
Learning Libraries of Subroutines for Neurally-Guided Bayesian Program Learning

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Abstract

1 Successful approaches to program induction require a hand-engineered domain-
2 specific language (DSL), constraining the space of allowed programs and imparting
3 prior knowledge of the domain. We contribute a program induction algorithm
4 called ECC that learns a DSL while jointly training a neural network to efficiently
5 search for programs in the learned DSL. We use our model to solve symbolic
6 regression problems, edit strings, and synthesize functions on lists, showing how
7 the model learns a domain-specific library of program components for expressing
8 solutions to problems in the domain.

9 1 Introduction

10 Automatically inducing programs from examples is a long-standing goal of artificial intelligence.
11 Recent work has successfully used symbolic search techniques (e.g., Metagol: [1], FlashFill: [2]),
12 neural networks trained from a corpus of examples (e.g., RobustFill: [3]), and hybrids of neural and
13 symbolic methods (e.g., Neural-guided deductive search: [4], DeepCoder: [5]) to synthesize programs
14 for task domains such as string transformations, list processing, and robot navigation and planning.
15 However, all these approaches – symbolic, neural and neural-symbolic – rely upon a hand-engineered
16 *Domain-Specific Language* (DSL). DSLs contain an inventory of restricted programming primitives,
17 encoding domain-specific knowledge about the space of programs. In practice we often have only a
18 few input/output examples for each program to be induced, and thus success often hinges on having a
19 good DSL that provides a crucial inductive bias for what would otherwise be an unconstrained search
20 through the space of all computable functions. Here we ask, to what extent can we dispense with
21 such highly hand-engineered domain-specific languages?

22 We propose *learning* the DSL by inducing a library of domain-specific subroutines. We consider
23 the setting where we have a collection of related programming tasks, each specified by a set of
24 input/output examples. Starting from a weaker or more general library of primitives, we give an
25 algorithm for constructing a richer, more powerful, and better-tuned DSL. Our algorithm is called
26 **Explore/Compress/Compile** (ECC), and iterates between three different steps: an **Explore** step
27 uses the DSL to explore the space of programs, searching for ones that solve the tasks; a **Compress**
28 step modifies the DSL by discovering regularities in the programs found by the previous Explore step;
29 and a **Compile** step, which improves the program search procedure by training a neural network to
30 write programs in the current DSL, in the spirit of “amortized” or “compiled” inference [6]. We call
31 the neural net a **recognition model** (c.f. Hinton 1995 [7]). The learned DSL distills commonalities
32 across programs that solve tasks, helping the agent solve related program induction problems. The
33 neural recognition model ensures that searching for programs remains tractable even as the DSL (and
34 hence the search space for programs) expands.

35 Because any model may be encoded as a (deterministic or probabilistic) program, we carefully
36 delineate the scope of program learning problems considered here. We think of ECC as learning to

37 solve the kinds of problems that humans can solve relatively quickly – once they acquire the relevant
 38 domain expertise. These correspond to short programs – once you have the right DSL. Even with the
 39 right DSL, program search may be intractable, so we amortize the cost of program search by training
 40 a neural network to assist the search procedure.

41 We apply ECC to three domains: symbolic regression; FlashFill-style [2] string pro-
 42 cessing; and Lisp-style functions on lists. For each of these we initially provide a
 43 generic set of programming primitives in a Lisp-like language. Our algorithm then dis-
 44 covers its own domain-specific vocabulary for expressing solutions in the domain (Tbl. 1).
 45

46 2 The ECC Algorithm

47 Our goal is to induce a DSL while
 48 finding programs solving each of the
 49 tasks. We take inspiration primar-
 50 ily from the Exploration-Compression
 51 algorithm for bootstrap learning [8].
 52 Exploration-Compression alternates
 53 between exploring the space of solu-
 54 tions to a set of tasks, and compress-
 55 ing those solutions to suggest new
 56 search primitives for the next explo-
 57 ration stage. We extend these ideas into an inference strategy that iterates through three steps: an
 58 **Explore** step uses the current DSL and recognition model to search for programs that solve the tasks.
 59 The **Compress** and **Compile** steps update the DSL and the recognition model, respectively. Crucially,
 60 these steps bootstrap off each other (Fig. 2):

61 **Exploration: Searching for programs.** Our
 62 program search is informed by both the DSL
 63 and the recognition model. When these improve,
 64 we find more programs solving the tasks.

65 **Compression: Improving the DSL.** We in-
 66 duce the DSL from the programs found in the
 67 exploration phase, aiming to maximally compress
 68 (or, raise the prior probability of) these
 69 programs. As we solve more tasks, we hone in
 70 on DSLs that more closely match the domain.

71 **Compilation: Learning a neural recognition**
 72 **model.** We update the recognition model by
 73 training on two data sources: samples from the
 74 DSL (as in the Helmholtz Machine’s “sleep”
 75 phase), and programs found by the search proce-
 76 dure during exploration. As the DSL improves
 77 and as search finds more programs, the recogni-
 78 tion model gets more data to train on, and better data.

Domain	Part of the learned DSL
Regression	<code>(+ (* real x) real)</code> <i>(a linear function of x)</i>
Strings	<code>(map (lambda (x) (if (= x a) b x)))</code> <i>(replace occurrences of a w/ b)</i>
Lists	<code>(map (lambda (x) (+ x k)) l)</code> <i>(add k to every element of list l)</i>

Figure 1: Examples of structure found in DSLs learned by our algorithm. ECC builds a new DSL by discovering and reusing useful subroutines.

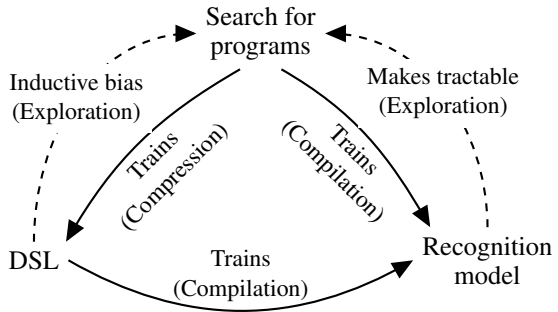


Figure 2: ECC solves for programs, the DSL, and a neural network (recognition model). Each of these steps iteratively bootstraps off of the others.

79 2.1 Hierarchical Bayesian Framing

80 ECC takes as input a set of *tasks*, written X , each of which is a program induction problem. It has at
 81 its disposal a *likelihood model*, written $\mathbb{P}[x|p]$, which scores the likelihood of a task $x \in X$ given a
 82 program p . Its goal is to solve each of the tasks by writing a program, and also to infer a DSL, written
 83 \mathcal{D} . We equip \mathcal{D} with a real-valued weight vector θ , and together (\mathcal{D}, θ) define a generative model
 84 over programs. We frame our goal as maximum a posteriori (MAP) inference of (\mathcal{D}, θ) given X .

85 Writing J for the joint probability of (\mathcal{D}, θ) and X , we want the \mathcal{D}^* and θ^* solving:

$$J(\mathcal{D}, \theta) \triangleq \mathbb{P}[\mathcal{D}, \theta] \prod_{x \in X} \sum_p \mathbb{P}[x|p] \mathbb{P}[p|\mathcal{D}, \theta]$$

$$\mathcal{D}^* = \arg \max_{\mathcal{D}} \int J(\mathcal{D}, \theta) d\theta \quad \theta^* = \arg \max_{\theta} J(\mathcal{D}^*, \theta) \quad (1)$$

86 The above equations summarize the problem from the point of view of an ideal Bayesian learner.
 87 However, Eq. 1 is wildly intractable because evaluating $J(\mathcal{D}, \theta)$ involves summing over the infinite
 88 set of all programs. In practice we will only ever be able to sum over a finite set of programs. So, for
 89 each task, we define a finite set of programs, called a *frontier*, and only marginalize over the frontiers:
 90 **Definition.** A *frontier of task x* , written \mathcal{F}_x , is a finite set of programs s.t. $\mathbb{P}[x|p] > 0$ for all $p \in \mathcal{F}_x$.

91 Using the frontiers we define the following intuitive lower bound on the joint probability, called \mathcal{L} :

$$J \geq \mathcal{L} \triangleq \mathbb{P}[\mathcal{D}, \theta] \prod_{x \in X} \sum_{p \in \mathcal{F}_x} \mathbb{P}[x|p] \mathbb{P}[p|\mathcal{D}, \theta] \quad (2)$$

92 ECC does approximate MAP inference by maximizing this lower bound on the joint probability,
 93 alternating maximization w.r.t. the frontiers (Exploration) and the DSL (Compression):

94 **Program Search: Maxing \mathcal{L} w.r.t. the frontiers.** Here (\mathcal{D}, θ) is fixed and we want to find new
 95 programs to add to the frontiers so that \mathcal{L} increases the most. \mathcal{L} most increases by finding programs
 96 where $\mathbb{P}[x, p|\mathcal{D}, \theta]$ is large.

97 **DSL Induction: Maxing $\int \mathcal{L} d\theta$ w.r.t. the DSL.** Here $\{\mathcal{F}_x\}_{x \in X}$ is held fixed, and so we can
 98 evaluate \mathcal{L} . Now the problem is that of searching the discrete space of DSLs and finding one
 99 maximizing $\int \mathcal{L} d\theta$. Once we have a DSL \mathcal{D} we can update θ to $\arg \max_{\theta} \mathcal{L}(\mathcal{D}, \theta, \{\mathcal{F}_x\})$.

100 Searching for programs is hard because of the large combinatorial search space. We ease this
 101 difficulty by training a neural recognition model, $q(\cdot|\cdot)$, during the compilation phase: q is trained to
 102 approximate the posterior over programs, $q(p|x) \propto \mathbb{P}[p|x, \mathcal{D}, \theta] = \mathbb{P}[x|p] \mathbb{P}[p|\mathcal{D}, \theta]$, thus amortizing
 103 the cost of finding programs with high posterior probability.

104 **Neural recognition model: tractably maxing \mathcal{L} w.r.t. the frontiers.** Here we train a neural
 105 network, q , to predict a distribution over programs conditioned on a task. The objective of q is to
 106 assign high probability to programs p where $\mathbb{P}[x, p|\mathcal{D}, \theta]$ is large, because including those programs
 107 in the frontiers will most increase \mathcal{L} .

108 2.2 Exploration: Searching for Programs

109 Now our goal is to search for programs solving the tasks. We use the simple search strategy of
 110 enumerating programs from the DSL in decreasing order of their probability, and then checking if an
 111 enumerated program p assigns positive probability to a task ($\mathbb{P}[x|p] > 0$); if so, we incorporate p into
 112 the frontier \mathcal{F}_x .

113 To make this concrete we need to define what programs actually are and what form $\mathbb{P}[p|\mathcal{D}, \theta]$ takes.
 114 We represent programs as λ -calculus expressions. λ -calculus is a formalism for expressing functional
 115 programs that closely resembles the Lisp programming language. λ -calculus includes variables,
 116 function application, and the ability to create new functions. Throughout this paper we will write λ -
 117 calculus expressions in Lisp syntax. Our programs are all strongly typed. We use the Hindley-Milner
 118 polymorphic typing system [9] which is used in functional programming languages like OCaml. Type
 119 variables are always written using lowercase Greek letters and we write $\alpha \rightarrow \beta$ to mean a function
 120 that takes an input of type α and returns something of type β . We use the notation $p : \tau$ to mean that
 121 the λ -calculus expression p has the type τ . For example, to describe the type of the identity function
 122 we would say $(\text{lambda } (x) x) : \alpha \rightarrow \alpha$. We say a type α *unifies* with τ if every expression $p : \alpha$
 123 also satisfies $p : \tau$. Furthermore, the act of *unifying* a type α with τ is to introduce constraints on
 124 the type variables of α to ensure that α unifies with τ . See Supplement for more detail on program
 125 representation. With this notation in hand we now define DSLs:

126 **Definition:** (\mathcal{D}, θ) . A DSL \mathcal{D} is a set of typed λ -calculus expressions. A weight vector θ for a DSL
 127 \mathcal{D} is a vector of $|\mathcal{D}| + 1$ real numbers: one number for each DSL primitive $e \in \mathcal{D}$, written θ_e , and a
 128 weight controlling the probability of a variable occurring in a program, θ_{var} .

Algorithm 1 Generative model over programs

```

129 function sample( $\mathcal{D}, \theta, \mathcal{E}, \tau$ ):
130   Input: DSL ( $\mathcal{D}, \theta$ ), environment  $\mathcal{E}$ , type  $\tau$ 
131   Output: a program whose type unifies with  $\tau$ 
132   if  $\tau = \alpha \rightarrow \beta$  then
133     var  $\leftarrow$  an unused variable name
134     body  $\sim$  sample( $\mathcal{D}, \theta, \{\text{var} : \alpha\} \cup \mathcal{E}, \beta$ )
135     return (lambda (var) body)
136   end if
137   primitives  $\leftarrow \{p | p : \tau' \in \mathcal{D} \cup \mathcal{E}$ 
138     if  $\tau$  can unify with  $\text{yield}(\tau')$ 
139     Draw  $e \sim$  primitives, w.p.  $\propto \theta_e$  if  $e \in \mathcal{D}$ 
140     w.p.  $\propto \frac{\theta_{\text{var}}}{|\text{variables}|}$  if  $e \in \mathcal{E}$ 
141   Unify  $\tau$  with  $\text{yield}(\tau')$ .
142    $\{\alpha_k\}_{k=1}^K \leftarrow \text{args}(\tau')$ 
143   for  $k = 1$  to  $K$  do
144      $a_k \sim$  sample( $\mathcal{D}, \theta, \mathcal{E}, \alpha_k$ )
145   end for
146   return ( $e \ a_1 \ a_2 \ \dots \ a_K$ )
147   where:
148    $\text{yield}(\tau) = \begin{cases} \text{yield}(\beta) & \text{if } \tau = \alpha \rightarrow \beta \\ \tau & \text{otherwise.} \end{cases}$ 
149    $\text{args}(\tau) = \begin{cases} [\alpha] + \text{args}(\beta) & \text{if } \tau = \alpha \rightarrow \beta \\ [] & \text{otherwise.} \end{cases}$ 

```

The purpose of the recognition model is to amortize the cost of searching for programs. It does this by learning to predict programs which are probable under (\mathcal{D}, θ) while also assigning high likelihood for a task according to $\mathbb{P}[x|p]$. Concretely, the recognition model q is a neural network that predicts, for each task $x \in X$, a weight vector $q(x) = \theta^{(x)} \in \mathbb{R}^{|\mathcal{D}|+1}$. Together with the DSL, this defines a distribution over programs, $\mathbb{P}[p|\mathcal{D}, \theta = q(x)]$. We abbreviate this distribution as $q(p|x)$. The crucial aspect of this framing is that the neural network leverages the structure of the learned DSL, so it is *not* responsible for generating programs wholesale. We share this aspect with DeepCoder [5] and [15].

We want a recognition model that closely approximates the true posteriors over programs. We formulate this as minimizing the expected KL-divergence, $\mathbb{E}[\text{KL}(\mathbb{P}[p|x, \mathcal{D}, \theta] || q(p|x))]$, or equivalently maximizing $\mathbb{E}[\sum_p \mathbb{P}[p|x, \mathcal{D}, \theta] \log q(p|x)]$, where the expectation is taken over tasks. One could take this expectation over the empirical distribution of tasks, like how an autoencoder is trained [16]; or, one could take this expectation over samples from the generative model, like how a Helmholtz machine is trained [17]. We found it useful to maximize both an autoencoder-style objective \mathcal{L}_{AE} and a Helmholtz-style objective \mathcal{L}_{HM} , giving the objective for a recognition model, $\mathcal{L}_{\text{RM}} = \mathcal{L}_{\text{AE}} + \mathcal{L}_{\text{HM}}$:

$$\mathcal{L}_{\text{HM}} = \mathbb{E}_{(p,x) \sim (\mathcal{D}, \theta)} [\log q(p|x)] \quad \mathcal{L}_{\text{AE}} = \mathbb{E}_{x \sim X} \left[\sum_{p \in \mathcal{F}_x} \frac{\mathbb{P}[x, p|\mathcal{D}, \theta]}{\sum_{p' \in \mathcal{F}_x} \mathbb{P}[x, p'|\mathcal{D}, \theta]} \log q(p|x) \right]$$

The \mathcal{L}_{HM} objective is essential for data efficiency: all of our experiments train ECC on only a few hundred tasks, which is too little for a high-capacity neural network q . Once we bootstrap a (\mathcal{D}, θ) , we can draw unlimited samples from (\mathcal{D}, θ) and train q on those samples.

Evaluating \mathcal{L}_{HM} involves sampling programs from the current DSL, running them to get their outputs, and then training q to regress from the input/outputs to the program. Since these programs map inputs to outputs, we need to sample the inputs as well. Our solution is to sample the inputs from the empirical observed distribution of inputs in X .

2.4 Compression: Learning a Generative Model (a DSL)

The purpose of the DSL is to offer a set of abstractions that allow an agent to easily express solutions to the tasks at hand. In the ECC algorithm we infer the DSL from a collection of frontiers. Intuitively,

Alg. 1 is a procedure for drawing samples from the generative model (\mathcal{D}, θ) . In practice, we enumerate programs in order of their probability under Alg. 1 rather than sample them.

Why enumerate, when the program synthesis community has invented many sophisticated algorithms that search for programs? [10, 11, 12, 13, 14]. We have two reasons: (1) A key point of our work is that learning the DSL, along with a neural recognition model, can make program induction tractable, even if the search algorithm is very simple. (2) Enumeration is a general approach that can be applied to any program induction problem. Many of these more sophisticated approaches require special conditions on the space of programs.

A drawback of using an enumerative search algorithm is that we have no efficient means of solving for arbitrary constants that might occur in the program. In Sec. 3, we will show how to find programs with real-valued constants by automatically differentiating through the program and setting the constants using gradient descent.

2.3 Compilation: Learning a Neural Recognition Model

Example programs in frontiers	Proposed subexpression
<pre>(lambda (a b) (fold b (cons ", " a) (lambda (x z) (cons x z)))) (lambda (a b) (fold a b (lambda (x z) (cons x z))))</pre>	<pre>(fold a b (lambda (x z) (cons x z)))</pre>

Figure 3: The DSL induction algorithm proposes subexpressions of programs to add to the DSL. These subexpressions are taken from programs in the frontiers (left column), and can introduce new variables (right column: a and b). Here, the proposed subexpression appends two lists.

we want the algorithm to look at the frontiers and generalize beyond them, both so the DSL can better express the current solutions, and also so that the DSL might expose new abstractions which will later be used to discover more programs.

Recall from Sec. 2.1 that we want the DSL maximizing $\int \mathcal{L} d\theta$. We replace this marginal with an AIC approximation, giving the following objective for DSL induction:

$$\log \mathbb{P}[\mathcal{D}] + \arg \max_{\theta} \sum_{x \in X} \log \sum_{p \in \mathcal{F}_x} \mathbb{P}[x|p] \mathbb{P}[p|\mathcal{D}, \theta] + \log \mathbb{P}[\theta|\mathcal{D}] - \|\theta\|_0 \quad (3)$$

We induce a DSL by searching locally through the space of DSLs, proposing small changes to \mathcal{D} until Eq. 3 fails to increase. The search moves work by introducing new λ -expressions into the DSL. We propose these new expressions by extracting subexpressions from programs already in the frontiers. These subexpressions are fragments of the original programs, and can introduce new variables (Fig. 3), which then become new functions in the DSL. The idea of storing and reusing fragments of expressions comes from Fragment Grammars [18] and Tree-Substitution Grammars [19].

We define a prior distribution over DSLs which penalizes the sizes of the λ -calculus expressions in the DSL, and put a Dirichlet prior over the weight vector:

$$\mathbb{P}[\mathcal{D}] \propto \exp \left(-\lambda \sum_{p \in \mathcal{D}} \text{size}(p) \right) \quad \mathbb{P}[\theta|\mathcal{D}] = \text{Dir}(\theta|\alpha) \quad (4)$$

where $\text{size}(p)$ measures the size of the syntax tree of program p , λ acts as a regularizer on the size of the DSL, and α is a concentration parameter controlling the smoothness of the prior over θ .

To appropriately score each proposed \mathcal{D} we must reestimate the weight vector θ . Although this may seem very similar to estimating the parameters of a probabilistic context free grammar, for which we have effective approaches like the Inside/Outside algorithm [20], our DSLs are context-sensitive due to the presence of variables in the programs and also due to the polymorphic typing system. In the Supplement we derive a tractable MAP estimator for θ . Putting it all together, Alg. 2 describes how we combine program search, recognition model training, and DSL induction.

Algorithm 2 The ECC Algorithm

Input: Initial DSL \mathcal{D} , set of tasks X , iterations I
Hyperparameters: Enumeration timeout T
Initialize $\theta \leftarrow$ uniform
for $i = 1$ **to** I **do**
 $\mathcal{F}_x^\theta \leftarrow \{p | p \in \text{enum}(\mathcal{D}, \theta, T) \text{ if } \mathbb{P}[x|p] > 0\}$ (**Explore**)
 $q \leftarrow$ train recognition model, maximizing \mathcal{L}_{RM} (**Compile**)
 $\mathcal{F}_x^q \leftarrow \{p | p \in \text{enum}(\mathcal{D}, q(x), T) \text{ if } \mathbb{P}[x|p] > 0\}$ (**Explore**)
 $\mathcal{D}, \theta \leftarrow \text{induceDSL}(\{\mathcal{F}_x^\theta \cup \mathcal{F}_x^q\}_{x \in X})$ (**Compress**)
end for
return \mathcal{D}, θ, q

3 Symbolic Regression Experiments

As a simple first example of how our algorithm works, we apply ECC to symbolic regression problems. For each of these problems, the agent observes points along the curve of a function, and must write a program that fits those points. We initially equip our learner with addition, multiplication, and division, and task it with solving 200 symbolic regression problems, each either a polynomial of degree 1–4 or a rational function. Our recognition model here is a

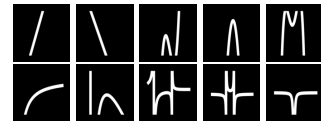


Figure 4: Recognition model input for symbolic regression. While the DSL learns subroutines for rational functions & polynomials, the recognition model jointly learns to look at a graph of the function (above) and predict which of those subroutines is appropriate for ex-

convolutional network that observes an image of the target function’s graph (Fig. 4) – visually, different kinds of polynomials and rational functions produce different kinds of graphs, and so the recognition model can learn to look at a graph and predict what kind of function best explains it. A key difficulty, however, is that these problems are best solved with programs containing real numbers. Our solution to this difficulty is to allow the system to write programs with real-valued parameters, and then fit those parameters by automatically differentiating through the programs the system writes and use gradient descent to fit the parameters. We define the likelihood model, $\mathbb{P}[x|p]$, by assuming a Gaussian noise model for the input/output examples, and penalize the use of real-valued parameters using the BIC [21].

ECC learns a DSL containing templates for polynomials of different orders, as well as ratios of polynomials (Fig. 5). The algorithm also discovers programs that minimize the number of continuous degrees of freedom. For example, it learns to represent linear functions with the program `(* real (+ x real))`, which has two continuous degrees of freedom, and represents quartic functions using the invented DSL primitive f_6 in Tbl. 5 which has five continuous parameters. This phenomenon arises from our Bayesian framing – both the bias towards shorter programs and the likelihood model’s BIC penalty.

$$\begin{aligned} f_0(x) &= (* \text{ real } (+ x \text{ real})) \\ f_1(x) &= (f_0 (* x (+ \text{ real } x))) \\ f_2(x) &= (/ (/ x \text{ real}) x) \end{aligned}$$

Figure 5: Some learned subroutines for symbolic regression. The system starts with addition, multiplication, division, and real numbers, and learns to build rational functions and polynomials up to 4th order.

4 Sequence manipulating programs

We apply ECC to text editing (Section 4.1) and list processing (Section 4.2). For both these domains we initially provide the system with a generic minimal set of programming primitives, and use a bidirectional GRU [22] for the recognition model. The initial set of primitives includes routines commonly found in Lisp or Scheme interpreters: `fold`, `unfold`, `if`, `map`, `length`, `index`, `=`, `+`, `-`, `0`, `1`, `cons`, `car`, `cdr`, `nil`, and `is-nil`.

4.1 String Editing

Synthesizing programs that manipulate strings is a classic problem in the programming languages and AI literatures [15, 23], and algorithms that learn string editing programs ship in Microsoft Excel [2]. However, this prior work presumes a ready-made DSL, expertly crafted to suit string editing. We show ECC can instead start out with generic Lisp primitives and recover many of the higher-level building blocks that have made these other system successful. We automatically generated 600 string editing tasks with 4 input/output examples each (Fig. 6) and model strings as lists of characters. At first, ECC cannot find any correct programs for most of the tasks. It assembles a DSL (Tbl. 1) that lets it rapidly explore the space of programs and find solutions to all of the tasks.

How well does the learned DSL generalized to real text-editing scenarios? We tested, but did not train, our system on problems from the SyGuS [24] program synthesis competition. Before any learning, ECC solves 32/108 of the problems with an average search time of 11 minutes. After learning, it solves 80/108, and does so much faster, solving them in an average of 29 seconds. As of the 2017 SyGuS competition, the best-performing algorithm solves 86/108 problems, and does so with a *different hand-engineered DSL for each problem*. Here we learned a single DSL that applied generically to all of the tasks, and perform comparably to the best prior work.

4.2 List Functions

Synthesizing programs that manipulate data structures is a widely studied problem in the programming languages community [12]. We consider this problem within the context of learning functions that manipulate lists. We created 225 Lisp-style list manipulation tasks, each with 15 input/output examples (Tbl. 2). Our data set is challenging along two dimensions: many of the functions are very complicated, and the agent must learn to solve these complicated problems from only 225 tasks. Our

```

f0(a,b) = (fold a b (lambda (x y) (cons x y))))
(f0: Appends lists (of characters))
f1(s,c) = (fold s s (lambda (a x) (cdr (if (= c x) s a))))
(f1: Drop first characters from s until c reached)
f2(s) = (unfold s empty? car (lambda (z) (f1 z SPACE)))
(f2: Abbreviates a sequence of words)

```

Table 1: Some string editing learned subroutines

Input	Output	Input 1	Input 2	Output
Temple Annalisa Haven 185	TAH1	Launa	Withers	Launa Withers
Lara Gregori Bradford	LGB	Rudolf	Akiyama	Rudolf Akiyama
$f(s) = (f_2 \ s)$		$f(a,b) = (f_0 \ a \ (cons \ " \ b))$		

Figure 6: Two string edit tasks (top) and the programs ECC writes for them (bottom). f_0 and f_2 are subroutines written by ECC, defined in Tbl. 1.

266 data set primarily consists of arithmetic operations upon sequences, and so, in addition to the Lisp
267 primitives provided for the text editing experiments, we additionally start the system out with the
268 following primitives: `mod`, `*`, `>`, `is-square`, `is-prime`.

269 A complete repertoire of higher-order functions is a staple of functional programming standard
270 libraries. Although we provided ECC with some of the standard higher-order functions, like `fold`
271 and `unfold`, we did not include others. When trained on these list functions, our system rediscovers
272 and then reuses the higher-order function `filter` **Lucas: not sure if it actually does this! It would**
273 **be cool if we can write something like this though.**

274 4.3 Quantitative Results

275 We compare with four baselines on held-out tasks:

276 **Ours (no NN)**, which lesions the recognition model.

277 **RF/DC**, which holds the generative model (\mathcal{D}, θ) fixed and learns a recognition model only from
278 samples from the fixed generative model. This is equivalent to our algorithm with $\lambda = \infty$ (Sec. 2.4)
279 and $\mathcal{L}_{RM} = \mathcal{L}_{HM}$ (Sec. 2.3). We call this baseline RF/DC because this setup is closest to how
280 RobustFill [3] and DeepCoder [5] are trained. We can not compare directly with these systems,
281 because they are engineered for one specific domain, and do not have publicly available code and
282 datasets.

283 **PCFG**, which lesions the recognition model, learns θ , and fixes \mathcal{D} . This is equivalent to our algorithm
284 with $q(x) = \theta$ and $\lambda = \infty$, and is like learning the parameters of a PCFG while not learning any of
285 the structure.

286 **Enum**, which does no learning and just enumerates a frontier. This is equivalent to our first wake
287 cycle.

Name	Input	Output
append-4	[7 0 2]	[7 0 2 4]
len	[3 5 12 1]	4
has-2	[4 5 7 4]	false
repeat-2	[7 0]	[7 0 7 0]
drop-3	[0 3 8 6 4]	[6 4]
count-head-in-tail	[1 2 1 1 3]	2
rotate-2	[8 14 1 9]	[1 9 8 14]
pow-3	[10 4 13]	[1000 64 2197]
keep-mod-5	[5 9 14 6 3 0]	[5 0]

Table 2: Sample tasks from our list function domain

```

 $f_0(i, \ell) = (\text{singleton } (\text{index } i \ \ell))$ 
  ( $f_0$ : Put the  $i$ -th index into a list)
 $f_1(i, \ell) = (++) \ \ell \ (f_0 \ i \ \ell)$ 
  ( $f_1$ : Append the  $i$ -th index)
 $f_2(n, \ell) = (\text{any } (\text{lambda } (x) \ (= \ n \ x)) \ \ell)$ 
  ( $f_2$ : Whether  $n$  appears in the list)
 $f_3(i, \ell) = (\text{index } (\text{negate } i) \ (\text{sort } \ell))$ 
  ( $f_3$ : Get the  $i$ -th largest number)
 $f_4(n, \ell) = (\text{mapi } (\text{lambda } (i \ x) \ (\text{mod } x \ n)) \ \ell)$ 
 $f_5(k, \ell) = (\text{mapi } (\text{lambda } (i \ x) \ (+ \ x \ k)) \ \ell)$ 
 $f_6(k, n, \ell) = (f_4 \ n \ (f_5 \ k \ \ell))$ 
  ( $f_6$ : Caesar shift of  $k$  in integers modulo  $n$ )

```

Table 3: Some learned DSL primitives for list functions

	Ours	Ours (no NN)	RF/DC	PCFG	Enum
<i>Symbolic Regression</i>					
% solved	98%	94%	0.7%	0%	2%
Solve time	2.7s	2.8s	3.6s	—	2.1s
MDL (nats)	9.3	11.0	2.3	—	4.6
<i>String Editing</i>					
% solved	99%	82%	9%	24%	18%
Solve time	0.9s	2.2s	2.7s	2.3s	2.4s
<i>List functions</i>					
% solved	86%	84%	60%	74%	70%
Solve time	0.8s	0.7s	1.0s	1.0s	1.1s

Table 4: % solved w/ 5 sec timeout. Solve time: averaged over solved tasks. RF/DC: trained like RobustFill/DeepCoder. PCFG: model w/o structure learning. Enum: model w/o any learning. MDL: $-\mathbb{E} [\mathbb{P}[x|p]]$. For domains other than symbolic regression MDL is 0 nats. For symbolic regression MDL is a proxy for # of continuous parameters.

288 For each domain, we are interested both in how many tasks the agent can solve and how quickly
 289 it can find those solutions. For symbolic regression, we also care about the quality of the solution,
 290 as measured by the likelihood model $\mathbb{P}[x|p]$, e.g. did the agent correctly explain a linear function
 291 using two numbers, or did it introduce extraneous parameters? Tbl. 4 compares our model against
 292 these baselines. Our full model consistently improves on the baselines, sometimes dramatically
 293 (string editing and symbolic regression). The recognition model consistently increases the number of
 294 solved held-out tasks, and lesioning it also slows down the convergence of the algorithm, taking more
 295 wake/sleep cycles to reach a given number of tasks solved (Fig. 7). This supports the view of the
 296 recognition model as a way of accelerating the search over programs.

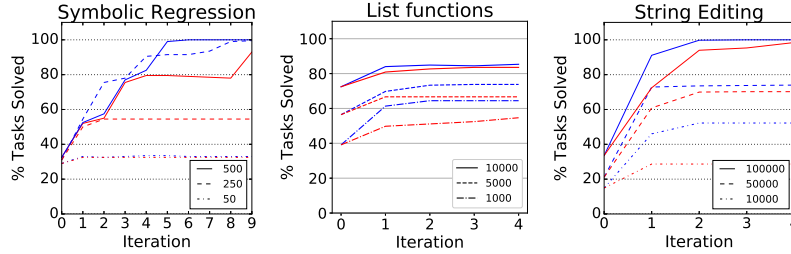


Figure 7: Learning curves for ECC both with (blue) and without (red) the recognition model as the frontier size is varied (solid/dashed/dotted lines).

5 Related Work

Our work is far from the first for learning to learn programs, an idea that goes back to Solomonoff [25]:

Deep learning: Much recent work in the ML community has focused on creating neural networks that regress from input/output examples to programs [3, 26, 15, 5]. These neural networks are typically trained with strong supervision (i.e., with annotated ground-truth programs) on massive data sets (i.e., hundreds of millions [3]). Our work considers a weakly-supervised regime where ground truth programs are not provided and the agent must learn from a few hundred tasks.

Inventing new subroutines for program induction: Several program induction algorithms, most prominently the EC algorithm [8], take as their goal to learn new, reusable subroutines that are shared in a multitask setting. We find this work inspiring and motivating, and extend it along two dimensions: (1) we propose a new algorithm for inducing reusable subroutines, based on Fragment Grammars [18]; and (2) we show how to combine these techniques with bottom-up neural recognition models. Other instances of this related idea are [27], Schmidhuber’s OOPS model [28], and predicate invention in ILP [29].

Our work is an instance of Bayesian Program Learning (BPL; see [30, 8, 31, 27]). Previous BPL systems have largely assumed a fixed DSL (but see [27]), and our contribution here is a general way of doing BPL with less hand-engineering of the DSL.

6 Contribution and Outlook

We contribute an algorithm, ECC, that learns to program by bootstrapping a DSL with new domain-specific primitives that the algorithm itself discovers, together with a neural recognition model that learns how to efficiently deploy the DSL on new tasks. We believe this integration of top-down symbolic representations and bottom-up neural networks – both of them learned – could help make program induction systems more generally useful for AI. Many directions remain open. Two immediate goals are to integrate more sophisticated neural recognition models [3] and program synthesizers [10], which may improve performance in some domains over the generic methods used here. Another direction is to explore DSL meta-learning: Can we find a *single* universal primitive set that could effectively bootstrap DSLs for new domains, including the four domains considered, but also many others?

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