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

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Wake/Sleep DSL Induction

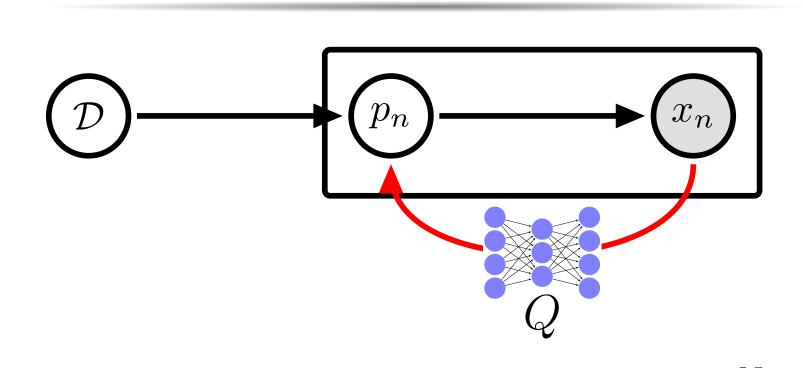
Domain Specific Language (DSL): A finely-tuned program representation, specialized to a domain of programming tasks. Prior work in program learning largely uses hand-engineered DSLs.

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 (Recognition model)
- Sleep-G: improve DSL (Generative model)

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

$$\underbrace{p_n^* = \underset{p_n}{\operatorname{arg\,max}} \mathbb{P}[x_n|p_n]\mathbb{P}[p_n|\mathcal{D}^*]}_{\mathbf{Wake}} \\
\mathcal{D}^* = \underset{\mathcal{D}}{\operatorname{arg\,max}} \mathbb{P}[\mathcal{D}] \prod_{n} \sum_{p_n} \mathbb{P}[x_n|p_n]\mathbb{P}[p_n|\mathcal{D}] \\
\underbrace{\operatorname{Sleep-G}}$$

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

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

Train on two sources of data:

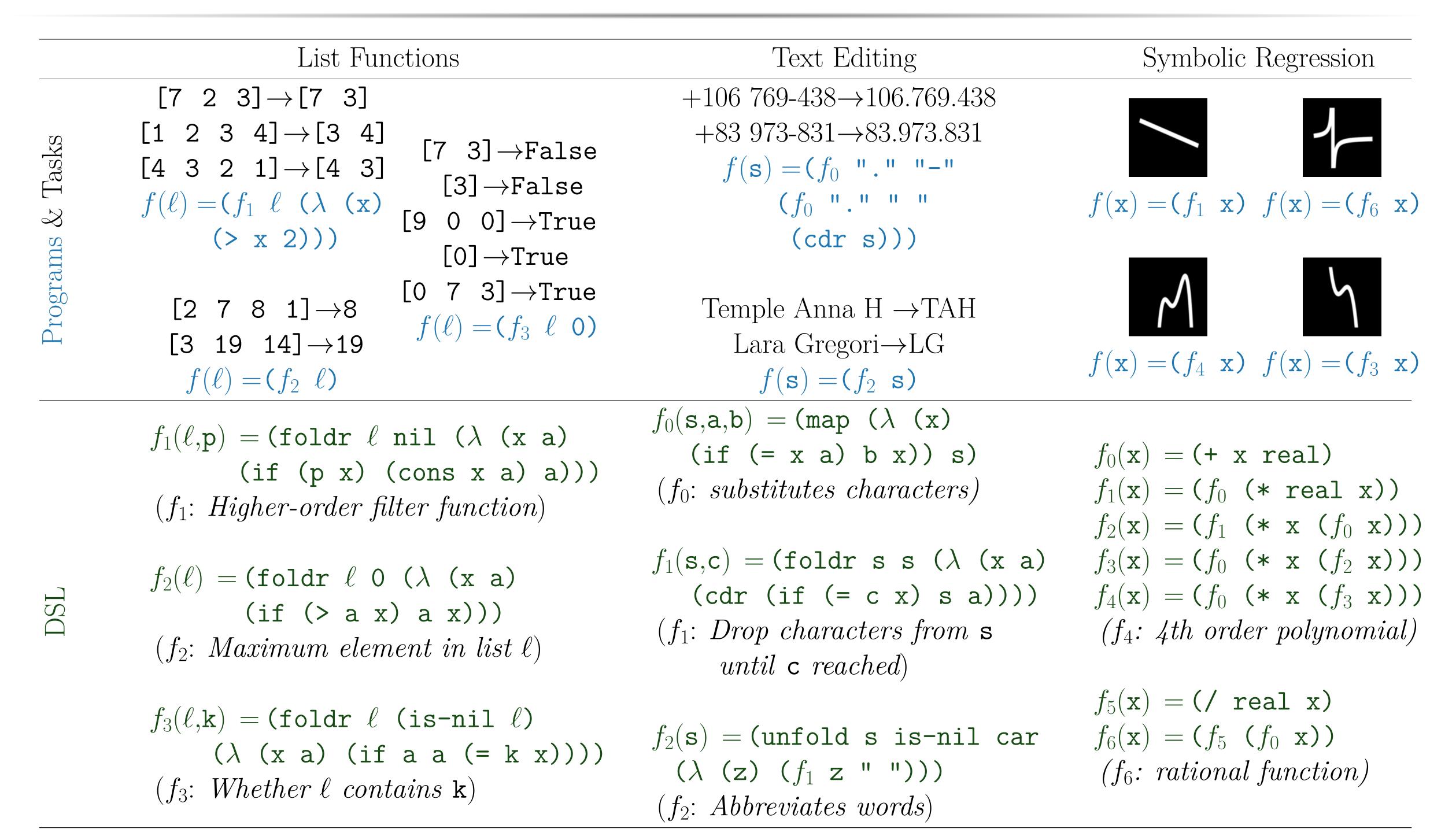
Samples ("Dreams") from
 DSL: Unlimited data, but only
 high-quality if generative model 𝒯 is
 good. Like Helmholtz Machine's
 recognition model training. Loss:

 $\mathbb{E}_{(p,x)\sim\mathcal{D}}\left[\log Q(p|x)\right]$

• 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



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)

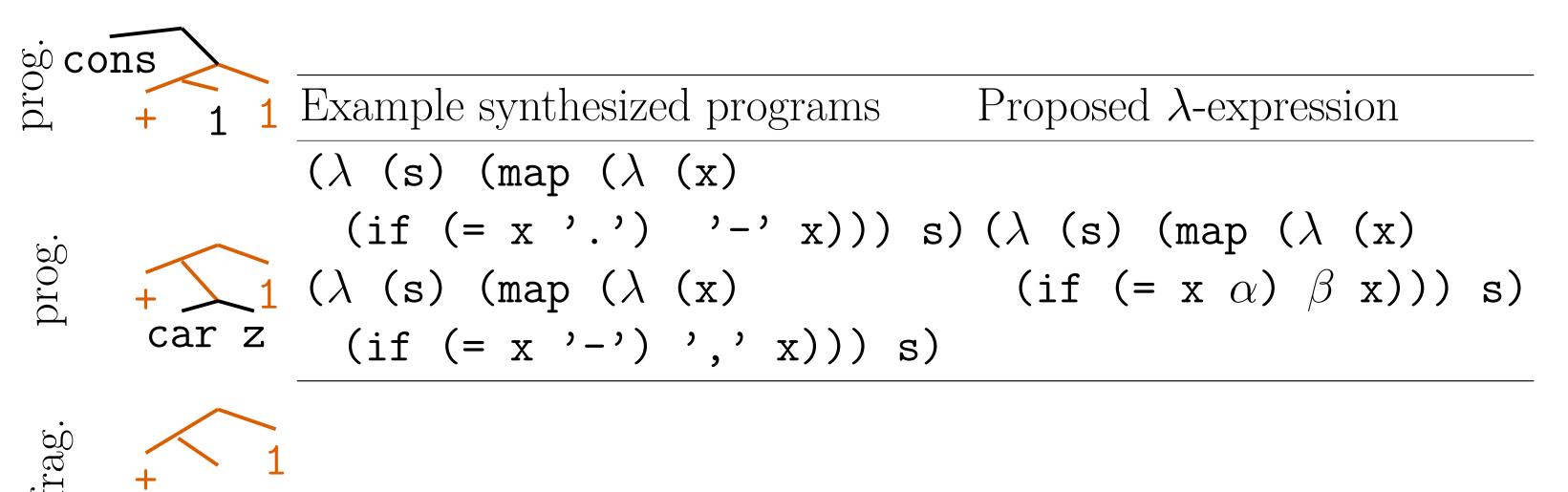
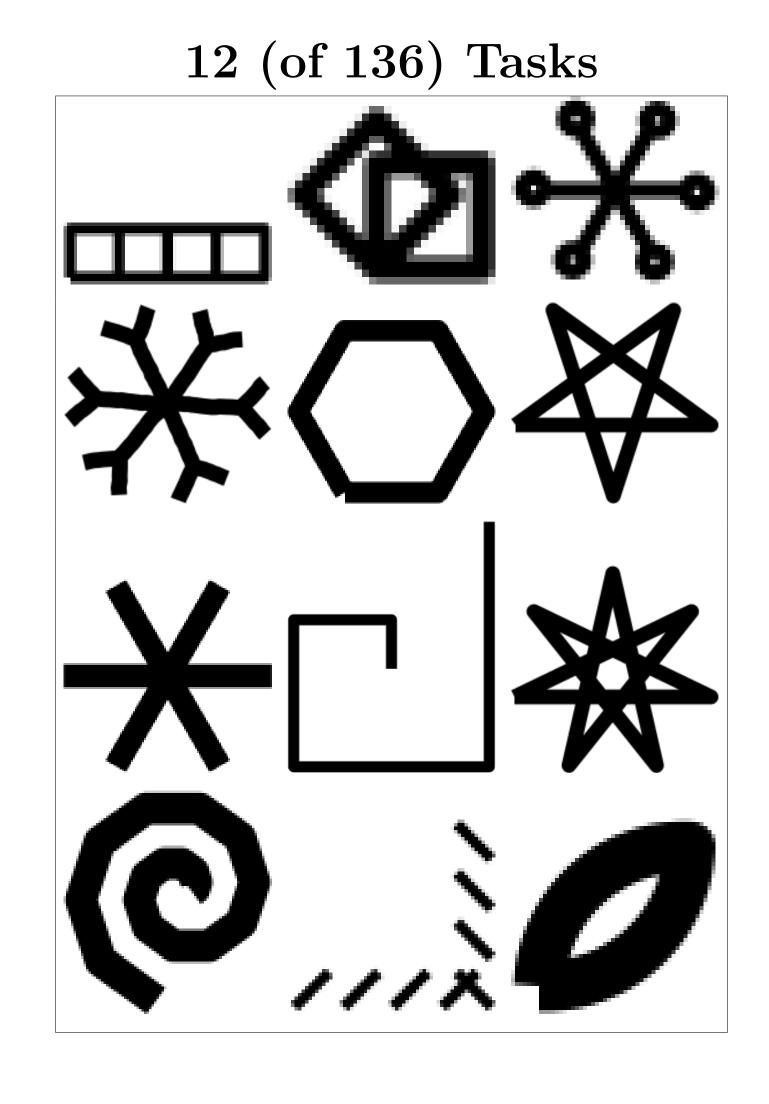
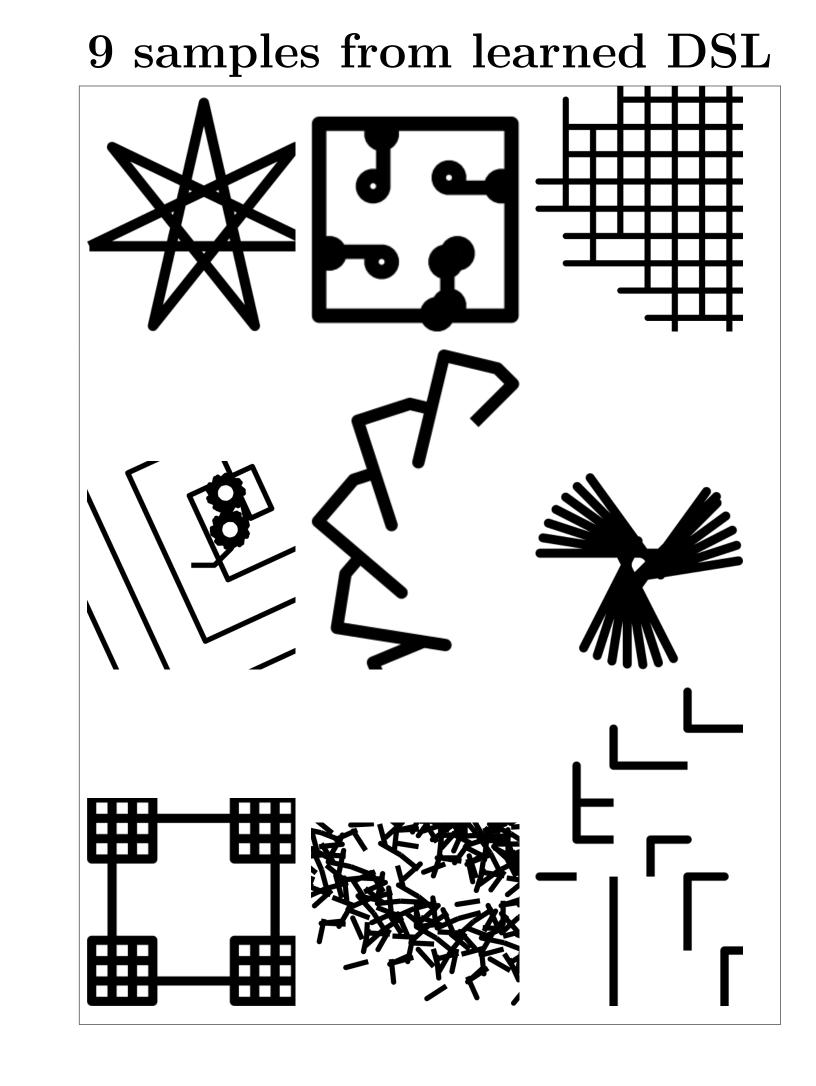


Figure 1: **Left:** syntax trees of two programs sharing common structure, highlighted in orange, from which we extract a fragment and add it to the DSL (bottom). **Right:** actual programs, from which we extract fragments that perform character substitutions.

Generative models of images: Turtle/LOGO Graphics



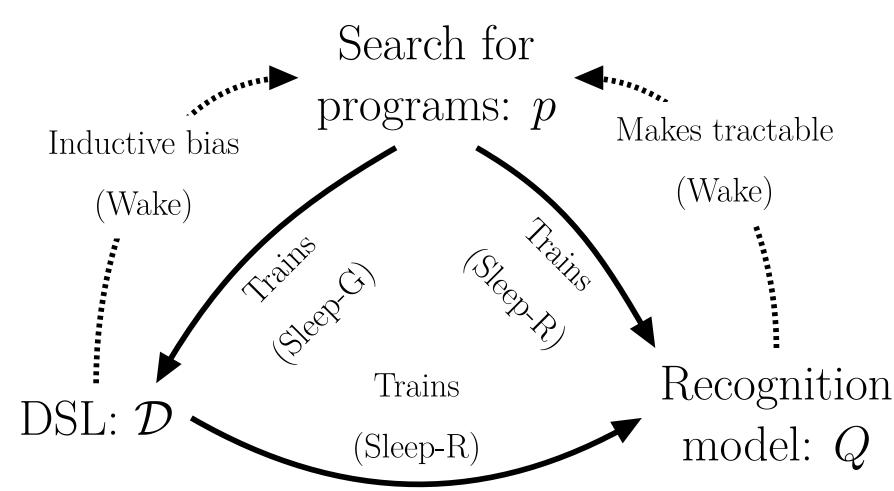


Left: Agent controls a 'pen' – tasked with drawing pictures. Right: During Sleep-R, 'dream' by sampling programs from learned DSL and rendering them.

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

	<u></u>		
Samples from generative models			
1.61	DQDF	343.8	
?	F	241.2	
?	F	647.5	
1.2	KI	246.8	
Learned DSL			

Learned DSL

 $f_1 = \u\w*$ $f_2(x) = (x | f_1) *$ $f_3 = f_2("") = (\u\w*) *$ $(f_3: whitespace delimited words)$

 $f_4(x) = (x*x)$ (f4: 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.