

Growing libraries of concepts with wake-sleep program induction

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Joint with: Lucas Morales, Armando Solar-Lezama, Joshua B. Tenenbaum

Heavy inspiration from: Eyal Dechter

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MIT

The Language of Thought

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The Language of Thought

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The Language and Thought Series

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A FORMAL THEORY OF INDUCTIVE INFERENCE, Part I*†

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Engineering the language of thought

Universal Theory

Theory

Model

Data

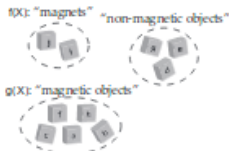
Magnetism

Core Predicates: $f(X)$, $g(X)$

Surface Predicates: $interacts(X,Y)$

Laws:

$interacts(X,Y) \leftarrow f(X) \wedge f(Y)$
 $interacts(X,Y) \leftarrow f(X) \wedge g(Y)$
 $interacts(X,Y) \leftarrow interacts(Y,X)$



Probabilistic Horn Clause Grammar

Taxonomy

Core Predicates: $s(X,Y)$, $t(X,Y)$

Surface Predicates: $has_a(X,Y)$, $is_a(X,Y)$

Laws:

$is_a(X,Y) \leftarrow s(X,Y)$
 $has_a(X,Y) \leftarrow t(X,Y)$
 $has_a(X,Y) \leftarrow is_a(X,Z) \wedge has_a(Z,Y)$
 $is_a(X,Y) \leftarrow is_a(X,Z) \wedge is_a(Z,Y)$



"a shark is a fish"
 "a bird can fly"
 "a canary can fly"
 "a salmon can breathe"
 ...

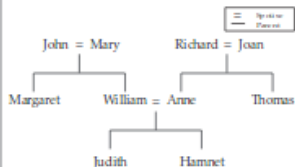
Kinship

Core Predicates: $u(X)$, $v(X,Y)$, $w(X,Y)$

Surface Predicates: $female(X)$, $child(X,Y)$, $parent(X,Y)$, $spouse(X,Y)$, $father(X,Y)$, ...

Laws:

$female(X) \leftarrow u(X)$
 $spouse(X,Y) \leftarrow v(X,Y)$
 $spouse(X,Y) \leftarrow v(Y,X)$
 $child(X,Y) \leftarrow w(X,Y)$
 $child(X,Y) \leftarrow child(X,Z) \wedge spouse(Z,Y)$
 $father(X,Y) \leftarrow \neg female(X) \wedge child(X,Y)$
 ...



"John is William's father"
 "John is Judith's grandfather"
 "Judith is Hamnet's sister"
 "Margaret is Judith's aunt"
 ...

Engineering the language of thought



Growing a domain-specific language of thought

Goal: acquire domain-specific knowledge needed to induce a class of programs

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Goal: acquire domain-specific knowledge needed to induce a class of programs

- Library of concepts (declarative knowledge)
- Search strategy (procedural knowledge)

DSL: Library of concepts

Tasks and Programs

```
[7 2 3] → [7 3]
[1 2 3 4] → [3 4]
[4 3 2 1] → [4 3]    [7 3] → False
f(ℓ) = (f1 ℓ (λ (x)    [3] → False
    (> x 2)))          [9 0 0] → True
                        [0] → True
                        [0 7 3] → True
                        f(ℓ) = (f3 ℓ 0)
[2 7 8 1] → 8
[3 19 14] → 19
f(ℓ) = (f2 ℓ)
```

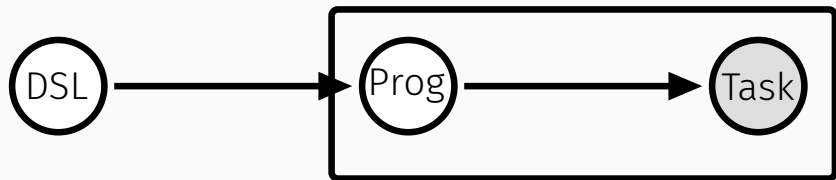
DSL

```
f0(ℓ,r) = (foldr r ℓ cons)
          (f0: Append lists r and ℓ)
f1(ℓ,p) = (foldr ℓ nil (λ (x a)
    (if (p x) (cons x a) a)))
          (f1: Higher-order filter function)
f2(ℓ) = (foldr ℓ 0 (λ (x a)
    (if (> a x) a x)))
          (f2: Maximum element in list ℓ)
f3(ℓ,k) = (foldr ℓ (is-nil ℓ)
    (λ (x a) (if a a (= k x))))
          (f3: Whether ℓ contains k)
```

- **Wake:** Solve problems by writing programs
- **Sleep:** Improve DSL and neural recognition model:
 - **Sleep-G:** Improve DSL (**G**enerative model)
 - **Sleep-R:** Improve **R**ecognition model

Combines ideas from Wake-Sleep & Exploration-Compression algorithm by Eyal Dechter

DSL learning as Bayesian inference



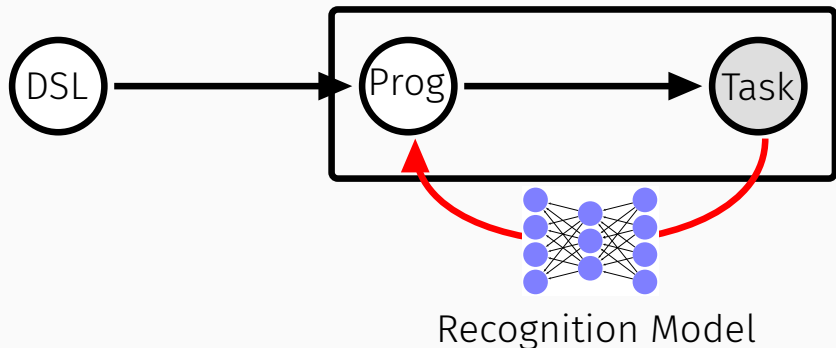
[Dechter et al., 2013] [Liang et al, 2010]; [Lake et al, 2015]

Gray: Observed.

White: Latent.

Boxed (plate): Repeated.

DSL learning as **amortized** Bayesian inference



Recognition model: Neural net.

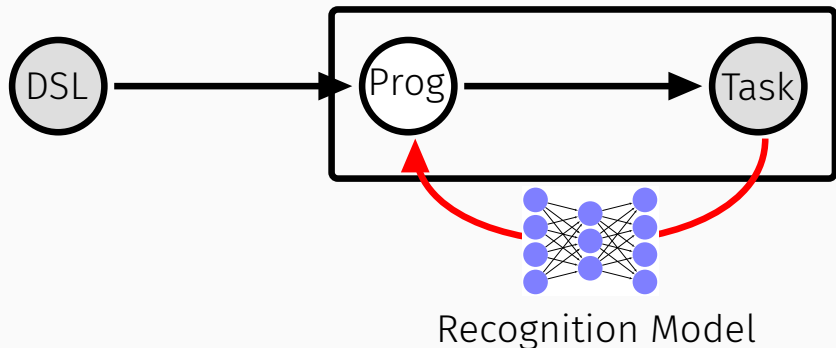
Red: Bottom-up inference.

Gray: Observed.

White: Latent.

Boxed (plate): Repeated.

Wake: Problem solving



Recognition model: Neural net.

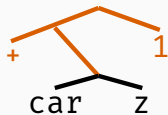
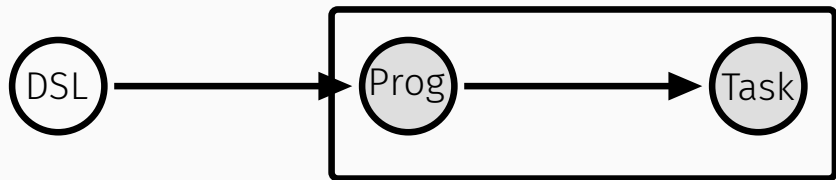
Red: Bottom-up inference.

Gray: Observed.

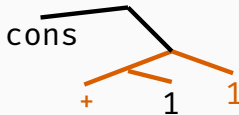
White: Latent.

Boxed (plate): Repeated.

Sleep-G: Memory consolidation



Program



Program

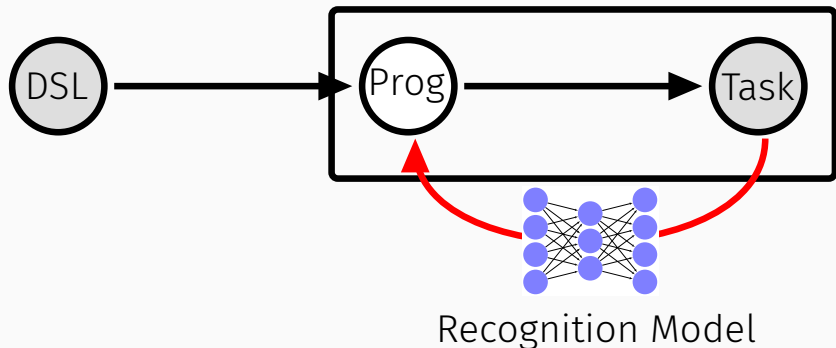


DSL Fragment

Fragment Grammars: O'Donnell 2015.

Orange: Code fragments.

Sleep-R: Objective

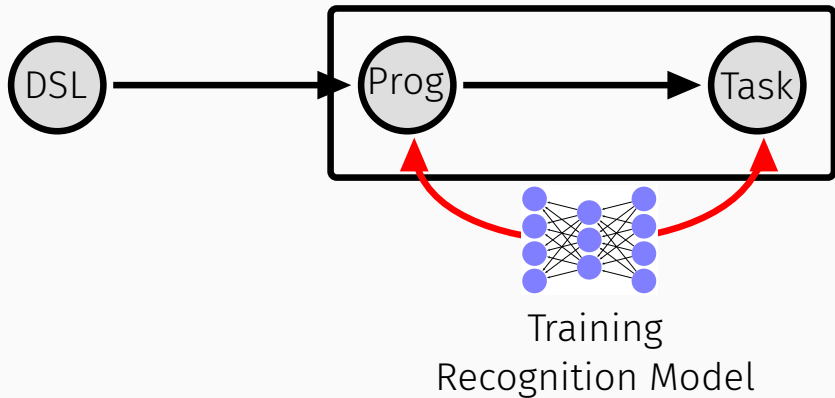


Recognition model predicts distribution over program, conditional on task.

Training: (program, task) pairs

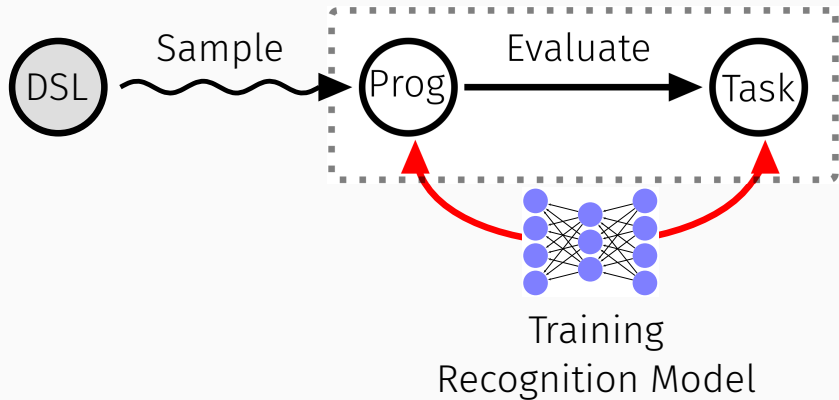
Objective: Predict program w/ (1) high prior under DSL & (2) high likelihood for task

Sleep-R: Experience replay



Train on (program, task) pairs found during waking

Sleep-R: Dreaming



Train on (program, task) pairs sampled from DSL

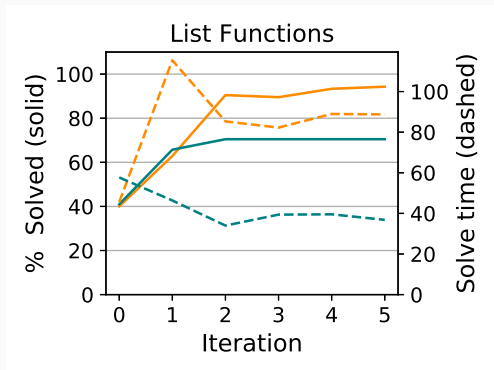
List functions

Created+investigated by Lucas Morales

Name	Input	Output
repeat-3	[7 0]	[7 0 7 0 7 0]
drop-3	[0 3 8 6 4]	[6 4]
rotate-2	[8 14 1 9]	[1 9 8 14]
count-head-in-tail	[1 2 1 1 3]	2
keep-div-5	[5 9 14 6 3 0]	[5 0]
product	[7 1 6 2]	84

Discovers 38 concepts, including 'filter'

List functions: Learning curves on hold out tasks



Learning curves for DreamCoder both with (in orange) and without (in teal) the recognition model. Solid lines: % holdout testing tasks solved w/ 10m timeout. Dashed lines: Average solve time, averaged only over tasks that are solved.

Turtle graphics

Created+Investigated by Mathias Sablé Meyer

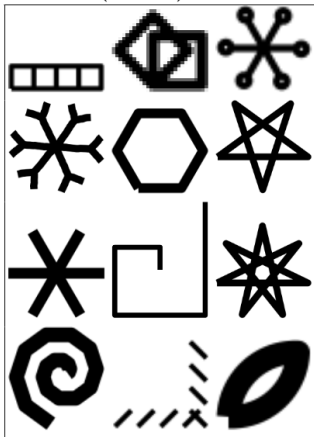
- pen up/pen down
- move pen (forward+rotate)
- get/set pen state
- 'for' loops

```
1 # Hexagon
2 for n in range(6):
3     move(distance=1cm, angle= 2pi / 6)
4
5 # Spiral
6 for n in range(20):
7     move(distance = n cm, angle= 2pi / 4)
```

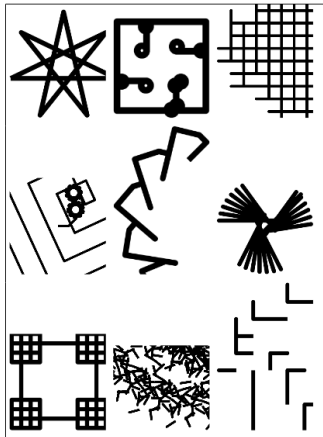
Turtle graphics

Created+Investigated by Mathias Sablé Meyer

12 (of 136) Tasks



9 samples from learned DSL



Left: Agent controls a ‘pen’ – tasked with drawing pictures. **Right:** During Sleep-R ‘dream’ by sampling programs from learned DSL and rendering them.

Takeaway:

- Humans flexibly adapt to diverse sets of new problem domains
 - DreamCoder takes a step in this direction

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Future work

- More human-like learning: intelligently composing new tasks,

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- Humans flexibly adapt to diverse sets of new problem domains
 - DreamCoder takes a step in this direction

Future work

- More human-like learning: intelligently composing new tasks,
- Theory learning
- Planning