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

Kevin Ellis, Lucas Morales, Mathias Sablé Meyer, Maxwell Nye, Armando Solar-Lezama, Joshua B. Tenenbaum

Massachusetts Institute of Technology

Wake/Sleep DSL Induction

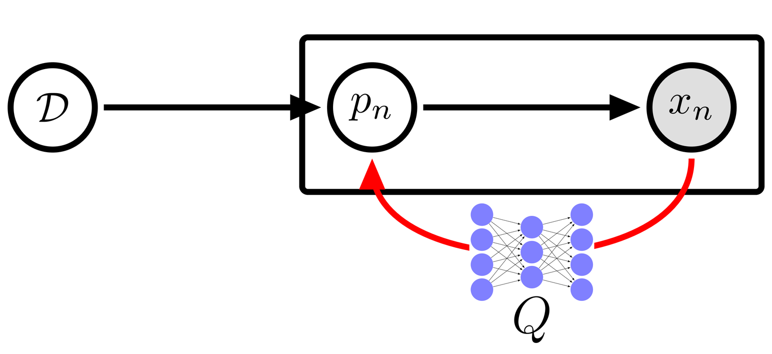
Domain Specific Language (DSL): A finely-tuned program representation, specialized to a domain of programming tasks. Prior work in program learning largely uses hand-engineered DSLs.

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: $\mathbb{P}[x|\mathcal{D}]$

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

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

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

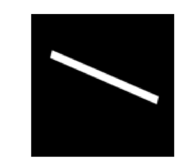
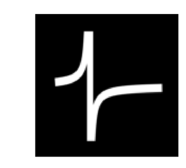
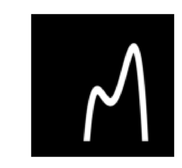
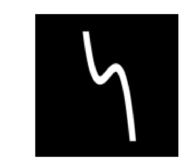
$$\underbrace{\min_Q \mathrm{KL}\left(\mathbb{P}[p|x,\mathcal{D}]||Q(p|x)\right)}_{\textbf{Sleep-R}}$$

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

	List Functions	Text Editing	Symbolic Regression

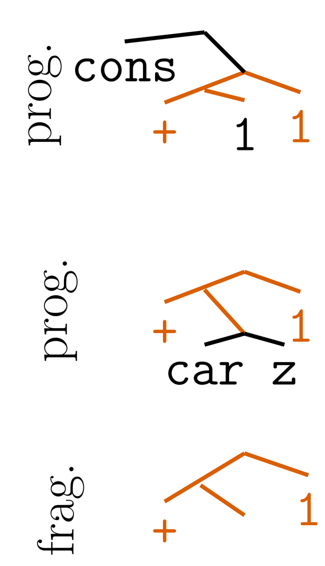
Programs & Tasks	`[7 2 3]`→`[7 3]`
	`[1 2 3 4]`→`[3 4]`
	`[4 3 2 1]`→`[4 3]`
	$f(\ell)$ `=(`f_1 ℓ `(`λ `(x) (> x 2)))`
	
	`[7 3]`→`False`
	`[3]`→`False`
	`[9 0 0]`→`True`
	`[0]`→`True`
	`[0 7 3]`→`True`
	$f(\ell)$ `=(`f_3 ℓ `0)`
	
	`[2 7 8 1]`→`8`
	`[3 19 14]`→`19`
	$f(\ell)$ `=(`f_2 ℓ`)`
		+106 769-438→106.769.438
		+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)
			 
			f(x) =(f_1 x) f(x) =(f_6 x)
			 
			f(x) =(f_4 x) f(x) =(f_3 x)

DSL	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`)	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*)	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:

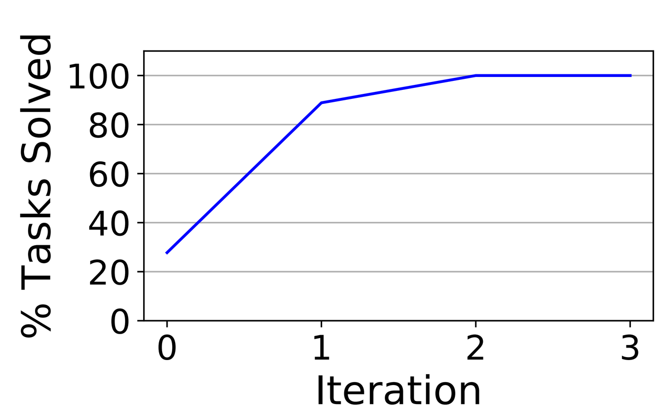
```
\l*\l   ((\u\u)*)|F   ( |\u\w*)*
```

Samples from synthesized generative models:

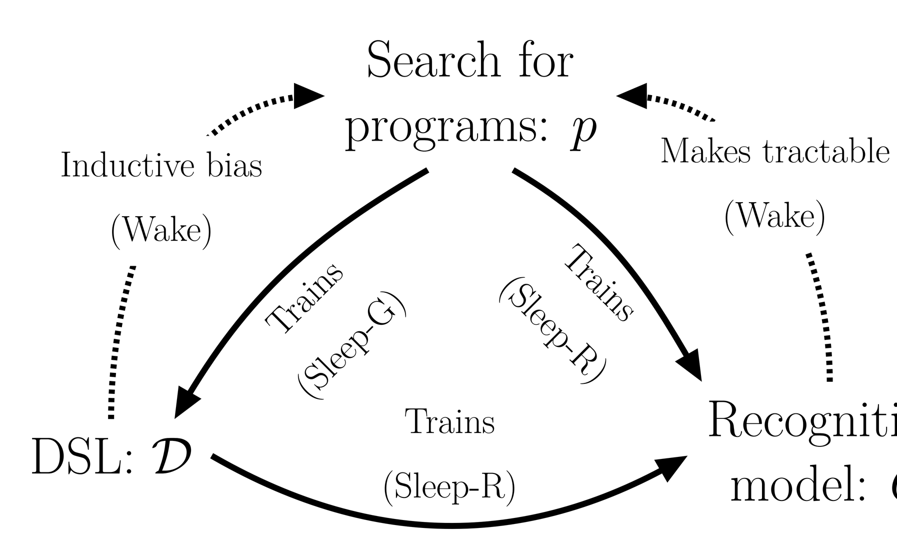
ya	DQDF	Vr DR
glrwfdcnc	F	BeF lKQ
mgs	F	W
piljnl	KI	kqBfZ 0
kj	F	ON
zci	GL	Bttc
sxpm	F	S

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 ⟹ DSL+recognition model get more data
- DSL improves ⟹ easier search, recognition model gets better data
- Recognition model improves ⟹ 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

We gratefully acknowledge collaboration with Eyal Dechter, whose EC algorithm (Dechter et al, IJCAI 2013) provided the inspiration for DreamCoder, and Luke Hewitt, who graciously provided us with a regex learning data set.