IMPERIAL COLLEGE OF SCIENCE, TECHNOLOGY AND MEDICINE

EXAMINATIONS 2015

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

Tuesday 24 March 2015, 10:00
Duration: 120 minutes

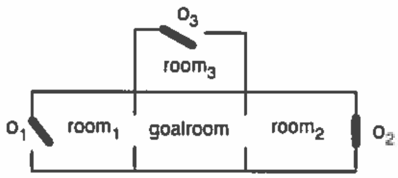
Answer THREE questions

Paper contains 4 questions
Calculators not required

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

a Let B be a set of definite clauses and e a single definite clause. Explain what $Bot(B,e)$ is, give its formal definition, and state what is meant by a hypothesis H being derived by bottom generalisation.

b Consider the problem domain of a robot moving within a building. The map of the building is given below. There are four rooms: $room_1$, $room_2$, $room_3$ and $goalRoom$. The first three rooms have a door to their respective $outside$ points o_1, o_2 and o_3. The doors of $room_1$ and $room_3$ are open, whereas the door of $room_2$ is closed (doors are drawn with thick segments). $room_1$ and $room_2$ each connect with the $goalRoom$ through an archway.



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:

$$B = \left\{ \begin{array}{lll} \multicolumn{3}{l}{\%\mathit{description\ of\ the\ map}} \\ \mathit{pos}(o_1). & \mathit{room}(\mathit{room1}). & \mathit{outside}(o_1, \mathit{room}_1). \\ \mathit{pos}(o_2). & \mathit{room}(\mathit{room2}). & \mathit{outside}(o_2, \mathit{room}_2). \\ \mathit{pos}(o_3). & \mathit{room}(\mathit{room3}). & \mathit{outside}(o_3, \mathit{room}_3). \\ \mathit{pos}(X) \leftarrow \mathit{room}(X). & \mathit{room}(\mathit{goalRoom}). & \mathit{doorOpen}(o_1, \mathit{room}_1). \\ \mathit{doorOpen}(o_3, \mathit{room}_3). & \mathit{archway}(\mathit{room}_1, \mathit{goalRoom}). & \mathit{archway}(\mathit{room}_2, \mathit{goalRoom}). \\ \multicolumn{3}{l}{\%\mathit{general\ rules}} \\ \multicolumn{3}{l}{\mathit{enter}(\mathit{Pos1}, \mathit{Pos2}) \leftarrow \mathit{goThrough}(\mathit{Pos1}, \mathit{Pos2}).} \\ \multicolumn{3}{l}{\mathit{getTo}(\mathit{Pos1}, \mathit{FinalPos}) \leftarrow \mathit{room}(\mathit{Pos2}),\ \mathit{enter}(\mathit{Pos1}, \mathit{Pos2}),\ \mathit{goThrough}(\mathit{Pos2}, \mathit{FinalPos}).} \end{array} \right\}$$

$$M = \left\{ \begin{array}{l} \mathit{modeh}(\mathit{goThrough}(+\mathit{pos}, +\mathit{room})). \\ \mathit{modeb}(\mathit{outside}(+\mathit{pos}, +\mathit{room})). \\ \mathit{modeb}(\mathit{archway}(+\mathit{room}, +\mathit{pos})). \\ \mathit{modeb}(\mathit{doorOpen}(+\mathit{pos}, +\mathit{room})). \\ \mathit{modeb}(\mathit{room}(+\mathit{room})). \end{array} \right\} \qquad E^+ = \{\mathit{getTo}(o_1, \mathit{goalRoom}).\} \qquad E^- = \left\{ \begin{array}{l} \mathit{getTo}(o_3, \mathit{goalRoom}). \\ \mathit{getTo}(o_2, \mathit{goalRoom}). \end{array} \right\}$$

i) Use Hybrid Abductive Inductive Learning algorithm to show that the following hypothesis H is an inductive solution for the task T.

$$H = \left\{ \begin{array}{l} \mathit{goThrough}(\mathit{Pos1}, \mathit{Pos2}) \leftarrow \mathit{doorOpen}(\mathit{Pos1}, \mathit{Pos2}) \\ \mathit{goThrough}(\mathit{Pos1}, \mathit{Pos2}) \leftarrow \mathit{archway}(\mathit{Pos1}, \mathit{Pos2}) \end{array} \right\}$$

ii) State whether H can be computed by Progol5, and explain why or why not. (No proof is required.)

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

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

a Consider the following sets B and E of clauses, and mode declarations M:

$$B = \left\{ \begin{array}{l} even(s(X)) \leftarrow odd(X) \\ even(0) \end{array} \right\} \qquad M = \left\{ \begin{array}{l} modeh(*, odd(+nat)) \\ modeb(*, even(+nat)) \end{array} \right\}$$

$$E = \{odd(s(s(s(0))))\}$$

i) Construct the Kernet Set K of B and E, considering only terms with at most three nesting of the function symbol s. Assume nat to be the predefined type of natural numbers, including 0, $s(0)$, $s(s(0))$, and $s(s(s(0)))$.

ii) State what is meant by a hypothesis being derived by Kernel Set Subsumption.

b Consider the learning task $T = \langle B, E^+, E^-, M \rangle$ where B, E^+, E^- and M are defined as follows:

$$B = \left\{ \begin{array}{l} person(john) \\ person(fred) \\ shoplifts(fred, jewellery) \\ thing(jewellery) \\ guilty(X) \leftarrow steals(X) \end{array} \right\} \quad M = \left\{ \begin{array}{l} modeh(\star, sentenced(+person)) \\ modeh(\star, steals(+person)) \\ modeb(\star, guilty(+person)) \\ modeb(\star, shoplifts(+person, \#thing)) \end{array} \right\}$$

$$E^+ = \{sentenced(fred)\} \qquad E^- = \{sentenced(john)\}$$

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.

$$H = \left\{ \begin{array}{l} sentenced(X) \leftarrow guilty(X) \\ steals(X) \leftarrow shoplifts(X, jewellery) \end{array} \right\}$$

iii) State whether H is derivable by Kernel Set Subsumption, and explain why or why not.

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

3 Consider the following two ASP programs:

$$B = \left[\begin{array}{l} male(X) \leftarrow \text{not } female(X), person(X). \\ female(X) \leftarrow \text{not } male(X), person(X). \\ person(p1). \\ person(p2). \\ has\_job(p1, monarch). \\ has\_job(p2, jester). \\ job(monarch). \\ job(jester). \end{array}\right]$$

$$H = \left[\begin{array}{l} king(X) \leftarrow male(X), has\_job(X, monarch). \\ entertainer(X) \leftarrow has\_job(X, jester). \end{array}\right]$$

a 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 $E^+ = \{king(p1)\}$ and $E^- = \{king(p2)\}$. Explain, using your answer to part (i), why H is a brave inductive solution of T_1.

iii) Consider the learning task T_2 with background knowledge B, and examples $E^+ = \{entertainer(p2)\}$ and $E^- = \{king(p2)\}$. Is H a cautious inductive solution of T_2? Explain why, using your answer to part (i).

iv) Given the background knowledge B, write down examples E^+ and E^- composing a Learning from Answer Sets task $T_3 = \langle B, E^+, E^- \rangle$ such that the inductive solutions of T_3 are exactly the brave inductive solutions of T_1 which are also cautious inductive solutions of T_2.

(Note: it is not necessary to consider a search space for T_3).

b Consider the following mode declarations:

$$M = \left[\begin{array}{l} modeh(1, entertainer(+person)) \\ modeh(1, king(+person)) \\ modeb(1, male(+person)) \\ modeb(1, has\_job(+person, \#job)) \end{array}\right] \quad (V_{max} = 1, L_{max} = 2)$$

i) Write down a maximal set of skeleton rules for the mode declarations M.

ii) Write down the ASPAL encoding of the brave induction task T_1 given the mode declarations M.

iii) Give an Answer Set of the program constructed in part (ii) which demonstrates that H is an inductive solution of the task.

The two parts carry, respectively, 45% and 55% of the marks.

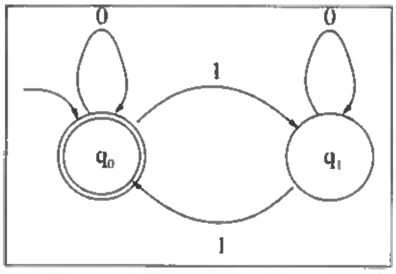
4a Let

B_1 be $father(ted, bob) \leftarrow$
B_2 be $mother(jill, jane) \leftarrow$
$B = B_1 \wedge B_2$ be the background knowledge
$E = parent(ted, bob) \leftarrow$ be an example and $M = P(x,y) \leftarrow Q(x,y)$ be a metarule.

i) Letting H stand for the hypothesis, state the condition for Meta-Interpretive Learning which H, B, E and M must satisfy.

ii) For B and E above, within the context of Inverse Entailment what is $\perp$ (the most specific hypothesis)? Explain.

b Consider the *Parity* finite state acceptor below.



In each case below explain your answer.

i) Give a Prolog program in the form of a Definite Clause Grammar for Parity.

ii) Provide a set of 5 positive examples of sequences for Parity.

iii) Give a 3 clause Prolog meta-interpreter for regular languages.

iv) Provide the set of abduced ground facts which when added to your meta-interpreter make it accept Parity sequences.

c Consider once more the *Parity* finite state acceptor from part b in the context of Bayesian Meta-Interpretive Learning. In each case below explain your answer.

i) Show diagrammatically the stochastic derivation of the Parity acceptor from the sequence *0101*.

ii) Using your diagram calculate the probability of the Parity acceptor given the example sequence *0101*.

iii) Describe the difference between sampling with and without replacement.

iv) What is the computational advantage of sampling hypotheses without replacement?

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

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