Part II
Concept Learning 2

(12 points) Structured questions. Answer in the space provided on the script.

1. (12 points) Consider the hypothetical task of learning the target concept $MLGrade$ to understand the factors affecting the grades of students enrolled in an ML class and the hypothesis space H that is represented by a conjunction of constraints on input attributes, as previously described on page 7 of the "Concept Learning" lecture slides. Each constraint on an input attribute can be a specific value, don't care (denoted by '$?$'), and no value allowed (denoted by '$\emptyset$'), as previously described on page 5 of the "Concept Learning" lecture slides. Each input instance is represented by the following input attributes:

   - $AttendClass$ (with possible values $Always$, $Sometimes$, $Rarely$),
   - $FinalsGrade$ (with possible values $Good$, $Average$, $Poor$),
   - $ProjectGrade$ (with possible values $Good$, $Average$, $Poor$), and
   - $LoveML$ (with possible values Yes, No).

   For example, a typical hypothesis in H is

   $$\langle ?, Average, ?, Yes \rangle \ .$$

   Trace the CANDIDATE-ELIMINATION algorithm (reproduced below in Fig. 1) for the hypothesis space H given the sequence of positive ($MLGrade = Pass$) and negative ($MLGrade = Fail$) training examples from Table 1 below (i.e., show the sequence of S and G boundary sets).

1. $G \leftarrow$ maximally general hypotheses in H
2. $S \leftarrow$ maximally specific hypotheses in H
3. For each training example d
   - If d is a positive example
     - Remove from G any hypothesis inconsistent with d
     - For each $s \in S$ not consistent with d
       * Remove s from S
       * Add to S all minimal generalizations h of s s.t.
         h is consistent with d, and
         some member of G is more general than or equal to h
       * Remove from S any hypothesis that is more general than another hypothesis in S
   - If d is a negative example
     - Remove from S any hypothesis inconsistent with d
     - For each $g \in G$ not consistent with d
       * Remove g from G
       * Add to G all minimal specializations h of g s.t.
         h is consistent with d, and
         some member of S is more specific than or equal to h
       * Remove from G any hypothesis that is more specific than another hypothesis in G

Figure 1: CANDIDATE-ELIMINATION algorithm.

Example	Input Instances				Target Concept
Student	$AttendClass$	$FinalsGrade$	$ProjectGrade$	$LoveML$	$MLGrade$
1. $Ryutaro$	$Sometimes$	$Good$	$Poor$	Yes	$Pass$
2. $Haibin$	$Sometimes$	$Good$	$Average$	Yes	$Pass$
3. $Jinho$	$Rarely$	$Average$	$Average$	No	$Fail$
4. $Jingfeng$	$Sometimes$	$Poor$	$Average$	No	$Fail$

Table 1: Positive ($MLGrade = Pass$) and negative ($MLGrade = Fail$) training examples for target concept $MLGrade$.

Solution:

$$
\begin{aligned}
G_0 &= \{\langle ?, ?, ?, ? \rangle\} \\
S_0 &= \{\langle \emptyset, \emptyset, \emptyset, \emptyset \rangle\}
\end{aligned}
$$

$G_1 =$

$S_1 =$

$G_2 =$

$S_2 =$

$S_3 =$

$G_3 =$

$S_4 =$

$G_4 =$

Suppose that the target concept c is in the hypothesis space H (i.e., $c \in H$) and an active learner has already observed the set D of 4 training examples in Table 1 above. State **every** possible input instance (i.e., assuming such a student exists) that the active learner can query next for the 5-th training example to reduce the version space $VS_{H,D}$ by at least half. Note that the active learner does not know the output label $c(x)$ of any input instance x that it has not yet observed.

Hint: Draw the version space $VS_{H,D}$.

Solution:

Part V
Neural Networks

(20 points) Structured questions. Answer in the space provided on the script.

1. (4 points) Supposing the weights w_1 and w_2 of a perceptron (see page 6 of "Neural Networks" lecture slides) are both set to the value of **–1**, derive the largest possible range of the values of w_0 that can be set for the perceptron to represent the NAND gate (i.e., NAND(x_1, x_2)). Assume that the inputs x_1 and x_2 and output $o(x_1, x_2)$ of the perceptron are Boolean with the values of **1 or –1**. Show the steps of your derivation. **No marks will be awarded for not doing so.**

   Solution:

2. (8 points) Supposing the weights $w_1, w_2, \ldots, w_n$ of a perceptron (see page 6 of "Neural Networks" lecture slides) are all set to the value of **1**, derive the largest possible range of the values of w_0 (in terms of n) that can be set for the perceptron to represent the OR function. That is, the perceptron outputs false if all n Boolean inputs to the perceptron are false, and true otherwise. Assume that the inputs $x_1, x_2, \ldots, x_n$ and output $o(x_1, x_2, \ldots, x_n)$ of the perceptron are Boolean with the values of **1 (i.e., true) or –1 (i.e., false)**. Show the steps of your derivation. **No marks will be awarded for not doing so.**

   Solution:

Solution:

3. (8 points) Construct and draw a network of perceptron units with **only one hidden layer (of four units)** that implements (x_1 XOR x_2) XOR x_3 based on the following rules:

- There should be only one (Boolean) output unit and an input unit for every (Boolean) input.
- A Boolean is **–1** if false, and **1** if true.
- The activation function of every (non-input) unit is a -1 to 1 step function (refer to page 6 of the "Neural Networks" lecture slides), including that of the output unit.
- **Your weights must take on one of the following values: –1, 0, 1, 3.**
- You don't have to draw edges with weight 0.

Hint: Observe the truth table of (x_1 XOR x_2) XOR x_3.

Solution:

END OF PAPER