DreamCoder: Bootstrapping Domain-Specific Languages for Neurally-G Program Learning

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Wake/Sleep DSL Induction

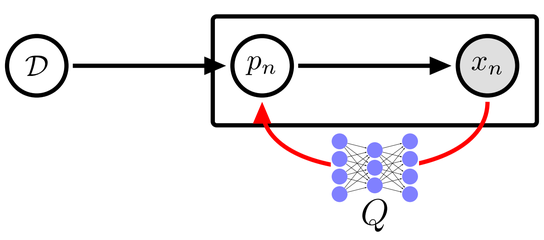
Domain Specific Language (DSL): A finely-tuned program representation, specialized to a domain of programming tasks. Prior work in program learning largely uses hand-engineered DSLs.

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

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

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

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

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

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 domai

	List Functions		Text Editing

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

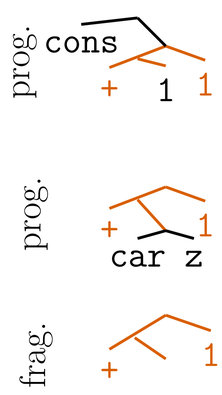
	`[2 7 8 1]`→`8`
	`[3 19 14]`→`19`
	$f(\ell)$ = `(`f_2 ℓ`)`
			Temple Anna H →TAH
			Lara Gregori→LG
			f(`s`) = `(`f_2 `s)`

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_0(`s,a,b`) = `(map (`λ `(x) (if (= x a) b x)) s)` (*f_0: substitutes characters*)
	$f_2(\ell)$ = `(foldr` ℓ `0 (`λ `(x a) (if (> a x) a x)))` (*f_2: Maximum element in list ℓ*)		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_3(`ℓ,k`) = `(foldr` ℓ `(is-nil` ℓ`) (`λ `(x a) (if a a (= k x))))` (*f_3: Whether ℓ contains* `k`)		f_2(`s`) = `(unfold s is-nil car (`λ `(z) (`f_1 `z " ")))` (*f_2: Abbreviates words*)

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

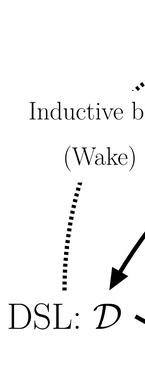
Fragment Grammars: Inducing a DSL

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



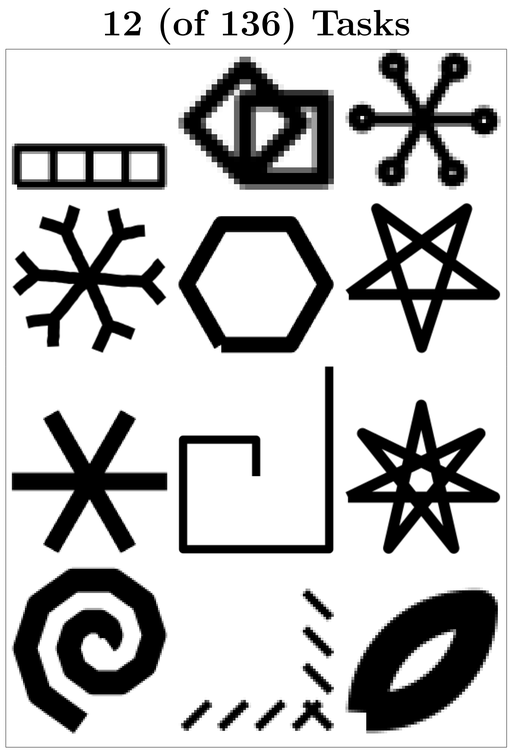
Example synthesized programs	Proposed λ-expression
`(`λ `(s) (map (`λ `(x) (if (= x '.') '-' x))) s)`	`(`λ `(s) (map (`λ `(x) (if (= x` α`)` β `x))) s)`
`(`λ `(s) (map (`λ `(x) (if (= x '-') ',' x))) s)`	

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.

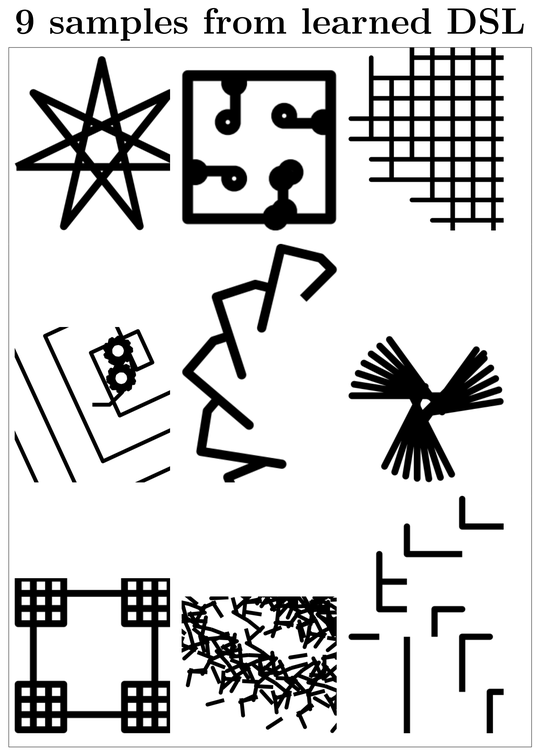


Generative models of images: Turtle/LOGO Graphics

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.

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1.2

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$f_3 = f_2$
(f_3:
$f_4(x) =$

Lea

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sion, co
program
on 64 C
`zip`, `un`
`incr`, `d`

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.