

Library Learning for Neurally-Guided Bayesian Program Induction

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¹: MIT. ²: ENS Paris-Saclay.

List processing:

[5 2 9] → [9 2 5]

[1 1 2 2] → [2 2 1 1]

[1 2 3 2] → [2 3 2 1]

Text editing:

P Kohli → Dr. Kohli

Sumit Gulwani → Dr. Gulwani

Danny Tarlow → Dr. Tarlow

Symbolic regression:



$$ax^3 + bx^2 + cx + d$$



$$a/(x - b)$$

Explore/Compress/Compile (EC²) learns to solve programming tasks like these by growing a library of code and training a neural net to search for programs written using the library

Library Learning

Tasks and Programs

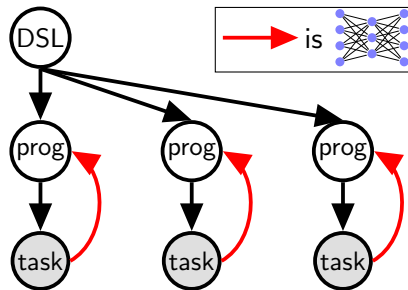
$[7\ 2\ 3] \rightarrow [7\ 3]$
 $[1\ 2\ 3\ 4] \rightarrow [3\ 4]$
 $[4\ 3\ 2\ 1] \rightarrow [4\ 3]$ $[7\ 3] \rightarrow \text{False}$
 $f(\ell) = (f_1\ \ell\ (\lambda\ (x)\ (\lambda\ (y)\ (>\ x\ 2))))$ $[3] \rightarrow \text{False}$
 $[9\ 0\ 0] \rightarrow \text{True}$
 $[0] \rightarrow \text{True}$
 $[0\ 7\ 3] \rightarrow \text{True}$
 $[2\ 7\ 8\ 1] \rightarrow 8$ $f(\ell) = (f_3\ \ell\ 0)$
 $[3\ 19\ 14] \rightarrow 19$
 $f(\ell) = (f_2\ \ell)$

DSL

$f_0(\ell, r) = (\text{foldr}\ r\ \ell\ \text{cons})$
 (f_0 : *Append lists r and l*)
 $f_1(\ell, p) = (\text{foldr}\ \ell\ \text{nil}\ (\lambda\ (x\ a)\ (\text{if}\ (p\ x)\ (\text{cons}\ x\ a)\ a))))$
 (f_1 : *Higher-order filter function*)
 $f_2(\ell) = (\text{foldr}\ \ell\ 0\ (\lambda\ (x\ a)\ (\text{if}\ (>\ a\ x)\ a\ x))))$
 (f_2 : *Maximum element in list l*)
 $f_3(\ell, k) = (\text{foldr}\ \ell\ (\text{is-nil}\ \ell)\ (\lambda\ (x\ a)\ (\text{if}\ a\ a\ (= k\ x))))$
 (f_2 : *Whether l contains k*)

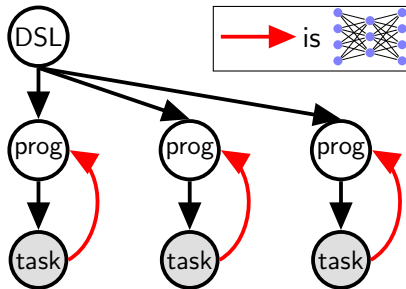
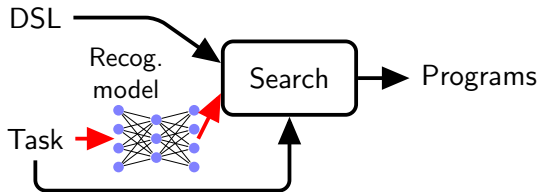
-
- ▶ Learned DSL primitives can call each other
 - ▶ Rediscovered higher-order functions like filter

Explore/Compress/Compile as Amortized Bayesian Inference



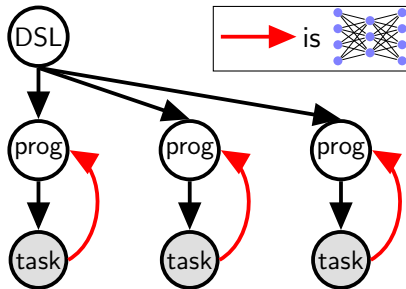
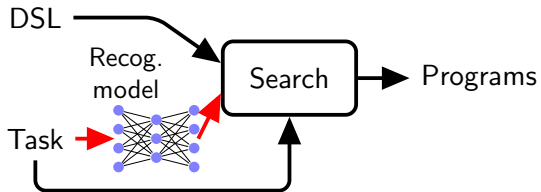
Explore/Compress/Compile as Amortized Bayesian Inference

Explore: Infer programs, fixing DSL and neural net

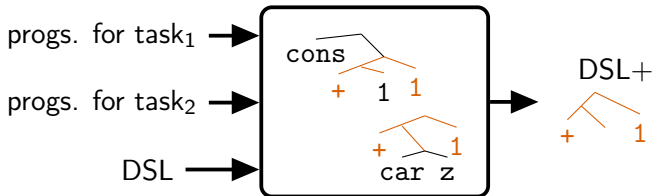


Explore/Compress/Compile as Amortized Bayesian Inference

Explore: Infer programs, fixing DSL and neural net

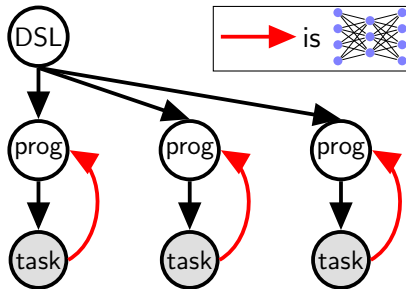
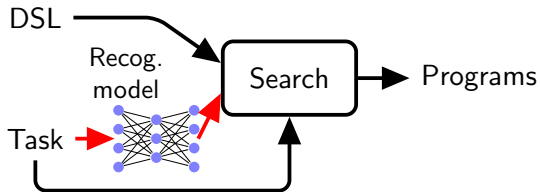


Compress: Update DSL, fixing programs

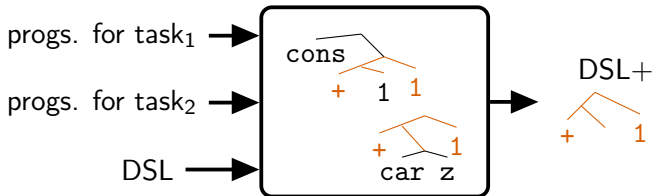


Explore/Compress/Compile as Amortized Bayesian Inference

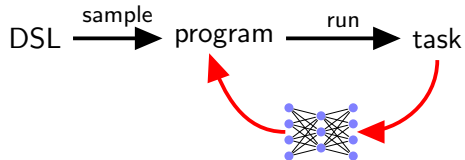
Explore: Infer programs, fixing DSL and neural net



Compress: Update DSL, fixing programs

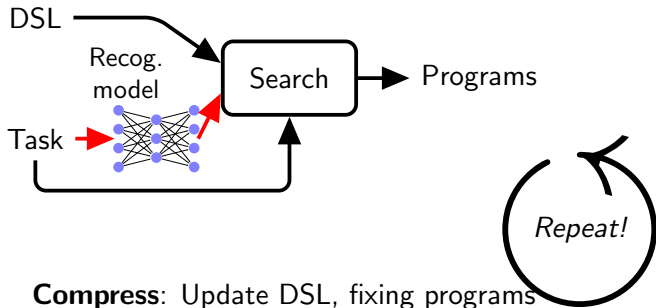


Compile: Train recognition model

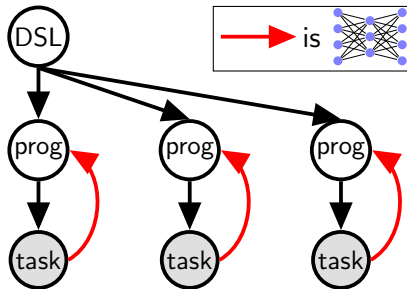
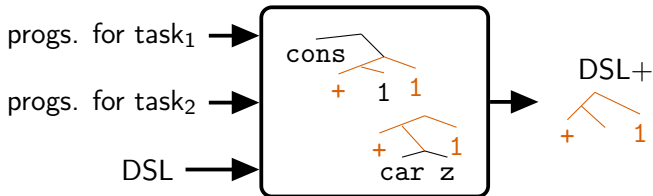


Explore/Compress/Compile as Amortized Bayesian Inference

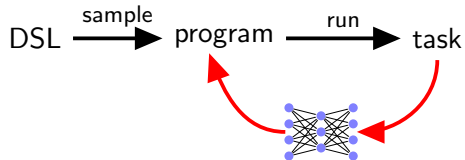
Explore: Infer programs, fixing DSL and neural net



Compress: Update DSL, fixing programs



Compile: Train recognition model



Domain: List processing

Starts with: foldr, unfold, if, map, length, index, =, +, -, 0, 1, cons, car, cdr, nil, is-nil, mod, *, >, is-square, is-prime.

236 human-interpretable list processing tasks.

Discovers 38 new DSL primitives, including filter

Name	Input	Output
repeat-2	[7 0]	[7 0 7 0]
drop-3	[0 3 8 6 4]	[6 4]
rotate-2	[8 14 1 9]	[1 9 8 14]
count-head-in-tail	[1 2 1 1 3]	2
keep-mod-5	[5 9 14 6 3 0]	[5 0]
product	[7 1 6 2]	84

With functional programming “problem set” + 93 hours on 64 CPUs, rediscovers:

map, foldr, unfold, range, length, index, zip, +some arithmetic routines

Domain: Text Editing

In the style of FlashFill (Gulwani 2012). Starts with: foldr, unfold, if, map, length, index, =, +, -, 0, 1, cons, car, cdr, nil, is-nil , plus string & character constants.

Input	Output
+106 769-438	106.769.438
+83 973-831	83.973.831
Temple Anna H	TAH
Lara Gregori	LG

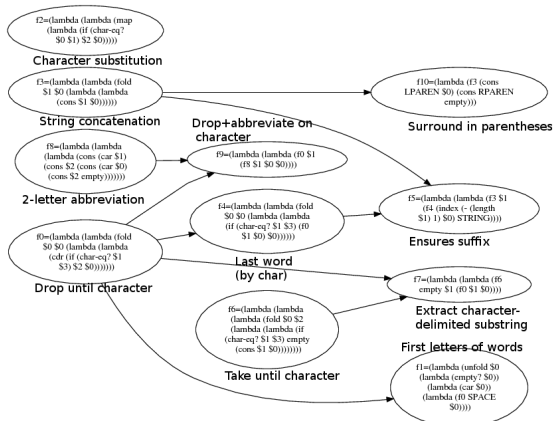






Figure: 11 learned DSL primitives over 3 successive iterations (3 columns). Learned primitives call each other (arrows).

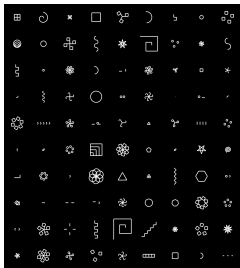
Domain: Symbolic regression from visual input

Starts with: plus, times, divide, real-number. Autograds through program
Bayesian likelihood $P[\text{data}|\text{prog}]$ favors fewer continuous parameters

Programs & Tasks		DSL
		$f_0(x) = (+ \ x \ \text{real})$
$f(x) = (f_1 \ x)$	$f(x) = (f_5 \ x)$	$f_1(x) = (f_0 \ (* \ \text{real} \ x))$
		$f_2(x) = (f_1 \ (* \ x \ (f_0 \ x)))$
$f(x) = (f_4 \ x)$	$f(x) = (f_3 \ x)$	$f_3(x) = (f_0 \ (* \ x \ (f_2 \ x)))$
		$f_4(x) = (f_0 \ (* \ x \ (f_3 \ x)))$
		$(f_4: 4th \ order \ polynomial)$
		$f_5(x) = (/ \ \text{real} \ (f_0 \ x))$
		$(f_5: rational \ function)$

New domain: Generative graphics programs (Turtle/LOGO)

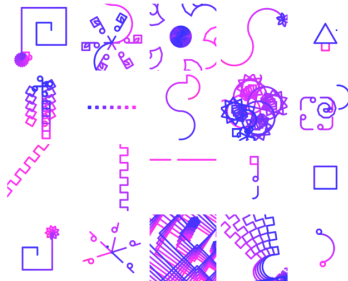
Training tasks



DSL samples before learning

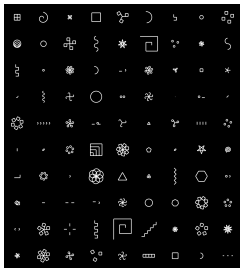


DSL samples after learning



New domain: Generative graphics programs (Turtle/LOGO)

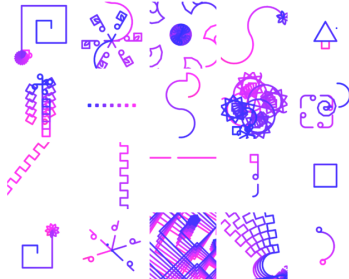
Training tasks



DSL samples before learning

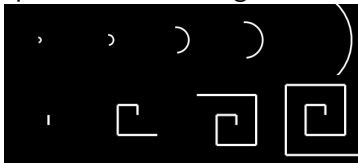


DSL samples after learning



Learned DSL contains parametric drawing routines:

Semicircle:



Greek Spiral:



Polygons & Stars:



Spiral:



S-Curves:



Circles:



Learning to program: Poster AB #24

```
f2(p,f,n,x) = (if (p x) nil  
                  (cons (f x) (f2 (n x))))
```

(f2: *unfold*)

```
f3(i,l) = (if (= i 0) (car l)  
              (f3 (f1 i) (cdr l))))
```

(f3: *index*)

```
f4(f,l,x) = (if (empty? l) x  
                 (f (car l) (f4 (cdr l))))
```

(f4: *fold*)

```
f5(f,l) = (if (empty? l) nil  
              (cons (f (car l)) (f5 (cdr l))))
```

(f5: *map*)

Symbolic Regression



$f(x) = (f_1 \ x)$



$f(x) = (f_6 \ x)$



$f(x) = (f_4 \ x)$



$f(x) = (f_3 \ x)$

```
f0(x) = (+ x real)  
f1(x) = (f0 (* real x))  
f2(x) = (f1 (* x (f0 x)))  
f3(x) = (f0 (* x (f2 x)))  
f4(x) = (f0 (* x (f3 x)))  
(f4: 4th order polynomial)  
f5(x) = (/ real x)  
f6(x) = (f5 (f0 x))  
(f6: rational function)
```

