Inducing Domain Specific Languages for Bayesian Program Learning

Anonymous Authors[1]

Abstract

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1. Introduction

Imagine an agent faced with a suite of new problems totally different from anything it has seen before. It has at its disposal a basic set of primitive actions it can compose to build solutions to these problems, but it is no idea what kinds of primitives are appropriate for which problems nor does it know the higher-level vocabulary in which solutions are best expressed. How can our agent get off the ground?

The AI and machine learning literature contains two broad takes on this problem. The first take is that the agent should come up with a better representation of the space of solutions, for example, by inventing new primitive actions: see *options* in reinforcement learning (Stolle & Precup, 2002), the EC algorithm in program synthesis (Dechter et al., 2013), or predicate invention in inductive logic programming (Muggleton et al., 2015). The second take is that the agent should learn a discriminative model mapping problems to a distribution over solutions: for example, policy gradient methods in reinforcement learning or neural models of program synthesis (Devlin et al., 2017; **?**). Our contribution is a general algorithm for fusing these two takes on the problem: we propose jointly inducing a representation language, called a *Domain Specific Language* (DSL), alongside a bottom-up discriminative model that regresses from problems to solutions. We evaluate our algorithm on four domains: building Boolean circuits; symbolic regression; FlashFill-style (**?**) string processing problems; and Lisp-style programming problems. We show that EC2.0 can construct a set of basis primitives suitable for discovering solutions in each of these domains

[1]Anonymous Institution, Anonymous City, Anonymous Region, Anonymous Country. Correspondence to: Anonymous Author <anon.email@domain.com>.

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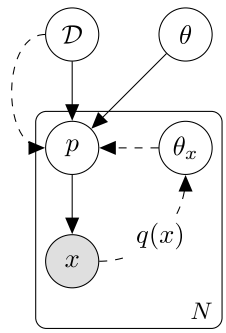


Figure 1: DSL $\mathcal{D}$ generates programs p by sampling DSL primitives with probabilities θ (Algorithm 1). We observe program outputs x. A neural network $q(\cdot)$ called the *recognition model* regresses from program outputs to a distribution over programs ($\theta_x = q(x)$). Solid arrows correspond to the top-down generative model. Dashed arrows correspond to the bottom-up recognition model.

We cast these problems as *Bayesian Program Learning* (BPL; see (Lake et al., 2013; Ellis et al., 2016; **?**)), where the goal is to infer from an observation x a posterior distribution over programs, $\mathbb{P}[p|x]$. A DSL $\mathcal{D}$ specifies the vocabulary in which programs p are written. We equip our DSLs with a *weight vector* θ; together, $(\mathcal{D}, \theta)$ define a probabilistic generative model over programs, $\mathbb{P}[p|\mathcal{D}, \theta]$. In this BPL setting, $\mathbb{P}[p|x] \propto \mathbb{P}[x|p]\mathbb{P}[p|\mathcal{D}, \theta]$, where the likelihood $\mathbb{P}[x|p]$ is domain-dependent. The solid lines in Fig. 1 the diagram this generative model. Alongside this generative model, we infer a bottom-up recognition model, $q(x)$, which is a neural network that regresses from observations to a distribution over programs.

2. Program Representation

We choose to represent programs using λ-calculus (Pierce, 2002). A λ-calculus expression is either:
A *primitive*, like the number 5 or the function `sum`.
A *variable*, like x, y, z
A λ*-abstraction*, which creates a new function. λ-abstractions have a variable and a body. The body is a λ-calculus expression. Abstractions are written as λvar.body.
An *application* of a function to an argument. Both the function and the argument are λ-calculus expressions. The

application of the function f to the argument x is written as $f\ x$.

For example, the function which squares the logarithm of a number is $\lambda x.\texttt{square}(\texttt{log}\ x)$, and the identity function $f(x) = x$ is $\lambda x.x$. The λ-calculus serves as a spartan but expressive Turing complete program representation, and distills the essential features of functional languages like Lisp.

However, many λ-calculus expressions correspond to ill-typed programs, such as the program that takes the logarithm of the Boolean `true` (i.e., `log true`) or which applies the number five to the identity function (i.e., $5\ (\lambda x.x)$). We use a well-established typing system for λ-calculus called *Hindley-Milner typing* (Pierce, 2002), which is used in programming languages like OCaml. The purpose of the typing system is to ensure that our programs never call a function with a type it is not expecting (like trying to take the logarithm of `true`). Hindley-Milner has two important features: Feature 1: It supports *parametric polymorphism*: meaning that types can have variables in them, called *type variables*. Lowercase Greek letters are conventionally used for type variables. For example, the type of the identity function is $\alpha \to \alpha$, meaning it takes something of type α and return something of type α. A function that returns the first element of a list has the type $\texttt{list}(\alpha) \to \alpha$. Type variables are not the same has variables introduced by λ-abstractions. Feature 2: Remarkably, there is a simple algorithm for automatically inferring the polymorphic Hindley-Milner type of a λ-calculus expression (Damas & Milner, 1982). A detailed exposition of Hindley-Milner is beyond the scope of this work.

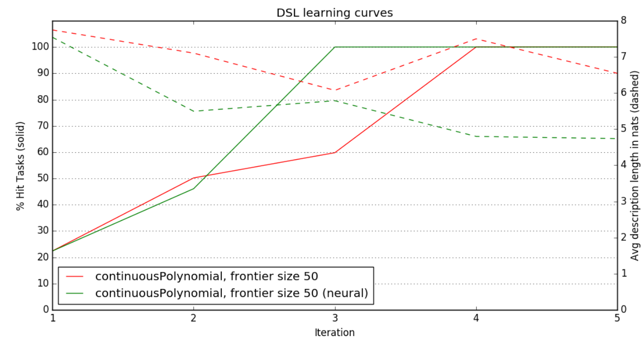
3. Experiments

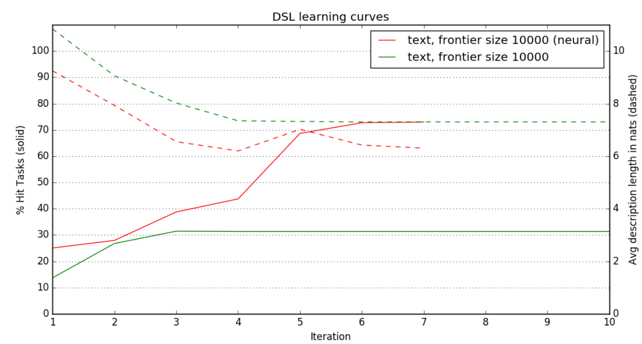
4. Model

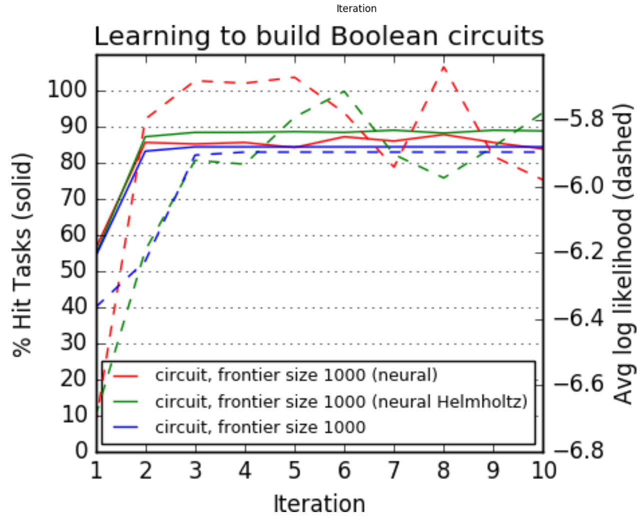
5. Implementation

6. Estimating the grammar parameters

I justify this estimator by proving that it maximizes a lower bound on the log likelihood of the data. Writing L for the log likelihood, θ for the parameters of the grammar, N for the number of random choices, A to range over the alternative choices for a random variable, $c(x)$ to mean the number of times that primitive x was used, and $a(x) = \sum_A \mathbb{1}[x \in A]$ to mean the number of times that primitive x could have







Algorithm 1 Generative model over programs

function sample($\mathcal{D}, \theta, \mathcal{E}, \tau$):
Input: DSL $\mathcal{D}$, weight vector θ, environment $\mathcal{E}$, type τ
Output: a program whose type unifies with τ
if $\tau = \alpha \to \beta$ **then**
  var $\leftarrow$ an unused variable name
  body $\sim$ sample($\mathcal{D}, \theta$, [var : α] $+ \mathcal{E}, \beta$)
  return λvar. body
end if

$$\text{primitives} \leftarrow \{p | p : \alpha \to \cdots \to \beta \in \mathcal{D} \cup \mathcal{E} \text{ if canUnify}(\tau, \beta)\}$$

Sample $e \sim$ primitives, w.p. $\propto \theta_e$ if $e \in \mathcal{D}$ and w.p. $\propto \frac{\theta_{var}}{|\text{variables}|}$ if $e \in \mathcal{E}$
Let $e : \alpha_1 \to \alpha_2 \to \cdots \to \alpha_K \to \beta$. Unify τ with β.
for $k = 1$ **to** K **do**
  $a_k \sim$ sample($\mathcal{D}, \theta, \mathcal{E}, \alpha_k$)
end for
return $e(a_1, a_2, \cdots, a_K)$

Algorithm 2 DSL Learner

Input: Initial DSL $\mathcal{D}$, set of tasks X, iterations I
Hyperparameters: Frontier size F
Output: DSL $\mathcal{D}$, weight vector θ, bottom-up recognition model $q(\cdot)$
Initialize $\mathcal{D}_0 \leftarrow \mathcal{D}$, $\theta_0 \leftarrow$ uniform, $q_0(\cdot) = \theta_0$
for $i = 1$ **to** I **do**
  for $x : \tau \in X$ **do**
    $\mathcal{F}_x \leftarrow \{z | z \in \text{enumerate}(\mathcal{D}_{i-1}, q_{i-1}(x), F) \cup \text{enumerate}(\mathcal{D}_{i-1}, \theta_{i-1}, F) \text{ if } \mathbb{P}[x|z] > 0\}$
  end for
  $\mathcal{D}_i, \theta_i \leftarrow$induceGrammar($\{\mathcal{F}_x\}_{x \in X}$)
  Define $Q_x(z) \propto \begin{cases} \mathbb{P}[x|z]\mathbb{P}[z|\mathcal{D}_i, \theta_i] & x \in \mathcal{F}_x \\ 0 & x \notin \mathcal{F}_x \end{cases}$
  $q_i \leftarrow \arg\min_q \sum_{x \in X} \text{KL}(Q_x(\cdot) || \mathbb{P}[\cdot | \mathcal{D}_i, q(x)])$
end for
return $\mathcal{D}^I, \theta^I, q^I$

been used:

$$L = \sum_x c(x) \log \theta_x - \sum_A \log \sum_{x \in A} \theta_x \tag{1}$$

$$= \sum_x c(x) \log \theta_x - N \mathbb{E}_A \log \sum_{x \in A} \theta_x \tag{2}$$

$$\geq \sum_x c(x) \log \theta_x - N \log \mathbb{E}_A \sum_{x \in A} \theta_x, \text{ Jensen's inequality} \tag{3}$$

$$= \sum_x c(x) \log \theta_x - N \log \frac{1}{N} \sum_A \sum_x \mathbb{1}[x \in A] \theta_x \tag{4}$$

$$\stackrel{+}{=} \sum_x c(x) \log \theta_x - N \log \sum_x a(x) \theta_x. \tag{5}$$

Differentiate with respect to θ_x and set to zero:

$$\frac{c(x)}{\theta_x} = N \frac{a(x)}{\sum_y a(y) \theta_y} \tag{6}$$

This equality holds if $\theta_x = c(x)/a(x)$:

$$\frac{c(x)}{\theta_x} = a(x). \tag{7}$$

$$N \frac{a(x)}{\sum_y a(y) \theta_y} = N \frac{a(x)}{\sum_y c(y)} = N \frac{a(x)}{N} = a(x). \tag{8}$$

If this equality holds then $\theta_x \propto c(x)/a(x)$:

$$\theta_x = \frac{c(x)}{a(x)} \times \underbrace{\frac{\sum_y a(y) \theta_y}{N}}_{\text{Independent of } x}. \tag{9}$$

Now what we are actually after is the parameters that maximize the joint log probability of the data+parameters, which I will write J:

$$J = L + \log \text{D}(\theta | \alpha) \tag{10}$$

$$\stackrel{+}{\geq} \sum_x c(x) \log \theta_x - N \log \sum_x a(x) \theta_x + \sum_x (\alpha_x - 1) \log \theta_x \tag{11}$$

$$= \sum_x (c(x) + \alpha_x - 1) \log \theta_x - N \log \sum_x a(x) \theta_x \tag{12}$$

So you add the pseudocounts to the *counts* ($c(x)$), but not to the *possible counts* ($a(x)$).

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Algorithm 3 Grammar Induction Algorithm

Input: Set of frontiers $\{\mathcal{F}_x\}$
Hyperparameters: Pseudocounts α, regularization parameter λ, AIC coefficient a
Output: DSL $\mathcal{D}$, weight vector θ
Define $\log \mathbb{P}[\mathcal{D}] \stackrel{+}{=} -\lambda \sum_{p\in\mathcal{D}} \text{size}(p)$
Define $L(\mathcal{D},\theta) = \prod_x \sum_{z\in\mathcal{F}_x} \mathbb{P}[z|\mathcal{D},\theta]$
Define $\theta^*(\mathcal{D}) = \arg\max_\theta \text{Dir}(\theta|\alpha)L(\mathcal{D},\theta)$
Define $\text{score}(\mathcal{D}) = \log \mathbb{P}[\mathcal{D}] + L(\mathcal{D},\theta^*) - a|\mathcal{D}|$
$\mathcal{D} \leftarrow$ every primitive in $\{\mathcal{F}_x\}$
while true **do**
  N $\leftarrow \{\mathcal{D}\cup\{s\}|x\in X, z\in\mathcal{F}_x, s$ a subtree of $z\}$
  $\mathcal{D}' \leftarrow \arg\max_{\mathcal{D}'\in N} \text{score}(\mathcal{D}')$
  if $\text{score}(\mathcal{D}') > \text{score}(\mathcal{D})$ **then**
    $\mathcal{D} \leftarrow \mathcal{D}'$
  else
    return $\mathcal{D}, \theta^*(\mathcal{D})$
  end if
end while

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