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Ultra-Strong Machine Learning
Comprehensibility of Programs Learned with
Inductive Logic Programming

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Motivation

- Michie (1988) - definition of **Ultra-Strong Machine Learning** requires a) predictive accuracy increase, b) hypotheses in symbolic form and c) **human performance increase from after study of machine-generated hypotheses**
- Mitchell (1997) - definition of Machine Learning in terms of **Predictive Accuracy** alone
- ILP and symbolic AI generally need **operational definition** of comprehensibility to distinguish communicable and non-communicable knowledge
- Testability in age of Mechanical Turk

Text comprehension tests

“For many years people believed the cleverest animals after man were chimpanzees. Now, however, there is proof that dolphins may be even cleverer than these big apes.”

Question: Which animals do people think may be the cleverest?

[<http://englishteststore.net>]

Program comprehension tests

$p(X,Y) :- p1(X,Z), p1(Z,Y).$

$p1(X,Y) :- \text{father}(X,Y).$

$p1(X,Y) :- \text{mother}(X,Y).$

$\text{father}(\text{john},\text{mary}). \text{mother}(\text{mary},\text{harry}).$

Question: $p(\text{john},\text{harry})?$

Experiment - chemistry domain

Background	Example	Target
q1(ab,ac)	exo(ac,an)	exo(X,Y) :- q1(X,Z), q1(Z,Y)
q2(aa,ac)	not exo(aa,ab)	exo(X,Y) :- q1(X,Z), q2(Z,Y)
q1(ad,ag)	exo(ab,ag)	exo(X,Y) :- q2(X,Z), q2(Z,Y)
q2(ad,ae)	not exo(ad,ai)	exo(X,Y) :- q2(X,Z), q1(Z,Y)
...	...	

Definitions

- Comprehensibility - proportion of correct answers after inspection of program $[C]$
- Inspection time $[T]$ - time taken to read program
- Predicate recognition $[R]$ - mean proportion predicates correctly recognised
- Naming time $[N]$ - time to name predicate
- Textual complexity $[Sz]$ - program size
- Unaided Human Comprehension of Examples $C(S,E)$
- Machine-aided Human Comprehension of Examples $C(S,M(E))$

Experimental Hypotheses

- H1** $C \propto \frac{1}{T}$ - long inspection time related to incomprehension
- H2** $C \propto R$ - comprehension related to recognition of predicate
- H3** $C \propto \frac{1}{S_z}$ - long programs hard to understand
- H4** $R \propto \frac{1}{N}$ - long naming time related to lack of recognition
- H5** $C(S, E) < C(S, M(E))$ - improved human performance after studying machine-learned rules

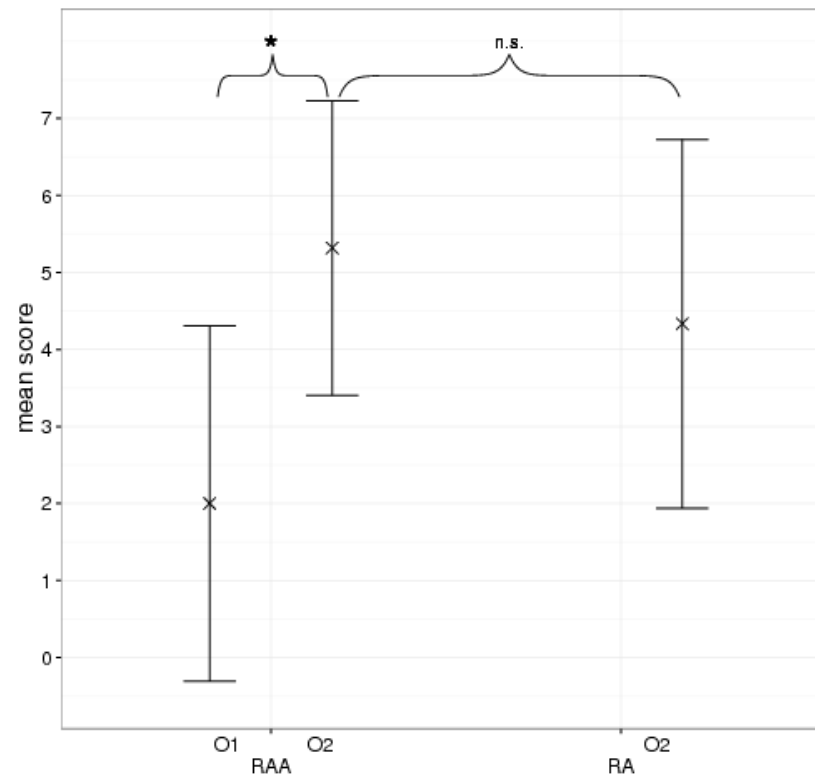
Experiment participants

Participants were undergraduate students of cognitive science (20 female, 23 male, mean age = 22.12 years, sd = 2.51) with a good background in Prolog.

Experimental Results - Family Relations

H1	Statistically confirmed
H2	Statistically confirmed
H3	Partially confirmed
H4	Partially confirmed - recursive ancestor exception
H5	Statistically confirmed

H5 result



Mean comprehensibility scores for rule acquisition and application (RAA) vs. rule application (RA)

Conclusions and further work

- First operational definition of **comprehensibility**
- First demonstration of Michie's Ultra-Strong Machine Learning
- Confirmation of hypotheses
- Difficulties in understanding **recursion**- eg ancestor/2
- Value of operational definition of comprehension to **AI systems development**
- **A theory of the Explainable**

Bibliography

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