IMPERIAL COLLEGE OF SCIENCE, TECHNOLOGY AND MEDICINE

EXAMINATIONS 2017

BEng Honours Degree in Computing Part III
BEng Honours Degree in Mathematics and Computer Science Part III
MEng Honours Degree in Mathematics and Computer Science Part III
MEng Honours Degrees in Computing Part III
MSc in Advanced Computing
MSc in Computing Science
MSc in Computing Science (Specialist)
for Internal Students of the Imperial College of Science, Technology and Medicine

This paper is also taken for the relevant examinations for the Associateship of the City and Guilds of London Institute

PAPER C304

LOGIC-BASED LEARNING

Monday 20 March 2017, 14:00
Duration: 120 minutes

Answer THREE questions

Paper contains 4 questions
Calculators not required

1 **This question is about learning methods based on inverse entailment.**

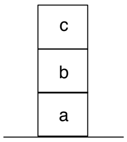
a Consider the following learning task $T = \langle B, E^+, E^-, M \rangle$:

$$B = \begin{cases} r(X,Y) \leftarrow q(X,Y). \\ s(a,b). \quad s(a,a). \\ t(b). \end{cases} \qquad M = \begin{cases} modeh(*, q(+any, +any)) \\ modeb(*, s(+any, +any)) \\ modeb(*, t(+any)) \end{cases} \qquad \begin{array}{l} E^+ = \{r(a,b)\} \\ E^- = \{r(a,a)\} \end{array}$$

i) State what it means to say that an hypothesis is complete and consistent.

ii) For the task T, give a hypothesis $H1$ that is not consistent, and a hypothesis $H2$ that is a solution derivable by Bottom Generalisation. Explain your answer.

b Consider a *block world* problem domain. A block world scenario composed of three blocks is given in the figure below.



Let $T = \langle B, E^+, E^-, M \rangle$ be a learning task whose background knowledge B, examples E^+ and E^-, and mode declarations M are defined as follows.

$$B = \left\{ \begin{array}{l} block(a). \quad block(b). \quad block(c). \quad touches(c,b). \quad touches(b,a). \quad free(c). \\ above(B1, B2) \leftarrow block(B3), block(B1), block(B2), \\ \qquad\qquad\qquad\qquad onTopOf(B3, B2), movedOn(B1, B3). \end{array} \right\}$$

$$M = \left\{ \begin{array}{l} modeh(movedOn(+block, +block)). \\ modeh(onTopOf(+block, +block)). \\ modeb(touches(+block, +block)). \\ modeb(free(+block)). \end{array} \right\} \qquad \begin{array}{l} E^+ = \{\ above(c,a).\ \} \\ \\ E^- = \left\{ \begin{array}{l} above(a,c). \\ above(c,c). \end{array} \right\} \end{array}$$

i) Use the hybrid abductive inductive learning algorithm (HAIL) to show that the following hypothesis H is an inductive solution for the task T.

$$H = \left\{ \begin{array}{l} movedOn(B1, B2) \leftarrow free(B1). \\ onTopOf(B1, B2) \leftarrow touches(B1, B2). \end{array} \right\}$$

ii) Give an alternative hypothesis $H1$, computable by HAIL, that has the same number of literals as H. Explain why it is a solution.

iii) State whether H can be computed by Progol5, and explain why or why not.

The two parts carry, respectively, 30% and 70% of the marks.

2 **This question is about meta-level learning.**

a Consider the problem domain of a simplified context free grammar. The learning task $T = \langle B, E^+, E^-, M \rangle$, defined below, aims at learning some context free grammar rules that allow the recognition of imperative sentences. Each word in a sentence is delimited by a position and is represented in terms of its grammatical constituent (e.g. np for noun phrase, vp for verb phrase). In the task below, the positive example is assumed to be the imperative sentence "*Book a flight*", which has 4 positions (e.g. $_0$ *Book* $_1$ *a* $_2$ *flight* $_3$), and the negative example is assumed to be the string "*A flight*".

$$B = \left\{ \begin{array}{llll} pos(0). & pos(1). & pos(2). & pos(3). \\ v(0,1). & det(1,2). & noun(2,3). & \\ \multicolumn{4}{l}{vp(P1,P3) \leftarrow v(P1,P2), np(P2,P3).} \\ \multicolumn{4}{l}{np(P1,P3) \leftarrow det(P1,P2), nominal(P2,P3).} \end{array} \right\}$$

$$M = \left\{ \begin{array}{l} modeh(sentence(+pos,+pos)). \\ modeh(nominal(+pos,+pos)). \\ modeb(vp(+pos,+pos)). \\ modeb(noun(+pos,+pos)). \end{array} \right\} \qquad \begin{array}{l} E^+ = \{ \ sentence(0,3). \ \} \\ \\ E^- = \{ \ sentence(1,3). \ \} \end{array}$$

i) Give the top-theory constructed by the top-directed abductive learning (TAL) algorithm for the learning task T.

ii) Show that the following hypothesis H is an inductive solution generated by the TAL algorithm.

$$H = \left\{ \begin{array}{l} sentence(P1,P2) \leftarrow vp(P1,P2). \\ nominal(P1,P2) \leftarrow noun(P1,P2). \end{array} \right\}$$

b Consider the hypothesis H given in part a(ii). State whether H can be derived by Kernel Set subsumption, and also whether it can be derived by Bottom Generalisation. Explain your answers.

The two parts carry, respectively, 75% and 25% of the marks.

3 a Consider the following two ASP programs:

$$B = \left[\begin{array}{ll} q(X) \leftarrow \text{not } p(X), s(X). & \\ r(1,a). & r(2,b). \\ s(1). & s(2). \\ t(a). & t(b). \end{array} \right] \qquad H = \left[\; p(X) \leftarrow \text{not } q(X), \text{not r(X, a)}, s(X). \; \right]$$

i) Write down the answer sets of $B \cup H$ (no proof required).

ii) Consider the learning task T_1 with background knowledge B and examples $E^+ = \{q(1)\}$ and $E^- = \{q(2)\}$. Is H a brave inductive solution of T_1? Explain using your answer to part a (i).

iii) Consider the learning task T_2 with background knowledge B and examples $E^+ = \{q(1)\}$ and $E^- = \{q(2)\}$. Is H a cautious inductive solution of T_2? Explain using your answer to part a (i).

b Consider the following mode declarations:

$$M = \left[\begin{array}{l} modeh(1, p(+s)) \\ modeb(1, \text{not } q(+s)) \\ modeb(1, \text{not } r(+s, \#t)) \end{array} \right]$$

i) Write down a maximal set of skeleton rules for the mode declarations M ($V_{max} = 1, L_{max} = 3$).

ii) Write down the ASP encoding of the task T_1 (from part a (ii)), which is produced by the ASPAL algorithm, given the mode declarations M.

iii) Give an answer set of the ASP program constructed in part b (ii) that demonstrates that H is a brave inductive solution of T_1.

c Consider the following two ASP programs:

$$B_2 = \left[\begin{array}{l} a(X) \leftarrow b(X), \text{not } c(X). \\ c(X) \leftarrow b(X), \text{not } a(X). \\ 0\{b(1), b(2)\}1. \end{array} \right] \qquad H_2 = \left[\; \leftarrow \text{not } b(1), \text{not } b(2). \; \right]$$

i) Write down the answer sets of $B_2 \cup H_2$ (no proof required).

ii) Write down examples E^+ and E^- such that $\langle B_2, E^+, E^- \rangle$ forms a learning from answer sets task T_{LAS} and H_2 is an optimal solution of T_{LAS}.

iii) Using your answer to part c (i), explain why there is no cautious induction task T_c with background knowledge B_2, such that H_2 is an optimal solution of T_c.

The three parts carry, respectively, 30%, 40%, and 30% of the marks.

4 a Consider the following two statements.

C: Herman lives in Berlin
D: Herman lives in Germany

In each case below explain your answer.

i) Represent statement **C** as a definite clause.

ii) Represent statement **D** as a definite clause.

iii) Define a background knowledge clause **B** which allows the clauses for **C** and **D** to be related according to their generality.

iv) What is the generality relation between the clauses for **C** and **D** given **B**?

b In each case below explain your answer.

i) Describe the general form of a meta-rule both a) *with* and b) *without* quantification.

ii) Explain the meaning of a) a meta-rule and b) an order constraint.

iii) Describe each of the meta-rules *Instance, Base, Chain, Tailrec* along with their associated order constraints.

c Consider the following Stochastic Logic Program.

$$\begin{array}{l} 0.5 : nate(0) \leftarrow \\ 0.5 : nate(s(N)) \leftarrow nate(N) \end{array}$$

i) Show the refutation of the goal $\leftarrow nate(s(s(0)))$.

ii) Calculate the probability of this derivation.

iii) What is the general formula for the probability of $nate(N)$ given this SLP?

The three parts carry, respectively, 20%, 45%, and 35% of the marks.