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# Logic-based and Probabilistic Symbolic Learning Lecture 1: Human vs Statistical Learning

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#### **Human vs Statistical Learning**

#### UK EPSRC Priority 2016-2021 - Human-like Computing

Characteristic	Human	Statistical
Examples	Few ( $\approx 1$ )	Many ( $\geq 10K$ )
per concept	[Tenenbaum, 2011]	
Concepts	Many ( $\geq 10K$ )	Few ( $pprox$ 1)
	[Brown et al, 2008]	
Background	Large	Small
knowledge	[Brown, 2000]	
Structure	Modular, re-useable	Monolithic
	[Omrod et al, 2004]	



- A girl watches a dance routine on television.
- Afterwards she reproduces the routine.
- The new dance moves are incorporated into her repertoire.
- Subsequent improvisation allows re-use of parts of routines.

#### **Example 2: Learning words in a language**



- Average undergraduate knows 20K words.
- Learning rate =  $\frac{20000}{20 \times 365}$  = 2.7 new words per day since birth.
- Presentations new word before assimilation  $\approx 1$  [Zipf's Law].
- Word assimilation involves visual, auditory, sense and context recognition of associated concept.



#### **Meta-Interpretive Learning [IJCAI 2013]**

**Prolog Meta-Interpreter** implements Learning as Interpretation.

Input to Meta-Interpreter: 1) Observations, 2) Meta-Rules, 3) Background Knowledge assignments (substitutions).

**Output from Meta-Interpreter:** Hypothesised assignments.

Metagol supports Problem decomposition by Predicate Invention and Learning recursion [MLJ 2015], Single example multi-task learning [ECAI 2014], Program Induction with resource and time-complexity optimisation [IJCAI 2015].



**stair(X,Y)** :- a(X,Y).

**stair(X,Y)** :- **a**(X,Z), **stair(Z,Y)**.

a(X,Y) :- vertical(X,Z), horizontal(Z,Y).

Learned in 0.08s on laptop from single image. Note Predicate invention and **recursion**.



#### Language applications

#### Formal grammars [MLJ 2014]

## **Dependent string transformations** [ECAI 2014]



#### Chain of programs from dependent learning

 $f_{03}(A,B) := f_{12_1}(A,C), f_{12}(C,B).$ 

 $f_{12}(A,B) := f_{12-1}(A,C), f_{12-2}(C,B).$ 

 $f_{12_1}(A,B) := f_{12_2}(A,C), skip1(C,B).$ 

 $f_{12_2}(A,B) := f_{12_3}(A,C), write_1(C,B,..).$ 

 $f_{12_3}(A,B) := copy1(A,C), f_{17_1}(C,B).$ 

 $f_{17}(A,B) := f_{17,1}(A,C), f_{15}(C,B).$ 

 $f_{17_1}(A,B) := f_{15_1}(A,C), f_{17_1}(C,B).$ 

 $f_{17_{-1}}(\mathsf{A},\mathsf{B}) := skipalphanum(\mathsf{A},\mathsf{B}).$ 

 $f_{15}(A,B) := f_{15_1}(A,C), f_{16}(C,B).$ 

 $f_{15_1}(A,B) := skipalphanum(A,C), skip1(C,B).$ 

 $f_{16}(\mathsf{A},\mathsf{B})$ :-  $copyalphanum(\mathsf{A},\mathsf{C}), skiprest(\mathsf{C},\mathsf{B}).$ 

**Other applications** 

Learning proof tactics [ILP 2015]

Learning data transformations [ILP 2015]

#### **Conclusions and Challenges**

- New form of Declarative Machine Learning [De Raedt, 2012]
- $H_2^2$  is tractable and Turing-complete fragment of High-order Logic
- Knuth-Bendix style ordering guarantees termination of queries
- Beyond classification learning strategy learning

#### Challenges

- Generalise beyond Dyadic logic
- Deal with classification noise
- Active learning
- Efficient problem decomposition
- Meaningful invented names and types

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