IMPERIAL COLLEGE OF SCIENCE, TECHNOLOGY AND MEDICINE

EXAMINATIONS 2018

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 19 March 2018, 14:00 Duration: 120 minutes

Answer THREE questions

Paper contains 4 questions Calculators not required

Section A (Use a separate answer book for this section)

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

Consider the problem domain of a control lighting system in a building, where the system has to learn to switch the light in an office when it detects movements and to close the blind in a office when it is dark.

Let $T = \langle B, E^+, E^-, M \rangle$ be a learning task for such a system, where B, E^+, E^- and M are defined as follows:

$$B = \left\{ \begin{array}{ll} office(o1). & office(o2). & office(o3). & sensor(s1). & sensor(s2). & blind(b1). \\ blind(b2). & blind(b3). & light(l1). & light(l2). & light(l3). & dark(o1). \\ dark(o3). & detectMovement(s1,o1). & detectMovement(s2,o2). \\ smartLight(L,B,O) \leftarrow switchLight(L,O), closeBlind(B,O). \end{array} \right\}$$

$$M = \left\{ \begin{array}{l} modeh(switchLight(+light, +office)). \\ modeh(closeBlind(+blind, +office)). \\ modeb(detectMovement(-sensor, +office)). \\ modeb(dark(+office)). \end{array} \right\} \\ E^+ = \left\{ \begin{array}{l} smartLight(l1, b1, o1). \\ smartLight(l2, b2, o2). \\ smartLight(l3, b3, o3). \end{array} \right\}$$

Consider the following hypothesis *H*:

$$H = \left\{ \begin{array}{l} switchLight(L,O) \leftarrow detectMovement(S,O). \\ closeBlind(B,O) \leftarrow dark(O). \end{array} \right\}$$

- a Prove that H is an inductive solution of the task T under the definition of learning from entailment.
- b Use the hybrid abductive inductive learning algorithm HAIL to construct the Kernel Set that HAIL generates to compute H as the inductive solution of T.
- c Show whether Progol5 can compute H as an inductive solution for the given learning task T. A proof is required.

The three parts carry, respectively, 25%, 40%, and 35% of the marks.

2 This question is about meta-level learning.

Consider the problem domain of a normative system for granting citizenship in a country. Let $T = \langle B, E^+, E^-, M \rangle$ be a simplified learning task for such a system, where B, E^+, E^- and M are defined as follows:

$$B = \left\{ \begin{array}{ll} person(john). & person(tom). & age(tom, 18). & age(john, 18). \\ bornOut(john). & permResidence(john). & nat(18). \\ naturalized(X) \leftarrow permResidence(X), adult(X). \end{array} \right\}$$

$$M = \left\{ \begin{array}{l} modeh(citizen(+person)). \\ modeh(adult(+person)). \\ modeb(naturalized(+person)). \\ modeb(age(+person, \# nat)). \end{array} \right\} \quad E^+ = \left\{ \begin{array}{l} citizen(john). \\ E^- = \left\{ \begin{array}{l} citizen(tom). \\ \end{array} \right\} \end{array}$$

- a State whether the learning task *T* accepts an inductive solution derivable by Kernel Set Subsumption. Explain your answer.
- b Consider the following hypothesis H:

$$H = \left\{ \begin{array}{l} citizen(P) \leftarrow naturalized(P). \\ adult(P) \leftarrow age(P, 18). \end{array} \right\}$$

- i) Use the Top-directed abductive learning algorithm (TAL) to prove that H is a complete inductive solution of the learning task T. Discuss whether H is also a consistent inductive solution of T.
- ii) Give the top theory that the TopLog algorithm would generate to solve the learning task T.

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

Section B (Use a separate answer book for this section)

Consider the following two ASP programs:

$$B = \begin{bmatrix} p(X,Y) \leftarrow q(X), r(Y), \text{not } p(Y,X). \\ p(Y,X) \leftarrow q(X), r(Y), \text{not } p(X,Y). \\ s(1,a). \quad s(2,b). \\ t1(1). \quad t1(2). \quad t2(a). \quad t2(b). \end{bmatrix} \qquad H = \begin{bmatrix} q(X) \leftarrow t1(X), s(X,a). \\ r(X) \leftarrow t1(X), s(X,b). \end{bmatrix}$$

- i) Write down the answer sets of $B \cup H$ (no proof required).
- ii) Consider the learning task T_b with background knowledge B and examples $E^+ = \{p(1,2)\}\$ and $E^- = \{p(2,1)\}\$. Using your answer to part (i), explain why H is a brave inductive solution of T_h .
- Consider the following mode declarations:

$$M = \left[\begin{array}{l} modeh(1,q(+t1)) \\ modeh(1,r(+t1)) \\ modeb(2,s(+t1,\#t2)) \end{array} \right]$$

- i) Write down a maximal set of skeleton rules for the mode declarations M $(V_{max} = 2, L_{max} = 2).$
- ii) Write down the ASP encoding of the task T_b (from part a (ii)), which is produced by the ASPAL algorithm, given the mode declarations M.
- Give an answer set of the ASP program constructed in part b (ii) that demonstrates that H is a brave inductive solution of T_b .
- Consider the following two ASP programs:

$$B_2 = [heads \leftarrow not \ tails.] \quad H_2 = [tails \leftarrow not \ heads.]$$

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

For each of the following learning frameworks, either write down examples E^+ and E^- such that $\langle B_2, E^+, E^- \rangle$ forms a task T under that framework and H_2 is an optimal inductive solution of T, or explain why no such examples exist.

- ii) Brave induction.
- Cautious induction.
- iv) Learning from Answer Sets.

The three parts carry, respectively, 15%, 50%, and 35% of the marks.

Section C (Use a separate answer book for this section)

4a Let B_1 be $animal(X) \leftarrow bear(X)$

 B_2 be $bear(pooh) \leftarrow$

 $B = B_1 \wedge B_2$ be the background knowledge

 $E = nice(pooh) \leftarrow be an example.$

- i) Letting *H* stand for the hypothesis, state the condition in Inductive Logic Programming which *H*, *B* and *E* must satisfy.
- ii) For B and E above, what is \perp (the most specific hypothesis)? Explain.
- b In each case below explain your answer.
 - i) Give Prolog code for a general meta-interpretative learner.
 - ii) Describe the following meta-rules: Instance, Base, Chain, Tailrec.
- c Suppose you are given the Bayesian Meta-Interpreter represented as the SLP, R.

$$1: parse(S) \leftarrow parse(q0, S, []).$$

delta(Q, C, P).

$$\begin{array}{l} \frac{1}{2}: parse(Q, [], []) \leftarrow acceptor(Q). \\ \frac{1}{2}: parse(Q, [C|X], Y) \leftarrow \\ state(P), \\ parse(P, X, Y), \end{array}$$

$$\frac{1}{2}$$
: $state(q0) \leftarrow \frac{1}{2}$: $state(q1) \leftarrow$

- i) Show the derivation of the regular language a^*b^+ from the goal $\leftarrow parse([a, b, b])$.
- ii) Calculate the probability of this regular language given the example.

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