DreamCoder: Bootstrapping Domain-Specific Languages for Neurally-Guided Bayesian Program Learning

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Wake/Sleep DSL Induction

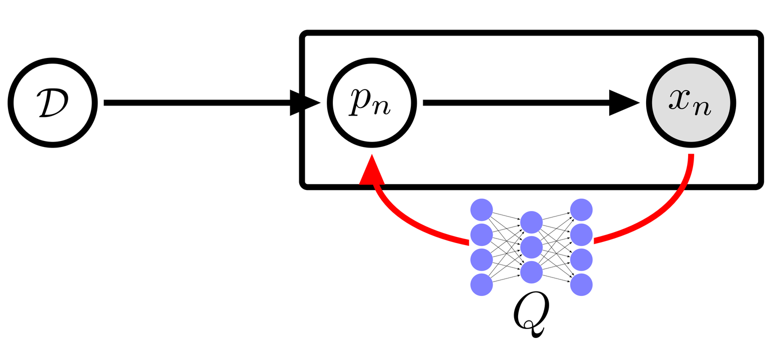
Domain Specific Language (DSL): A finely-tuned program representation, specialized to a domain of programming tasks. Prior work in program learning largely uses hand-engineered DSLs.

Approach: DreamCoder algorithm, which bootstraps a learned DSL while jointly training a neural net to search for programs in the learned DSL. Given a few hundred programming tasks, alternatingly:

- **Wake**: synthesize programs
- **Sleep-R**: train neural net (**R**ecognition model)
- **Sleep-G**: improve DSL (**G**enerative model)

Program representation: ≈Lisp; conditionals, variables, λ abstraction

Bayesian framing



Observe N **tasks**, written $\{x_n\}_{n=1}^N$, each a program synthesis problem.
Solve task x_n with latent program p_n
Likelihood model $\mathbb{P}[x_n|p_n]$ scores program p_n on task x_n
Latent **DSL** $\mathcal{D}$ acts as generative model over programs: $\mathbb{P}[x|\mathcal{D}]$

$$\underbrace{p_n^* = \arg\max_{p_n} \mathbb{P}[x_n|p_n]\mathbb{P}[p_n|\mathcal{D}^*]}_{\text{Wake}}$$

$$\underbrace{\mathcal{D}^* = \arg\max_{\mathcal{D}} \mathbb{P}[\mathcal{D}] \prod_n \sum_{p_n} \mathbb{P}[x_n|p_n]\mathbb{P}[p_n|\mathcal{D}]}_{\text{Sleep-G}}$$

Neural recognition model

Neural network $Q(p|x)$ predicts distribution over programs conditioned on tasks. Simple Q: just predicts probabilities of DSL productions. Goal: learn to invert generative model

$$\underbrace{\min_Q \mathrm{KL}\left(\mathbb{P}[p|x,\mathcal{D}]||Q(p|x)\right)}_{\text{Sleep-R}}$$

Train on two sources of data:

- **Samples ("Dreams") from DSL**: Unlimited data, but only high-quality if generative model $\mathcal{D}$ is good. Like Helmholtz Machine's recognition model training. Loss:
$$\mathbb{E}_{(p,x)\sim\mathcal{D}}\left[\log Q(p|x)\right]$$
- **Self-Supervised**: (x_n, p_n) pairs discovered during waking. Loss:
$$\frac{\mathbb{P}\left[x_n,p_n|\mathcal{D}\right]}{\sum_{(x_n,p_n')}\mathbb{P}\left[x_n,p_n|\mathcal{D}\right]}\log Q(p_n|x_n)$$

Model outputs for three different task domains

Programs & Tasks

List Functions

[7 2 3]→[7 3]
[1 2 3 4]→[3 4]
[4 3 2 1]→[4 3]
$f(\ell)$ =(f_1 ℓ (λ (x) (> x 2)))

[7 3]→False
[3]→False
[9 0 0]→True
[0]→True
[0 7 3]→True
$f(\ell)$ =(f_3 ℓ 0)

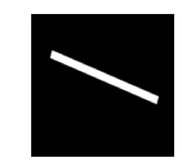
[2 7 8 1]→8
[3 19 14]→19
$f(\ell)$ =(f_2 ℓ)

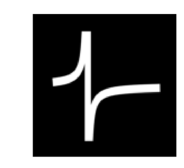
Text Editing

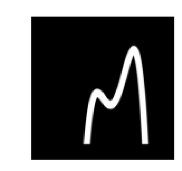
+106 769-438→106.769.438
+83 973-831→83.973.831
f(s) =(f_0 "." "-" (f_0 "." " " (cdr s)))

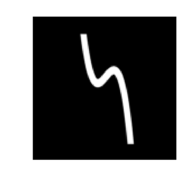
Temple Anna H →TAH
Lara Gregori→LG
f(s) =(f_2 s)

Symbolic Regression


f(x) =(f_1 x)


f(x) =(f_6 x)


f(x) =(f_4 x)


f(x) =(f_3 x)

DSL

List Functions

f_1(ℓ,p) =(foldr ℓ nil (λ (x a) (if (p x) (cons x a) a)))
(f_1: *Higher-order filter function*)

f_2(ℓ) =(foldr ℓ 0 (λ (x a) (if (> a x) a x)))
(f_2: *Maximum element in list* ℓ)

f_3(ℓ,k) =(foldr ℓ (is-nil ℓ) (λ (x a) (if a a (= k x))))
(f_3: *Whether* ℓ *contains* k)

Text Editing

f_0(s,a,b) =(map (λ (x) (if (= x a) b x)) s)
(f_0: *substitutes characters*)

f_1(s,c) =(foldr s s (λ (x a) (cdr (if (= c x) s a))))
(f_1: *Drop characters from* s *until* c *reached*)

f_2(s) =(unfold s is-nil car (λ (z) (f_1 z " ")))
(f_2: *Abbreviates words*)

Symbolic Regression

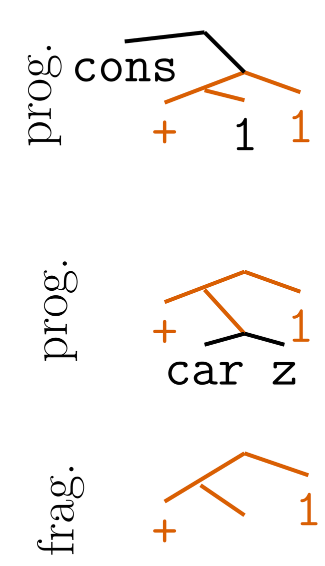
f_0(x) =(+ x real)
f_1(x) =(f_0 (* real x))
f_2(x) =(f_1 (* x (f_0 x)))
f_3(x) =(f_0 (* x (f_2 x)))
f_4(x) =(f_0 (* x (f_3 x)))
(f_4: *4th order polynomial*)

f_5(x) =(/ real x)
f_6(x) =(f_5 (f_0 x))
(f_6: *rational function*)

Top: Tasks from three domains we apply our algorithm to, each followed by the programs DreamCoder discovers for them. Bottom: Several examples from learned DSL. Notice that learned DSL primitives can call each other, and that DreamCoder rediscovers higher-order functions like `filter` (f_1 under List Functions)

Fragment Grammars: Inducing a DSL

Fragment grammars: introduced in computational linguistics (O'Donnell 2015)



Example synthesized programs	Proposed λ-expression
(λ (s) (map (λ (x) (if (= x '.') '-' x))) s) (λ (s) (map (λ (x) (if (= x '-') ',' x))) s)	(λ (s) (map (λ (x) (if (= x α) β x))) s)

Figure 1: **Left:** syntax trees of two programs sharing common structure, highlighted in orange, from which we extract a fragment and add it to the DSL (bottom). **Right:** actual programs, from which we extract fragments that perform character substitutions.

Ongoing work: Generative models

Learn probabilistic program (a regex) p_n from K strings $x_n = \{y_n^k\}_{k=1}^k$.
Likelihood model:

$$\mathbb{P}[x_n|p_n] = \prod_{k=1}^{K} \mathbb{P}[y_n^k|p_n]$$

Tasks:

cut	F	Moss Side
control	CL	Burnage
control	F	City Centre
cut	PCFL	Brooklands

Learned generative models:

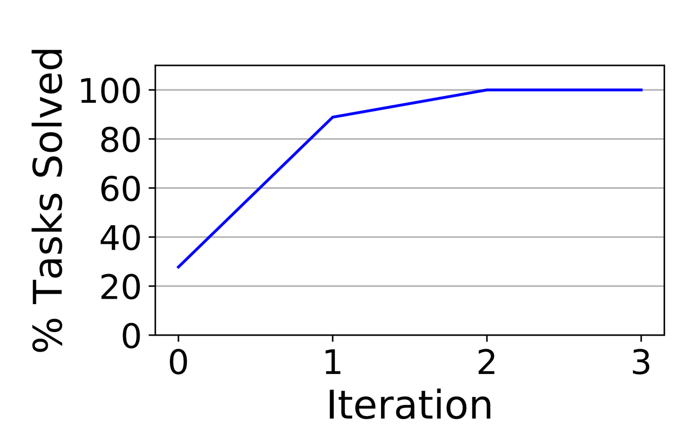
`\l*\l`	`((\u\u)*)|F`	`( |\u\w*)*`

Samples from synthesized generative models:

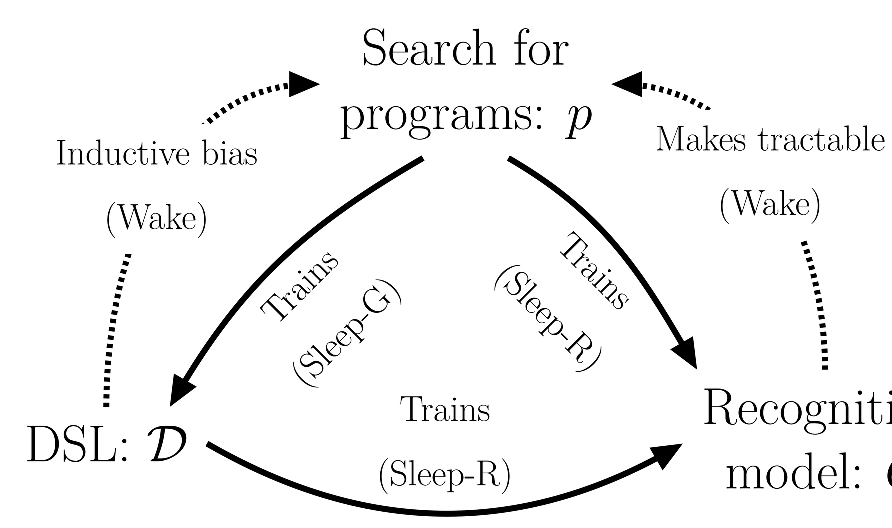
ya	DQDF	Vr DR
glrwfdcnc	F	BeF lKQ
mgs	F	W
piljnl	KI	kqBfZ 0
kj	F	ON
zci	GL	Bttc
sxpm	F	S

Learned DSL:

$f_1() =$ `\u\w*`
$f_2(x) =$ (x|f_1)* = (x|\u\w*)*
$f_3(x) = f_2$(space) =(|\u\w*)*
$f_4(x) =$ (x*x)
(equivalent to regex 'plus')
$f_5() = f_4$(\l) = \l*\l



Why this works: Bootstrapping



- Search finds new programs $\Longrightarrow$ DSL+recognition model get more data
- DSL improves $\Longrightarrow$ easier search, recognition model gets better data
- Recognition model improves $\Longrightarrow$ easier search

Learning from Scratch

Start w/ McCarthy 1959 Lisp: recursion, conditionals, lists. Train on 22 programming exercises. After 93 hours on 64 CPUs, rediscovers 9 functional programming staples: `map`, `fold`, `zip`, `unfold`, `index`, `length`, `range`, `incr`, `decr`.

Acknowledgements

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