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

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Wake/Sleep DSL Induction

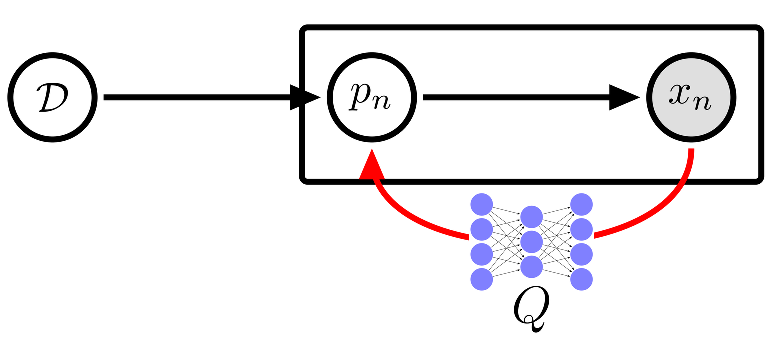
Domain Specific Language (DSL): A finely-tuned program representation, specialized to a domain of programming tasks. Prior work in program learning largely uses hand-engineered DSLs.

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

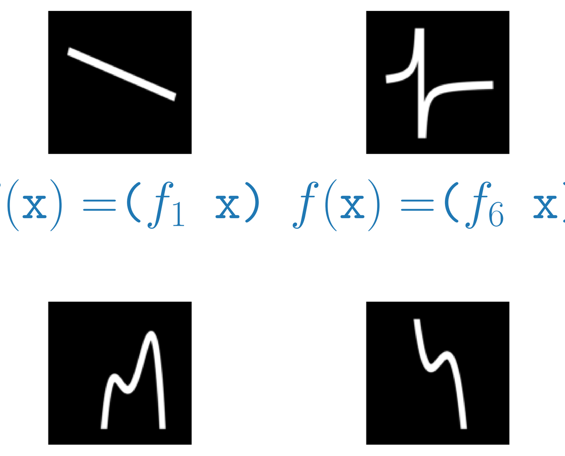
$$\underbrace{\min_Q \mathrm{KL}\left(\mathbb{P}[p|x,\mathcal{D}] || Q(p|x)\right)}_{\text{Sleep-R}}$$

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

	List Functions	Text Editing	Symbolic Regression

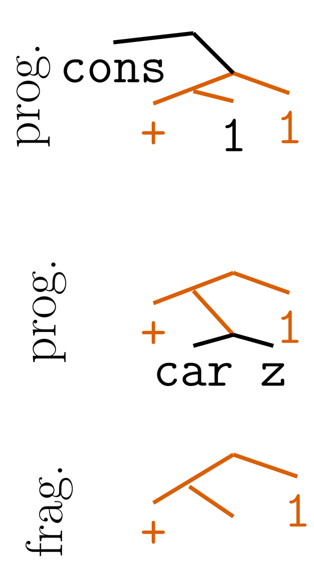
Programs & Tasks	`[7 2 3]→[7 3]`
	`[1 2 3 4]→[3 4]`
	`[4 3 2 1]→[4 3]`
	$f(\ell)$ `=(`f_1 ℓ `(λ (x) (> x 2)))`
	
	`[7 3]→False`
	`[3]→False`
	`[9 0 0]→True`
	`[0]→True`
	`[0 7 3]→True`
	$f(\ell)$ `=(`f_3 ℓ `0)`
	
	`[2 7 8 1]→8`
	`[3 19 14]→19`
	$f(\ell)$ `=(`f_2 ℓ`)`
		+106 769-438→106.769.438
		+83 973-831→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)

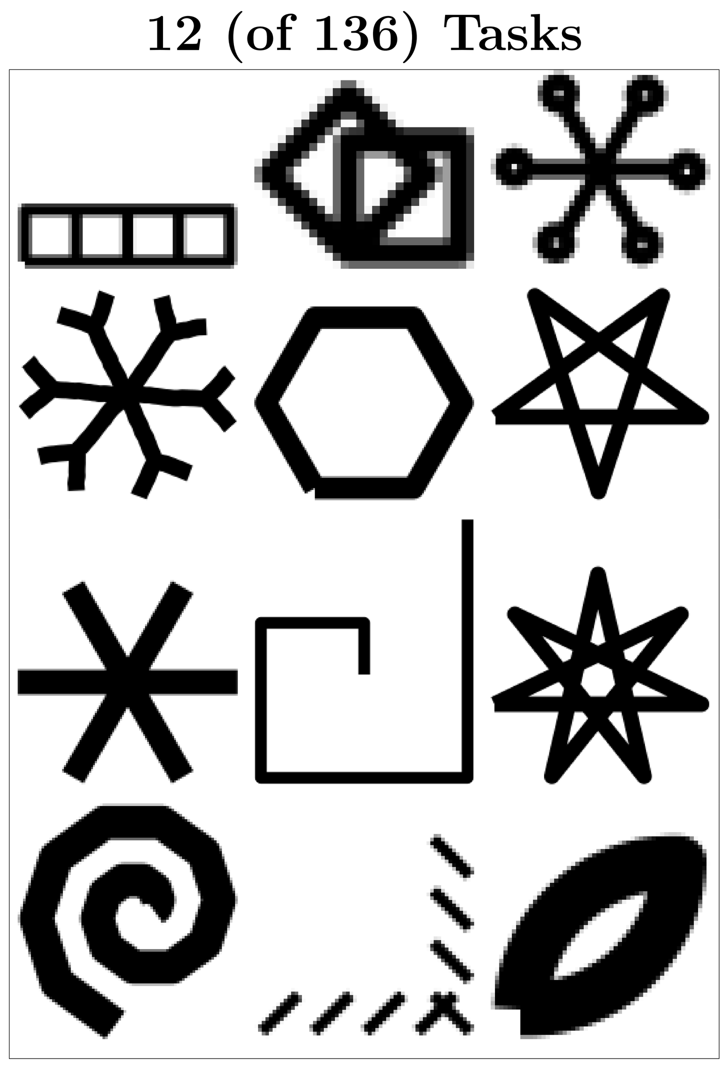


Example synthesized programs	Proposed λ-expression
`(λ (s) (map (λ (x) (if (= x '.') '-' x))) s)` `(λ (s) (map (λ (x) (if (= x '-') ',' x))) s)`	`(λ (s) (map (λ (x) (if (= x α) β x))) s)`

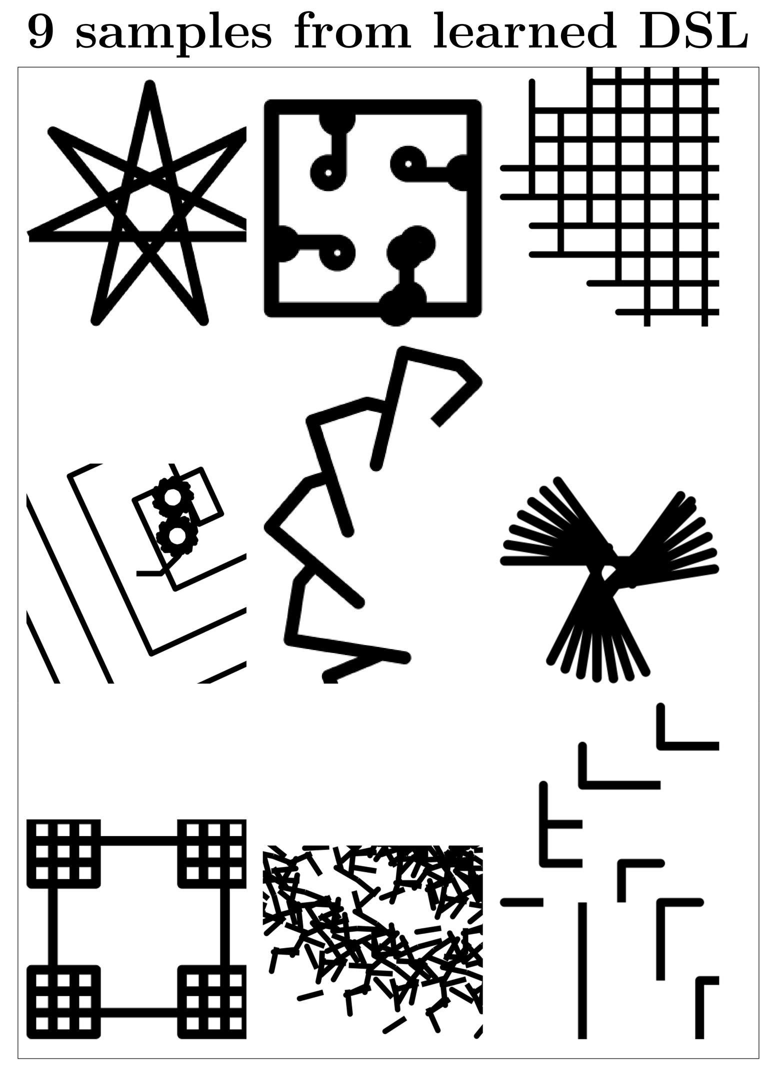
Figure 1: **Left:** syntax trees of two programs sharing common structure, highlighted in orange, from which we extract a fragment and add it to the DSL (bottom). **Right:** actual programs, from which we extract fragments that perform character substitutions.

Generative models of images: Turtle/LOGO Graphics

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.

Acknowledgements

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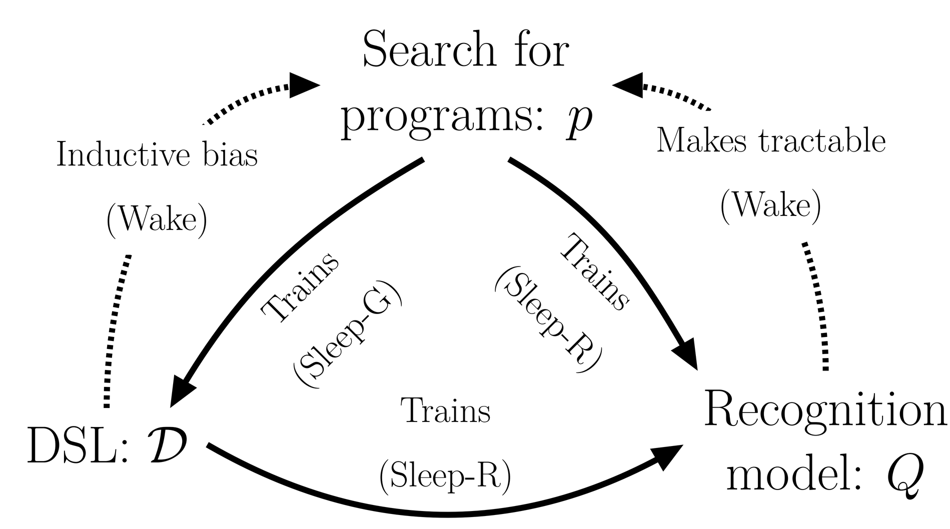
Why this works: Bootstrapping



Generative models of text

Three Tasks		
1.14531	F	110.9
?	CL	163.2
1.29857	F	207.3
?	PCFL	143.3

Three learned generative models		
`?|(1.\d+)`	`((\u\u)*)|F`	`\d\d\d.\d`

Samples from generative models		
1.61	DQDF	343.8
?	F	241.2
?	F	647.5
1.2	KI	246.8

Learned DSL

$f_1 =$ `\u\w*` $f_2(x) =$`(`x`|`f_1`)*`
$f_3 = f_2($`" "`$) =$`( |\u\w*)*`
(f_3: *whitespace delimited words*)
$f_4(x) =$ `(`x`*`x`)` (f_4: *regex 'plus'*)

Learning from Scratch

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