Efficient Pragmatic Program Synthesis with Informative Specifications

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Abstract

Providing examples is one of the most common way for end-users to interact with program synthesizers. However, program synthesis systems assume that examples consistent with the program are chosen at random, and do not exploit the fact that users choose examples pragmatically. Prior work [1] modeled program synthesis as pragmatic communication, but required an inefficient enumeration of the entire program space. In this paper, we show that it is possible to build a program synthesizer that is both pragmatic *and* efficient by approximating the joint distribution of programs with a product of independent factors, and performing pragmatic inference on each factor separately. This naive factored distribution approximates the exact joint distribution well when the examples are given pragmatically, and is compatible with a very simple neuro-symbolic synthesis algorithm.

1 Introduction

Program synthesizers are systems that take a specification of user intent as input, and synthesize a program in a *domain-specific language* (DSL) that satisfies the specification. Providing examples is the standard form of specification for end users of state-of-the-art program synthesizers, as examples are both intuitive for humans to provide and explicitly checkable by machines. However, program synthesizers typically assume the examples are chosen randomly [2, 3, 4, 5], and don't leverage the fact that humans choose examples pragmatically to convey their intent [6]. As a consequence, existing synthesizers are both *inefficient* – having to reason over a complex space of programs conditioned on *random* specifications, and *unintuitive* – not treating the given specification pragmatically.

Prior work [1] posed program synthesis as a reference game, allowing for the application of the Rational Speech Acts (RSA) model [7] towards pragmatic program synthesis. They have shown that by treating user given examples pragmatically, one can build synthesizers that are more intuitive to use and require fewer examples when compared to the non-pragmatic ones. However, the formulation in [1] considers each program as an atom, and requires multiple enumerations over the entire program space. This does not scale to combinatorially complex program spaces. Thus, one is left with a dilemma: One can either make a synthesizer pragmatic at the cost of extreme inefficiency, or make it efficient and scalable to a large space of programs at the cost of it being non-pragmatic.

We take a step towards making a program synthesizer that is both pragmatic and efficient by factorizing the distribution of programs as a set of independent production rules as prescribed by the DSL's grammar. This factorization completely disregards the complicated correlative structures between these production rules neccesary to faithfully model the space of programs given the specification.

Indeed, under a *literal* specification that doesn't actively constrain the number of consistent programs, this naive factorization will generate programs that fail to satisfy the specification nearly every time – it is a bad approximation. However, under a *pragmatic* specification that selects a smaller number

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of consistent programs and is thus more *informative*, the factorization preserves the sparsity of the joint distribution, and performs on par with a literal listener that explicitly models the exact joint distribution at a fraction of the inference cost. On the human speaker data of [1], the factored literal listener performs even *better* than its exact counterpart, suggesting that humans may intuitively be assuming a factored distribution while communicating to the synthesizers.

The factored representation also makes it efficient to perform the recursive reasoning required for RSA algorithm, as each factor is a distribution over a small number of concepts. We find that the factored pragmatic synthesizer achieves reasonably good performance when compared to its exact counterpart. More importantly, our factorized approach allows for the introduction of learned (i.e. neural symbolic) program synthesizers, which makes it applicable to large program spaces.

2 Efficient Pragmatic Synthesis

As in [1], we model program synthesis as a reference game between two agents – a speaker S and a listener L. The speaker chooses a specification – a set of examples $D = u_1 u_2 \dots u_n$ – to communicate a program h to the listener. In keeping with the literature on the Rational Speech Acts model, we also refer to an example as an *utterance*. The communication is successful if the listener is able to infer, or *synthesize*, the correct program given the speaker's utterances.

2.1 Exact Pragmatic Program Synthesis

In this communication game setting, the task of synthesis is to model the listener distribution $P_L(h|D)$ of programs given utterances. To model a *pragmatic* listener, [1] propose using the Rational Speech Acts (RSA) model [7] to recursively reason about a speaker generating utterances according to a speaker distribution $P_S(D|h)$ of utterances given a program.

The *literal listener* L_0 reasons about the *lexicon* $l(h, D)$. The lexicon function takes the value 1 if the program h is consistent with a specification D, and 0 otherwise. The literal listener is defined in Equation (1). The *pragmatic speaker* S_1 reasons about a literal listener. Since modelling a distribution over all specifications is intractable, [1] factorize the speaker distribution over specifications autoregressively into a product of distributions over utterances (eqs. (2) and (3)). The *pragmatic listener* L_1 reasons about S_1 to pragmatically synthesize programs (eq. (4)).

$$P_{L_0}(h|D) = \frac{l(h, D)}{\sum_{h'} l(h', D)} \tag{1}$$

$$P^{spec}_{S_1}(D|h) = \prod_{i=1}^{n} P^{utt}_{S_1}(u_i|h, u_1^{i-1}) \tag{2}$$

$$P^{utt}_{S_1}(u_i|h, u_1^{i-1}) = \frac{P_{L_0}(h|u_1^{i-1}, u_i)}{\sum_{u'_i} P_{L_0}(h|u_1^{i-1}, u'_i)} \tag{3}$$

$$P_{L_1}(h|D) = \frac{P^{spec}_{S_1}(D|h)}{\sum_{h'} P^{spec}_{S_1}(D|h')} \tag{4}$$

Under this formulation, the distribution $P(h|D)$ is over the space of all programs, making pragmatically considering all possible alternatives intractable outside of simple domains.

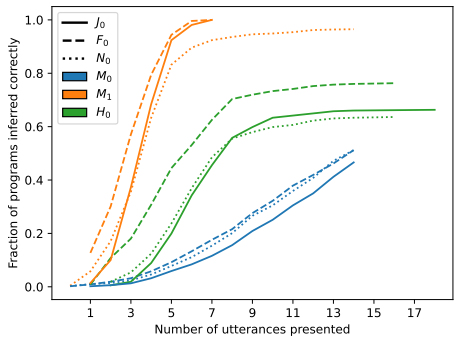
2.2 Efficient Synthesis with a Mean-field Approximation

Instead of viewing the program as an atomic referent, we view a program as a sequence of derivations in the grammar of the DSL. The grammar defines a set of K non-terminals, and a number of rules $N_i \to \alpha_i^1, \dots, N_i \to \alpha_i^n$ that expand N_i. Each step of the derivation selects a rule $N_i \to \alpha_i^j$, which expands a non-terminal N_i. We let R_i denote the rule $N_i \to \alpha_i^j$ that expands the non-terminal N_i in a program. When the production rules are not mutually dependent, the program can be simply represented as *a finite set of production values*: $\{R_1, R_2, \dots, R_K\}$.

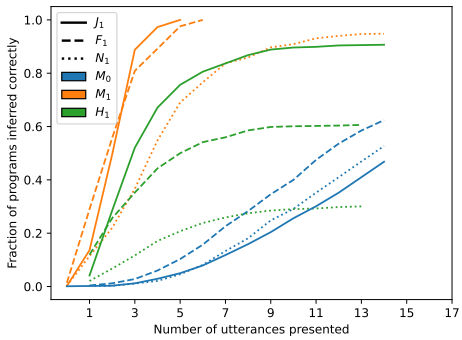
Under this representation of the program, we can use a *mean-field approximation* [8, Ch. 10] to naively factorize the distribution of programs $P(h|D)$ as

$$Q(h|D) = Q^1(R_1|D)Q^2(R_2|D) \cdots Q^K(R_K|D)$$

where $Q^i(N_i \to \alpha_i|D)$ is a distribution over rules that expand the non-terminal N_i. This approximation allows us to reason over each non-terminal independently. Appendix A shows that minimizing the forward KL distance between $P(h|D)$ and $Q(h|D)$ amounts to performing supervised learning on the marginal distribution of P on each factors Q^i separately.



(a) Literal listeners L_{J_0}, L_{F_0}, and L_{N_0}



(b) Pragmatic listeners L_{J_1}, L_{F_1}, and L_{N_1}

Figure 1: Comparison of different listeners interacting with different speakers S_{M_0}, S_H, and S_{M_1}, showing the fraction of programs correctly inferred after a number of utterances have been presented to the listener.

Pragmatic synthesis under the mean-field approximation amounts to carrying out the recursive computation for each productions independently (tractable as each Q^i operates over a small number of productions), similar to Equations (1) to (4). This is shown Equations (6) to (8). $Q^{i,spec}_{S_1}$ is defined autoregressively using $Q^{i,utt}_{S_1}$ as in $P^{spec}_{S_1}$.

The lexicon l^i for the i^{th} rule (eq. (5)) represents the fraction of all programs that satisfy the specification where the i^{th} non-terminal is expanded using the rule R_i. We can use this notion of the lexicon to compute the factorized literal listener as a marginal over all other factors, which is the best approximation under the factorization. Alternatively, the distribution $Q^i_{L_0}$ can be parametrized using a neural network trained to approximate the literal listener distribution. Given Q, we enumerate programs in decreasing order of probability until we find a consistent program, or run out of the search budget (Appendix B).

$$l^i(R_i, D) = \frac{\sum_{h:R_i \in h} l(h, D)}{\sum_h l(h, D)} \tag{5}$$

$$Q^i_{L_0}(R_i|D) = \frac{l^i(R_i, D)}{\sum_{R'_i} l^i(R'_i, D)} \tag{6}$$

$$Q^{i,utt}_{S_1}(u_j|R_i, u_1^{j-1}) = \frac{Q^i_{L_0}(R_i|u_1^{j-1}, u_j)}{\sum_{u'_j} Q^i_{L_0}(R_i|u_1^{j-1}, u'_j)} \tag{7}$$

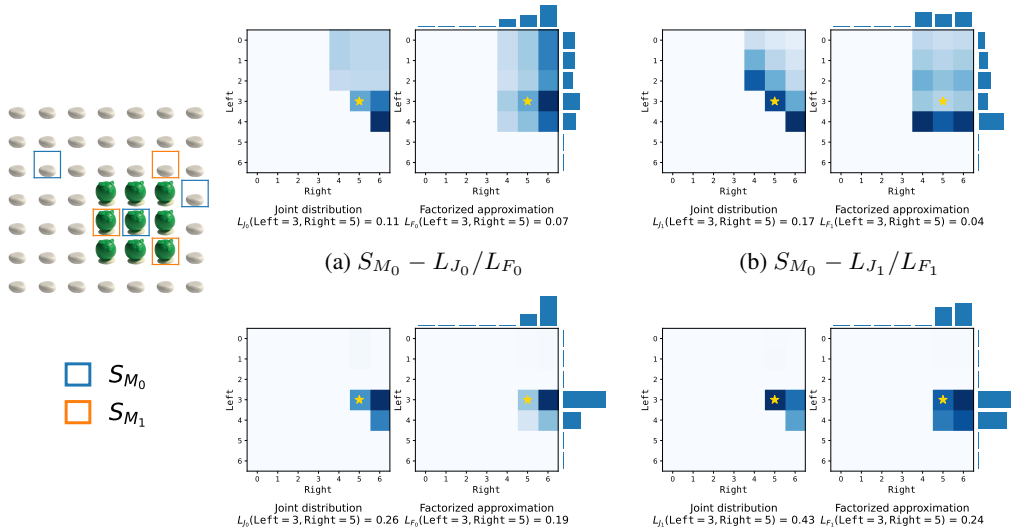
$$Q^i_{L_1}(R_i|D) = \frac{Q^{i,spec}_{S_1}(D|R_i)}{\sum_{R'_i} Q^{i,spec}_{S_1}(D|R'_i)} \tag{8}$$

3 Experiments

As an exploratory study, we evaluate our approach on a simple layout domain [1], where exact inference over the space of programs is possible. In this domain, a program is a pattern on a grid formed from a set of objects. These objects may be a colourless pebble, or a chicken or pig that may be red, green or blue. Each utterance reveals the object at one square on the grid, and the speaker has to communicate the pattern by revealing squares on the grid. The pattern is formed according to rules specified in the domain-specific language in Appendix D. The specification is a sequence of objects, specified by the coordinates of the object on the grid, and its shape and colour.

3.1 The Models

We consider 6 different listener models – literal and pragmatic variants of 3 different types of models. The first type is the models from [1], which enumerate the entire program space during inference. These are the *joint literal listener* L_{J_0} and the *joint pragmatic listener* L_{J_1}, since they model the full joint distribution from eqs. (1) and (4) respectively. The second type is based on the factorized listener distributions from eqs. (6) and (8). In this type, the literal listener distributions are obtained by enumerating over the space of programs. These are termed the *factorized literal listener* L_{F_0} and the *factorized pragmatic listener* L_{F_1}. The third type of model is also based on the factorized listener



(a) $S_{M_0} - L_{J_0}/L_{F_0}$ (b) $S_{M_0} - L_{J_1}/L_{F_1}$

(c) $S_{M_1} - L_{J_0}/L_{F_0}$ (d) $S_{M_1} - L_{J_1}/L_{F_1}$

Figure 2: Heatmaps showing the distribution over the rules for two different non-terminals in the DSL – `Left` and `Right` – that specify the left and right edges of the pattern respectively, under the specification shown on the left. Each case shows the distribution produced by one type of listener (literal L_{J_0}/L_{F_0} or pragmatic L_{J_1}/L_{F_1}) under a specification produced by a speaker model. In each case, the heatmap on the left shows the joint distribution over these two productions under the a joint listener model. The heatmap on the right shows the joint distribution over these two productions under a factorized model, with the distribution of each factor shown as a histogram. The rules that satisfy the program are indicated with a star.

distributions, but the literal listener distribution is approximated using a neural network (Appendix E). These are termed the *neural literal listener* L_{N_0} and the *neural pragmatic listener* L_{N_1}.

3.2 The Data

We use speaker models to generate specifications from 1000 randomly chosen programs from the DSL. We use a *literal speaker* S_{M_0} to randomly generate utterances that are true of the program, and a *pragmatic speaker* S_{M_1} to generate utterances under the joint speaker distribution in eq. (2). These are idealized cases of a perfectly literal and pragmatic (according to RSA) listeners respectively.

We perform experiments using speaker data from interactions between L_{J_0} and L_{J_1} and users collected by [1]. We denote a human speaker interacting with L_{J_0} as S_{H_0}, and a human speaker interacting with L_{J_1} as S_{H_1}. We must note that even when interacting with L_{J_0}, a human user does not behave in a perfectly literal manner. Details of how the data are processed are presented in Appendix C.

3.3 Results

In Figure 1a, we note that an idealized pragmatic speaker S_{M_1} allows all the literal listener models – L_{J_0}, L_{F_0}, and L_{N_0} – to perform well. This suggests that under pragmatic specifications from S_{M_1}, the factorized distribution of L_{F_0} approximates the exact, joint distribution L_{J_0} well, due to informative specification concentrating the probability mass in a smaller region. We illustrate this effect on a concrete instance in Figure 2. This affirms our intuition that a pragmatic specification should make inference *easier*, and allows for an extremely simple neuro-symbolic synthesizer. As expected, performance on uninformative specifications from S_{M_0} is poor for both literal and pragmatic models.

Surprisingly, the factored literal listener L_{F_0} performs *better* than the exact model L_{J_0} when given human generated specifications from interactions with a literal listener L_{J_0}. This suggests that humans may intuitively be assuming a factored distribution while communicating with the synthesizer, and

using examples to refer to specific rules in the DSL like the rule that selects a particular value for the cooridnates of one of the edges.

For the pragmatic listeners in Figure 1b, we note that the factored model L_{F_1} approximates the exact model L_{J_1} well when given idealized specifications from S_{M_1}. However, L_{F_1} performs worse than L_{J_1} on human-generated specifications from S_{H_1}. The human-generated specifications we use were collected during interactions between humans and L_{J_0} or L_{J_1}. During these interactions, humans may have adapted to specific idiosyncracies of the listener models. Since we use the data offline, such adaptation is not possible.

Also note that approximation errors of the neural model accumulate when different factors are combined, and during RSA's recursive reasoning process. This results in larger gaps between L_{N_1} and L_{F_1} than between L_{N_0} and L_{F_0}.

Thus, we can expect a neural-pragmatic approach to perform reasonably well once the following two conditions are met: (i) Better neural approximation of eq. (6) and (ii) the opportunity to interact directly with users.

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A Factorized Approximation of Joint Listener Distribution

For simplicity, let us consider a setting where $K = 2$. So, we have the joint distribution $P(h|D)$ approximated by $Q(h|D) = Q^1(R_1|D)Q^2(R_2|D)$.

We would like to minimize the quantity $KL(P(R_1R_2|D)||Q(R_1R_2|D))$.

$$
\begin{aligned}
&\min_{Q} KL(P(R_1R_2|D)||Q(R_1R_2|D)) \\
&= \min_{Q^1,Q^2} KL(P(R_1R_2|D)||Q^1(R_1|D)Q^2(R_2|D)) \\
&= \min_{Q^1,Q^2} \sum_{R_1,R_2} P(R_1R_2|D) \log \left(\frac{P(R_1R_2|D)}{Q^1(R_1|D)Q^2(R_2|D)} \right) \\
&= \min_{Q^1,Q^2} \sum_{R_1,R_2} P(R_1R_2|D) \log P(R_1R_2|D) - \sum_{R_1,R_2} P(R_1R_2|D) \log \left(Q^1(R_1|D)Q^2(R_2|D) \right) \\
&= \min_{Q^1,Q^2} - \sum_{R_1,R_2} P(R_1R_2|D) \log \left(Q^1(R_1|D)Q^2(R_2|D) \right) \\
&= \max_{Q^1,Q^2} \sum_{R_1,R_2} P(R_1R_2|D) \log \left(Q^1(R_1|D)Q^2(R_2|D) \right) \\
&= \max_{Q^1} \sum_{R_1,R_2} P(R_1R_2|D) \log Q^1(R_1|D) + \max_{Q^2} \sum_{R_1,R_2} P(R_1R_2|D) \log Q^2(R_2|D)
\end{aligned}
$$

We can maximize each term of the sum separately. Without loss of generalization, let's focus on Q^1.

$$
\begin{aligned}
&\max_{Q^1} \sum_{R_1,R_2} P(R_1R_2|D) \log Q^1(R_1|D) \\
&= \max_{Q^1} \sum_{R_1} \sum_{R_2} P(R_1R_2|D) \log Q^1(R_1|D) \\
&= \max_{Q^1} \sum_{R_1} \log Q^1(R_1|D) \sum_{R_2} P(R_1R_2|D) \\
&= \max_{Q^1} \sum_{R_1} P(R_1|D) \log Q^1(R_1|D) \\
&= \min_{Q^1} - \sum_{R_1} P(R_1|D) \log Q^1(R_1|D)
\end{aligned}
$$

We see that minimizing the KL divergence can be reduced to minimizing the cross-entropy loss between the factor of the mean-field approximation corresponding to a non-terminal symbol and the marginal of the joint distribution over all other non-terminals.

To train a learned model, we can sample programs and corresponding specfications and train with this objective,

$$
\min_{Q^1} \mathop{\mathbb{E}}_{r_1 \sim P(R_1|D)} [- \log Q^1(R_1|D)]
$$

B Search algorithm

Algorithm 1 describes the search algorithm. We use a best-first search algorithm, where we start with the highest probability program by considering the highest probability rule for each non-terminal. We then iterate over programs in decreasing order of probability. At each step, we replace one rule in the program with the next best alternative for that rule, and add it to a priority queue. We terminate the search when we find a consistent program, or exceed the search budget. For our experiments, we use a search budget of 50.

C Data processing

C.1 Speaker models

We use the speaker models S_{M_0} and S_{M_1} to generate specifications according to an idealized literal and pragmatic speaker distribution respectively. The literal speaker model S_{M_0} selects utterances

Algorithm 1 Best-first search for programs

Require: Specification D, distributions over rules $Q^i(R_i|D)$, search budget B
Ensure: Program $\langle R_1, \ldots, R_K \rangle$ which satisfies D
  for $i = 1$ to K **do**
    Sort rules R_i^j in decreasing order of $Q^i(R_i^j|D)$
  end for
  Searched set $S \leftarrow \{\}$
  Priority queue $P \leftarrow []$ ▷ Max priority queue with score p
  $\mathsf{enqueue}(P, \langle R_1^1, \ldots, R_K^1 \rangle)$ ▷ $p = \sum_i \log Q^i(R_i^1|D)$
  while $|S| < B$ **do**
    $\langle R_1^{j_1}, \ldots, R_K^{j_K} \rangle \leftarrow \mathsf{dequeue}(L)$
    if $\langle R_1^{j_1}, \ldots, R_K^{j_K} \rangle \in S$ **then**
      continue
    end if
    if $\langle R_1^{j_1}, \ldots, R_K^{j_K} \rangle$ is consistent with D **then**
      return $\langle R_1^{j_1}, \ldots, R_K^{j_K} \rangle$
    end if
    $S \leftarrow S \cup \{\langle R_1^{j_1}, \ldots, R_K^{j_K} \rangle\}$
    for $i = 1$ to K **do**
      if replacing $R_i^{j_i}$ with $R_i^{j_i+1}$ results in a valid program **then**
        $\mathsf{enqueue}(P, \langle R_1^{j_1}, \ldots, R_{i-1}^{j_{i-1}}, R_i^{j_i+1}, R_{i+1}^{j_{i+1}}, \ldots R_K^{j_K} \rangle)$ ▷ $p = \sum_i \log Q^i(R_i^{j_i}|D)$
      end if
    end for
  end while

that are true of the program with uniform probability. The pragmatic speaker model M_1 generates specifications autoregressively, at each step choosing the utterance with the highest probability according to Equation (3). For each program, we generate a specification of size 15 using each of the models S_{M_0} and S_{M_1} as a sequence of utterances $u_1, u_2, \ldots, u_n$.

A listener model is presented with incrementally larger prefixes of this sequence of utterances, and the synthesis is terminated if the intended program is correctly identified by the listener model.

C.2 User interaction data

For each model L_{J_0} and L_{J_1}, we have a set of trials collected by [1]. We term a user interacting with L_{J_0} as S_{H_0} and a user interacting with L_{J_1} as L_{H_1}. Each trial presents the user with a program in the DSL, and the user is taked with communicating the program to the model. The user reveals a sequence of utterances $u_1, u_2, \ldots, u_n$.

We consider the utterances as a sequence, in the other they were provided by the user. We process the specifications to remove duplicate utterances within a trial, and retain only the first occurrence of the utterance. We have a total of 371 trials for S_{H_0} and 386 trials for S_{H_1}.

The synthesis experiments are conducted in a similar manner to the experiments with data from speaker models.

D DSL Grammar

E Neural models

We train a 2-hidden layer MLP, with each hidden layer having 256 units, as a neural literal listener N_0. The input to this model is a $7 \times 7 \times 6$ tensor T. For each element of the specification (x, y, s, c), denoting the x-coordinate, y-coordinate, shape, and color (shape and color are mapped to an index between 0 and 2) respectively is encoded by setting $T[x, y, s] = 1$ and $T[x, y, 3 + c] = 1$. All other elements of the input are set to 0.

```
  Program → ⟨Shape, Colour⟩
    Shape → Box(Left, Right, Top, Bottom, Thickness,
            Outside, Inside)
     Left → 0 | 1 | 2 | 3 | ... | 6
    Right → 0 | 1 | 2 | 3 | ... | 6
      Top → 0 | 1 | 2 | 3 | ... | 6
   Bottom → 0 | 1 | 2 | 3 | ... | 6
Thickness → 1 | 2 | 3
        O → chicken | pig
        I → chicken | pig | pebble
   Colour → [red , green , blue][A2(A1)]
       A1 → x | y | x + y
       A2 → lambda z:0 | lambda z:1 | lambda z:2
            | lambda z:z%2 | lambda z:z%2+1 | lambda z:2*(z%2)
```

Figure 3: Grammar of the DSL

A common model for each production is trained for all productions. The model produces a 12×7 matrix Q, where Q_{ij} represents the probability that a rule R_j is chosen for the i^{th} factor. The loss for each factor is computed as described in Appendix A, and summed to obtain the total loss for a sample.

The model is trained by sampling a batch of programs from a set of 10000 programs, sampling a specification using the literal speaker model S_{M_0} for each program in the batch, and computing the loss between the predicted distribution for each factor and the ground truth value for factor.

The model is trained with a batch size of 8 and specifications comprising of 2 to 25 elements for 150,000 steps.