

- 1 Appendix
- 2 Appendix A (Lattices)

3 (a) Ordered set and lattice

- 4 An ordered set P is defined as a set in which an order relation \leq is given such that for any elements $a, b, c \in P$,
- 5 (i) $a \le a$;
- 6 (ii) $a \le b$ and $b \le a$ implies a = b;
- 7 (iii) $a \le b$ and $b \le c$ implies $a \le c$.
- 8 A lattice *L* is an ordered set in which, for any $x, y \in L$, "meet", $x \land y \in L$, and "join", $x \lor y \in L$ are defined,
- 9 where $x \land y \le x, x \land y \le y$; if $z \le x, z \le y$, then $z \le x \land y$ and $x \le x \lor y, y \le x \lor y$; if $x \le z, y \le z$, 10 then $x \lor y \le z$.

11 **(b) Distributive lattice**

12 A lattice *L* is a distributive lattice if and only if for any $a, b, c \in P$, $a \land (b \lor c) = (a \land b) \lor (a \land c)$.

13 (c) Complemented lattice

- 14 A lattice *L* is a complemented lattice if and only $\forall a \in L, \exists a^{\perp} \in L$ such that $a \land a^{\perp} = 0$ and $a \lor a^{\perp} = 0$
- 15 1, where 0 and 1 represent the least and the greatest element, respectively.

16 (d) Boolean lattice (classical logic)

17 A Boolean lattice is defined as a distributive complemented lattice.

18 (e) Orthocomplemented lattice

- 19 A lattice *L* is an orthocomplemented lattice if and only if $\forall a \in L, \exists a^{\perp} \in L$ such that
- 20 (i) $a \wedge a^{\perp} = 0$ or $a \vee a^{\perp} = 1$;
- 21 (ii) $a \le b \Longrightarrow b^{\perp} \le a^{\perp}$;
- 22 (iii) $a^{\perp \perp} = a$.
- 23 (f) Orthomodular lattice (quantum logic)
- An orthocomplemented lattice *L* is an orthomodular lattice if and only if $a \le b \Rightarrow b = a \vee (b \wedge a^{\perp})$, $\forall a, b \in L, a^{\perp} \in L$.
- 26 Appendix B (Rough set lattices)
- 27 (a) Equivalence relation

- Given a set *S*, $R \subseteq S \times S$ is an equivalence relation if and only if for $a, b, c \in S$,
- 29 (i) aRa;
- 30 (ii) *aRb* implies *bRa* and vice versa;
- 31 (iii) *aRb* and *bRc* implies *aRc*.

32 (b) Equivalence class

- 33 Given an equivalence relation $R \subseteq S \times S$, an equivalence class of $x \in S$ with respect to R is defined by
- 34 $[x]_R = \{y \in S | xRy\}$. A set viewed as an equivalence class is called a rough set.

35 (c) Approximation by a rough set

- 36 Given an equivalence relation $R \subseteq S \times S$, for any $X \subseteq S$, the lower approximation of X with respect to
- 37 *R*, denoted by $R_*(X)$, is defined as $R_*(X) = \{x \in S | [x]_R \subseteq X\}$, and the upper approximation of X
- 38 with respect to R, denoted by $R^*(X)$, is defined as $R^*(X) = \{x \in S | [x]_R \cap X \neq \emptyset\}$.

39 (d) Rough set lattice

- 40 Given two kinds of equivalence relations $R \subseteq S \times S$ and $K \subseteq S \times S$, $L = \{X \subseteq S | R^*(K_*(X)) = X\}$ can
- 41 be verified to be a lattice and is called a rough set lattice. In a rough set lattice, any element is a set,
- 42 and the order relation is defined by inclusion (\subseteq). Meet and join are defined as follows: For any

43 $X, Y \subseteq S, X \land Y = R^*(K_*(X \cap Y))$ and $X \lor Y = R^*(K_*(X \cup Y))$.

44 Note: In the text of this paper, a relation *R* between a set of one equivalence class and a set of other

45 equivalence classes is given, and the upper and lower approximations are replaced by H^* and D_* , 46 respectively, for the sake of convenience.

47 Appendix C (Algorithmic representations for excess Bayesian inference)

- 48 $//H = \{h_1, h_2, \dots, h_N\}, D = \{d_1, d_2, \dots, d_N\}$
- 49 $//M^t = \{M_1 = (h_1, d_1), M_2 = (h_p, d_p), \dots, M_m = (h_N, d_N), \}$
- 50 for $(k = 1; k \le m; k + +)$ {
- 51 // excess Bayesian inference with respect to a datum 52 for $(j = 1; j \le N; j + +)$ {
- 53 sum = 0;54 for $(i = \pi M_k; i \le 1)$

for
$$(i = \pi M_k; i \le \pi M_{k+1} - 1; i + +)$$
 {

$$sum = sum + P(d_i, h_j);$$

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55

57 for
$$(i = \pi M_k; i \le \pi M_{k+1} - 1; i + +)$$
 {

58
$$PP(d_i, h_j) = P(d_i, h_j)/sum;$$

}

}

}

59 60

61 for
$$(i = \pi M_k; i \le \pi M_{k+1} - 1; i + 1)$$
 {
62 for $(j = 1; j \le N; j + 1)$ {
63 $P(d_i, h_j) = PP(d_i, h_j);$
64 }
65 }
66 // excess Bayesian inference with respect to a hypothesis
67 for $(i = 1; i \le N; i + 1)$ {
68 $sum = 0;$
69 for $(j = \pi M_k; j \le \pi M_{k+1} - 1; j + 1)$ {
70 $sum = sum + P(d_i, h_j);$
71 }
72 for $(j = \pi M_k; j \le \pi M_{k+1} - 1; j + 1)$ {
73 $PP(d_i, h_j) = P(d_i, h_j)/sum;$
74 }
75 }
76 for $(j = \pi M_k; j \le \pi M_{k+1} - 1; j + 1)$ {
77 for $(i = 1; i \le N; i + 1)$ {
78 $P(d_i, h_j) = PP(d_i, h_j);$
79 }
80 }
81 // Amplifying the effect
82 for $(i = \pi M_k; i \le \pi M_{k+1} - 1; i + 1)$ {
79 for $(j = \pi M_k; j \le \pi M_{k+1} - 1; i + 1)$ {
70 for $(j = \pi M_k; j \le \pi M_{k+1} - 1; j + 1)$ {
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76 for $(j = \pi M_k; j \le \pi M_{k+1} - 1; j + 1)$ {
77 for $(j = \pi M_k; j \le \pi M_{k+1} - 1; j + 1)$ {
78 $P(d_i, h_j) = P(d_i, h_j);$ }
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