Beneficial and Harmful Explanatory Machine Learning

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XAI Background

Common drawbacks in relevant studies were identified and discussed in recent surveys which are summarised as follows:

- Under-specified and ambiguous definitions
- A lack of empirical data to support claims
- Limited references to valuable social science literature
- No or little accounting for humans' perspective
- Not enough emphasis recently on the harmful side

Objective: Explore comprehensibility of machine learned logic programs in interactive machine-human teaching contexts .

MIL and predicate invention

Meta-Interpretive Learning (MIL) is a sub-field of Inductive Logic Programming (ILP). Given higher-order clauses $\mathcal{M}$, examples $\mathcal{E}$ and background knowledge $\mathcal{B}$ all represented by logic programming, a MIL algorithm returns a program $\mathcal{H}$ that satisfies,

$$\forall e+ \in E \quad \mathcal{H} \cup \mathcal{B} \cup \mathcal{M} \models e+$$
$$\forall e- \in E \quad \mathcal{H} \cup \mathcal{B} \cup \mathcal{M} \not\models e-$$

MIL supports predicate invention, dependent learning, learning of recursions and higher-order programs.

Human comprehension

Given a definition D, a group of humans H, a symbolic machine learning algorithm M, the **explanatory effect** $E_{ex}(D, H, M(E))$ of the theory $M(E)$ learned from examples E is

$$E_{ex}(D, H, M(E)) = C_{ex}(D, H, M(E)) - C(D, H, E)$$

whereas $C_{ex}(D, H, M(E))$ denotes **machine-explained human comprehension**. $C(D, H, E)$ is the **unaided human comprehension** of examples E. We then relate the **explanatory effectiveness** of a theory to comprehensibility:

- $M(E)$ is *beneficial* to H if $E_{ex}(D, H, M(E)) > 0$
- $M(E)$ is *harmful* to H if $E_{ex}(D, H, M(E)) < 0$
- Otherwise, $M(E)$ does not have observable effect on H

Cognitive window

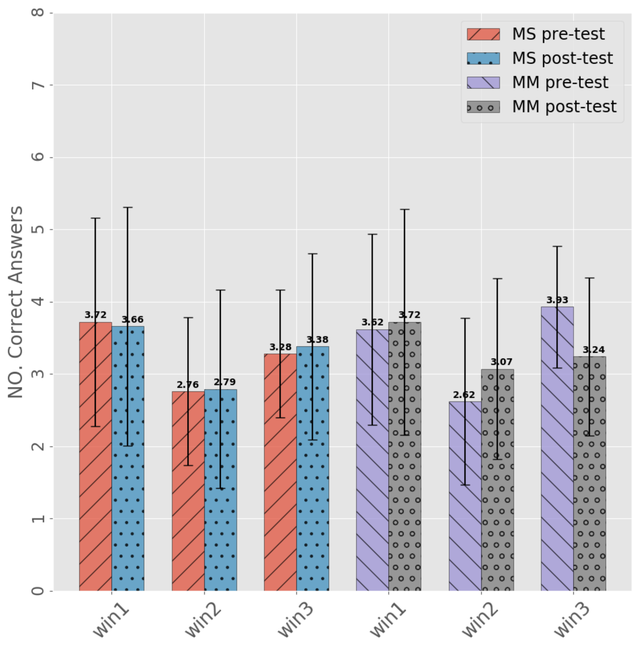
We estimate the mental execution complexity of a query by new variants of Kolmogorov complexity, **cognitive cost** of datalog program Cog and problem solution $CogP$. We hypothesise a bound on human hypothesis space size B and postulated a **cognitive window** which includes two constraints:

1. $E_{ex}(D, H, M(E)) < 0$ if $|S| > B(M(E), H)$
2. $E_{ex}(D, H, M(E)) \leq 0$ if $Cog(M(E), x) \geq CogP(E, \bar{M}, \phi, x)$

where |S| is the hypothesis space size of the program class. Rule verbalisation utilises declarative memory and an increase in computational complexity and working memory has a negative effect on human performance.

Results

MS and MM denote human self-learning and machine-aided learning.



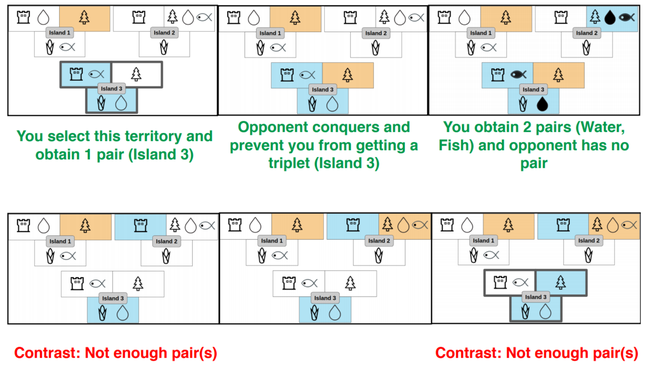
- **win1**: violates the cognitive cost constraint and $E_{ex} = 0$
- **win2**: does not violate cognitive window constraints and $E_{ex} > 0$
- **win3**: violates the hypothesis space size constraint, could only learn a maximum of four clauses and $E_{ex} < 0$

Materials

A MIL system ***MIPlain*** learns a complete and consistent logic program (win_1, win_2 and win_3 in the following table) for tasks win_1, win_2 and win_3 which are Noughts and Crosses positions with increasing minimax search depth.

Depth	Rules
1	`win_1(A,B):-move(A,B),won(B)`
2	`win_2(A,B):-move(A,B),win_2_1(B)`
	`win_2_1(A):-number_of_pairs(A,x,2), number_of_pairs(A,o,0)`
3	`win_3(A,B):-move(A,B),win_3_1(B)`
	`win_3_1(A):-number_of_pairs(A,x,1),win_3_2(A)`
	`win_3_2(A):-move(A,B),win_3_3(B)`
	`win_3_3(A):-number_of_pairs(A,x,0),win_3_4(A)`
	`win_3_4(A):-win_2(A,B),win_2_1(B)`

$MIPlain$ which is a variant of MIL game learning framework $MIGO$ learns a winning Noughts and Crosses strategy. We designed an isomorphic game of Noughts and Crosses which has a different spatial arrangement and uses graphical representations for row and diagonal positions. Textual explanations are translated from the program above. An example of visual and textual explanations used in our two-group human experiment is presented below.



Future and ongoing works

- More interactive human-machine explanatory teaching
- Teaching explanations from stochastic logic programs
- Improving explanatory beneficiality via sequential teaching
- Behavioural debugging of human errors by ILP