{smoke})$$

$$= \frac{1\% \times 90\%}{10\%}$$

$$= \frac{0.01 \times 0.09}{0.10}$$

$$= 0.09 = 9\%$$

Example: 2) What is the chance of rain during the day if there is cloud with probability 40%. Probability of Rain is 10%. The probability of cloud given that rain happens is 50%.

Soln:

$$P(\text{Rain}|\text{cloud}) = \frac{P(\text{rain}) \times P(\text{cloud}|\text{Rain})}{P(\text{cloud})}$$

$$= \frac{0.1 \times 0.5}{0.4}$$

$$= 0.125$$

chance of Rain $= 12.5\%$

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Application of Bayes' theorem.

1. Modelling Hypothesis:
It has wide application in the applied machine learing and establishes a relationship between the data and a model. Applied machine learning uses the process of testing and analysis of different hypotheses on given dataset.

II. Bayes Theorem for classification
The method of classification involves the labelling of a given data. It can be defined as the calculation of the conditional probability of a class label given a data sample.

a> Naive Bayes classified
b> Bayes optimal classifier

III. Uses of Bayes theorem in ML.
For the development of classification problem.
Other application rather than the classification include optimization and causual models.
a> Bayesian optimization
b> Bayesian Belief networks.

IV. Bayesian spam filtering
With the application of the Bayes theorem It can be predicted if the message is spam or not?