Program Synthesis with Pragmatic Communication

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Abstract

Program synthesis techniques construct or infer programs from user-provided specifications, such as input-output examples. Yet most specifications, especially those given by end-users, leave the synthesis problem radically ill-posed, because many programs may simultaneously satisfy the specification. Prior work resolves this ambiguity by using various inductive biases, such as a preference for simpler programs. This work introduces a new inductive bias derived by modeling the program synthesis task as rational communication, drawing insights from recursive reasoning models of pragmatics. Given a specification, we score a candidate program both on its consistency with the specification, and also whether a rational speaker would chose this particular specification to communicate that program. We develop efficient algorithms for such an approach when learning from input-output examples, and build a pragmatic program synthesizer over a simple grid-like layout domain. A user study finds that end-user participants communicate more effectively with the pragmatic program synthesizer over a non-pragmatic one.

1 Introduction

Programming is a frustrating process: as the computer executes your code literally, any error in communicating how the computer should run would result in a bug. Program synthesis [1] aims to address this problem by allowing the user to specify what the program should do; provided this specification, a program synthesizer infers a program that satisfies it. One of the most well-known program synthesizers is FlashFill [2], which synthesizes string transformations from input/output examples. For instance, “Gordon Freeman” → “G”, the FlashFill system infers the program: “first_letter(first_word(input))”. FlashFill works inside Microsoft Excel, and this program can then run on the rest of the spreadsheet, saving time for end-users. However, most specifications, especially those provided by a naive end-user, leave the synthesis problem ill-posed as there may be many programs that satisfy the specification. Here we introduce a new paradigm for resolving this ambiguity. We think of program synthesis as a kind of communication between the user and the synthesizer. Framed as communication we can deploy ideas from computational linguistics, namely pragmatics, the study of how informative speakers select their utterances, and how astute listeners infer intent from these “pragmatic” utterances [3]. Intuitively, a pragmatic program synthesizer goes beyond the literal meaning of the specification, and asks why an informative user would select that specification.

Resolving the ambiguity inherent in program synthesis has received much attention. Broadly, prior work imposes some form of inductive bias over the space of programs. In a program synthesizer without any built-in inductive bias [1], given a specification D, the synthesizer might return any program consistent with D. Interacting with such a synthesizer runs the risk of getting an unintuitive program that is only “technically correct”. For instance, given an example “Richard Feynman” →
“Mr Feynman”, the synthesizer might output a program that prints “Mr Feynman” verbatim on all inputs. Systems such as [4] introduce a notion of syntactic naturalness in the form a prior over the set of programs: \( P(\text{prog} | D) \propto 1[\text{prog} \vdash D] P_0(\text{prog}) \), where \( \text{prog} \vdash D \) means \( \text{prog} \) is consistent with spec \( D \), and \( P_0(\text{prog}) \) is a prior with parameters \( \theta \). For instance \( P_0 \) might disprefer constant strings. However, purely syntactic priors can be insufficient: the FlashFill-like system in [5] penalizes constant strings, making its synthesizer explain the “r” in “Mr Feynman” with the “r” from “Richard”; when the program synthesized from “Richard Feynman”→“Mr Feynman” executes on “Stephen Wolfram,” it outputs “Ms Wolfram.” This failure in part motivated the work in [6], which addresses failure such as these via handcrafted features. In this work we take a step back and ask: what are the general principles of communication from which these patterns of inductive reasoning could emerge?

We will present a qualitatively different inductive bias, drawing insights from probabilistic recursive reasoning models of pragmatics [7]. Confronted with a set of programs all satisfying the specification, the synthesizer asks the question, “why would a pragmatic speaker use this particular specification to communicate that program?” Mathematically our model works as follows. First, we model a synthesizer without any inductive bias as a literal listener \( L_0: P_{L_0}(\text{prog} | D) \propto 1[\text{prog} \vdash D] \). Second, we model a pragmatic speaker, which is a conditional distribution over specifications, \( S_1: P_{S_1}(D|\text{prog}) \propto P_{L_0}(\text{prog} | D) \). This “speaker” generates a specification \( D \) in proportion to the probability \( L_0 \) would recover the program \( \text{prog} \) given \( D \). Last, we obtain the pragmatic listener, \( L_1: P_{L_1}(\text{prog} | D) \propto P_{S_1}(D|\text{prog}) \), which is the synthesizer with the desirable inductive bias. It is worth noting that the inductive biases present in \( L_1 \) are derived from first principles of communication and the synthesis task, rather than trained on actual data of end-user interactions.

Algorithmically, computing these probabilities is challenging because they are given as unnormalized proportionalities. Specifically, \( P_{L_0} \), requires summing over the set of consistent programs given \( D \), and \( P_{S_1} \), requires summing over the set of all possible specifications given \( \text{prog} \). To this end, rather than tackling the difficult problem of searching for a correct program given a specification, a challenging research field in its own right [8][15], we work over a small enough domain such that the search problem can be efficiently solved with a simple version space algebra [17]. We develop an efficient inference algorithm to compute these probabilities exactly, and then build a functioning program synthesizer with these inference algorithms. In conducting a user study on Amazon Mechanical Turk, we find that naive end-users communicate more efficiently with a pragmatic program synthesizer compared to its literal variant. Concretely, this work makes the following contributions:

1. a systematic formulation of recursive pragmatics within program synthesis
2. an efficient implementation of an incremental pragmatic model via version space algebra
3. a user study demonstrating that end-users communicate their intended program more efficiently with pragmatic synthesizers

2 Program Synthesis as a Reference Game

We now formally connect program synthesis with pragmatic communication. We describe reference game, a class of cooperative 2-player games from the linguistic literature. We then cast program synthesis as an instance of a reference game played between a human speaker and a machine listener.

2.1 Program Synthesis

In program synthesis, one would like to obtain a program without explicitly coding for it. Instead, the user describes desirable properties of the program as a specification, which often takes in the form of a set of examples. Given these examples, the synthesizer would search for a program that satisfies these examples. In an interactive setting [18], rather than giving these examples all at once, the user gives the examples in rounds, based on the synthesizer’s feedback each round.

2.2 Reference Game

In a reference game, a speaker-listener pair \((S, L)\) cooperatively communicate a concept \( h \in H \) using some atomic utterances \( u \in U \). Given a concept \( h \), the speaker \( S \) chooses a set of utterances \( D = \{ u^1, \ldots, u^{|D|} | u^i \in U \} \) to describe the concept. The communication is successful if the original concept is recovered by the listener, i.e. \( h = L(S(h)) \). The communication is efficient if \( |D| \) is small.

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Therefore, it should be unsurprising that, given a reference game, a human speaker-listener pair would act pragmatically \[^3\]: The speaker is choosing didactic utterances that are most descriptive yet parsimonious to describe the concept, and the listener is aware that the speaker is being didactic while recovering the intended concept.

2.3 Program Synthesis as a Reference Game

It is easy to see why program synthesis is an instance of a reference game: The user would like to obtain a “concept” in the form of a “program”, the user does so by using “utterances” in the form of “examples”. See Figure 1. This formulation can explain in part the frustration of using a traditional synthesizer, or machine in general. Because while the user naturally assumes pragmatic communication, and selects the examples didactically, the machine/synthesizer is not pragmatic, letting the carefully selected examples fall on deaf ears.

![Figure 1: program synthesis as a reference game](image)

2.4 Reaching Consensus in Human-Machine Communication

Two strangers who speak different languages would not perform as well in a reference game as two close friends. Clearly, there needs to be a protocol shared between the speaker and the listener for effective communication to occur. Approaches such as \[^{19,20}\] use a corpus of human annotated data so that the machine can imitate the protocols of human communication directly. Works such as \[^{21,22}\] leverage both annotated data and pragmatic inference to achieve successful human-machine communication over natural language. This work shows that, in the context of program synthesis by examples, by building the concept of pragmatic communication into the synthesizer, the user can quickly adapt to communicate with the synthesizer effectively via human learning.\[^{1}\] This is advantageous because annotated user data is expensive to obtain. In this regard, our work is most similar to SHRDLURN \[^{23}\], where a pragmatic semantic parser was able to translate natural language utterances into a desirable program without being trained first on human annotated data.

3 Communicating Concepts with Pragmatics

We now describe how to operationalize pragmatics using a small, program-like reference game, where by-hand calculation is feasible. This exposition adapts formalism from \[^{18}\] for efficient implementation within program synthesizers.

**The Game.** Consider the following game. There are ten different concepts \(H = \{h_0 \ldots h_9\}\) and eight atomic examples \(\{u_0 \ldots u_7\}\). Each concept is a contiguous line segment on a horizontal grid of 4 cells, and each atomic example indicates whether a particular cell is occupied by the segment. One can view this example as an instance of predicate synthesis, where the program takes in the form of a predicate function \(h\), and the atomic examples as input-output pairs obtained by applying the predicate function on some input; i.e. \(u_0 = (cell_0, h(cell_0) = True)\). We can visualise the game with a **meaning matrix** (Figure 2), where each entry \((i,j)\) denotes whether \(h_j \vdash u_i\) (\(h_j\) is consistent with \(u_i\)). Given a set of examples \(D\), we say \(h \vdash D\) if \(\forall u \in D, h \vdash u\).

If a human speaker uses the set of examples \(D = \{u_2, u_4\}\), what is the most likely concept being communicated? We should expect it is \(h_5\), as \(u_2\) and \(u_4\) marks the end-points of the segment, despite

\[^2\]which is far more powerful than machine learning.
where the incremental probability \( P_{S_1}(h | D) \) is defined recursively with:
\[
P_{S_1}(u_i | h, u_1, \ldots, u_{i-1}) = \frac{P_{L_0}(h | u_i, u_1, \ldots, u_{i-1})}{\sum_{u'_i} P_{L_0}(h | u_i, u_1, \ldots, u'_i)}
\]

Applying this reasoning to our example in Figure 2 we see that \( P_{S_1}(u_2, u_4 | h_5) \) is:
\[
P_{S}(u_2 | h_5) P_{S}(u_4 | h_5, u_2) = \frac{P_{L_0}(h_6 | u_2)}{\sum_{u'} P_{L_0}(h_5 | u')} \frac{P_{L_0}(h_6 | u_2, u_4)}{\sum_{u''} P_{L_0}(h_5 | u_2, u'')} = 0.25 \times 0.3 = 0.075
\]

**3.1 Communication with Incremental Pragmatics**

The recursive pragmatic model derives a probabilistic speaker \( S_1 \) and listener \( L_1 \) pair given a meaning matrix, and the resulting communication protocol is shown to be both efficient and human usable \[24\]. Clearly, there are other ways to derive a speaker-listener pair that are highly efficient, for instance, training a pair of agents in a RL setting \[25\]. However, agents trained this way tends to deviate from how a human would communicate, essentially coming up with a highly efficient yet obfuscated communication protocol that is usable by the agents alone.

**Literal Listener \( L_0 \).** We start by building the literal listener \( L_0 \) from the meaning matrix. Upon receiving a set of examples \( D \), \( L_0 \) samples uniformly from the set of consistent concepts:
\[
P_{L_0}(h | D) \propto \mathbb{1}(h \vdash D), \quad P_{L_0}(h | D) = \frac{\mathbb{1}(h \vdash D)}{\sum_{h' \in H} \mathbb{1}(h' \vdash D)}
\]

Applying to our example in Figure 2 we see that \( P_{L_0}(h_5 | u_2, u_4) = \frac{1}{4} \).

**Incrementally Pragmatic Speaker \( S_1 \).** We now build a pragmatic speaker \( S_1 \) recursively from \( L_0 \). Here, rather than treating \( D \) as an unordered set, we view it as an ordered sequence of examples, and models the speaker’s generation of \( D \) incrementally, similar to autoregressive sequence generation in language modeling \[26\]. Let \( D = u^1 \ldots u^k \), then:
\[
P_{S_1}(D | h) = P_{S_1}(u_1, \ldots, u_k | h) = P_{S}(u_1 | h) P_{S}(u_2 | h, u_1) \ldots P_{S}(u_k | h, u_1 \ldots u_{k-1})
\]

**Informative Listener \( L_1 \).** Finally, we construct an informative listener \( L_1 \) which recursively reasons about the informative speaker \( S_1 \):
\[
P_{L_1}(h | D) \propto P_{S_1}(D | h), \quad P_{L_1}(h | D) = \frac{P_{S_1}(D | h)}{\sum_{h'} P_{S_1}(D | h')}
\]

In our example, \( P_{L_1}(h_5 | u_2, u_4) \approx 0.31, P_{L_1}(h_3 | u_2, u_4) \approx 0.28, P_{L_1}(h_3 | u_2, u_4) \approx 0.19, P_{L_1}(h_6 | u_2, u_4) \approx 0.21 \). As we can see, the intended concept \( h_5 \) is ranked first, in contrast to the uninformative listener \( L_0 \).
4 Efficient Computation of Incremental Pragmatics for Synthesis

We now describe an efficient computation of incremental pragmatics tailored to program synthesis. Our approach is tractable when the meaning matrix can be tractably enumerated; i.e. the product space of hypotheses and atomic examples, $H \times U$, is not too large, and describe an algorithm that runs in worst polynomial of $|H||U|$ time$^3$. State-of-the-art program synthesizers consider combinatorially large hypothesis spaces, and while our algorithm cannot yet scale to this regime, we believe computational principles elucidated here could pave the way for pragmatic synthesizers over combinatorially large program spaces, particularly with when this combinatorial space is manipulated with version space algebras, as in $[2][5][17]$. To this end, we employ version space algebra with aggressive precomputation to memoize the cost of pragmatic inference.

4.1 Formulation

We start by redefining some terms of pragmatics into the language of program synthesis. Let $h$ be a program and $H$ be the set of programs. Let $X$ be the domain of the program and $Y$ be the range of the program: $H : X \rightarrow Y$. An example $u$ is a pair $u = (x, y) \in X \times Y = U$. A program is consistent with an example, $h \vdash u$, if $u = (x, y) \wedge h(x) = y$.

4.2 Precomputations

We use a simple form of version space algebra $[17]$ to precompute and cache two kinds of mappings. First, we iterate over the rows of the meaning matrix and store, for each atomic example $u$, the set of programs that are consistent with it: $M_L[u] = \{h | h \vdash u\}$. Here $M_L$ is a map or a dictionary data structure, which can be thought of as an atomic speaker, that returns a set of consistent programs for every atomic example. Second, we iterate over the columns of meaning matrix, and store, for each program $h$, the set of atomic examples that are consistent with it $M_S[h] = \{u | h \vdash u\}$. $M_S$ can be thought of as an atomic listener, that returns a set of consistent programs for every atomic example.

4.3 Computing $P_{L_0}$

To compute $P_{L_0}(h|D)$, we first compute the set intersection $D[H] = \cap_{u \in D} M_L[u]$, which corresponds to the set of programs consistent under $D$. Note $D[H] = \{\}$ $\iff$ $h \not\in D$. Therefore, from Eq. $[1]$ we derive $P_{L_0}(h|D) = 0$ if $D[H] = \{\}$ and $\frac{1}{|D[H]|}$ otherwise.

4.4 Computing $P_{S_1}$

Computing $P_{S_1}$ amounts to computing a sequence of the incremental probability $P_S$ defined in Eq. $[3]$ The brunt of computing $P_S$ lies in the normalisation constant, $\sum_{u'} P_{L_0}(h|u_1, \ldots, u')$. We speed up this computation in two ways: First, we note that if $h \not\in u_1'$, the probability $P_{L_0}(h|u_1, \ldots, u_1')$ would be 0. Thus, we can simplify this summation using the atomic speaker $M_S[h]$ like so: $\sum_{u'} P_{L_0}(h|u_1, \ldots, u_1') = \sum_{u' \in M_S[h]} P_{L_0}(h|u_1, \ldots, u_1')$, which vastly reduce the number of terms within the summation. Second, recall that computing $P_{L_0}(h|D)$ amounts to computing the consistent set $D[H]$. We note that the only varying example inside the summation is $u_1'$, while all the previous examples $D_{prev} = \{u_1 \ldots u_{i-1}\}$ remains constant. This allows caching the intermediate results of the set intersection $D_{prev}[H] = \cap_{u \in D_{prev}} M_L[u]$ to be re-used in computing $D'[H] = M_L[u'] \cap D_{prev}[H]$ where $D' = D_{prev} \cup \{u_1\}$.

4.5 Computing $P_{L_1}$

Again, the brunt of the computation lies in the normalisation constant $\sum_{h'} P_{S_1}(D|h')$ of Eq. $[5]$ However, note that in case $h' \not\in D$, $P_{S_1}(D|h') = 0$. This would allow us to leverage the consistent set $D[H]$ to vastly reduce this summation: $\sum_{h'} P_{S_1}(D|h') = \sum_{h' \in D[H]} P_{S_1}(D|h')$

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$^3$When the meaning matrix is sparse, as is typical, it is faster
P -> if (x,y) in box(B,B,B,B) 
    then symbol(S,C) 
    else pebble 
B -> 0 | 1 | 2 | 3 | 4 | 5 | 6 
S -> ring(0,I,R,x,y) 
O -> chicken | pig 
I -> chicken | pig | pebble 
R -> 1 | 2 | 3 
C -> [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: DSL of pattern laying programs / rendering of 4 different programs on $7 \times 7$ grids

5 A Program Synthesis System with Pragmatics

To describe our program synthesis system with pragmatics, we only need to specify the space of programs, the space of atomic examples, and the meaning matrix; the rest will follow.

Programs. We consider a simple domain of programs that can layout grid-like patterns like those studied in [27,28]. Specifically, each program is a function that takes in a coordinate $(x,y)$ of a $7 \times 7$ grid, and place a particular symbol at that location. Symbols can be one of three shapes: chicken, pig, pebble, and be one of three colors: red, green, blue, with the exception that pebble is always colorless. A DSL and some of the programs renderings are shown in Figure 5. Here, box is the bounding box where the main pattern should be placed. ring is a function that takes two shapes and makes the outside shape $O$ wrap around the inside shape $I$ with a thickness of $R$. symbol is a function that takes in a shape and a color and outputs an appropriate symbol. We consider two programs $h_1$ and $h_2$ equivalent if they render to the same pattern over a $7 \times 7$ grid. After such de-duplication, there are a total of 17976 programs in our space of programs.

Atomic Examples. The space of atomic examples consists of tuples of form $((x, y), s)$, where $(x, y)$ is a grid coordinate, and $s$ is a symbol. As there are a total of 7 distinct symbols and the grid is $7 \times 7$, there are a total of 343 atomic examples in our domain.

Meaning Matrix. An entry of the meaning matrix denotes whether a program, once rendered onto the grid, would be consistent with an atomic example. For instance, let the upper-left pattern in Figure 3 be rendered from program $h_{1337}$, then, it will be consistent with the atomic examples $((0,0), pebble)$ and $((3,3), pig\_red)$, while be inconsistent with $((6,6), pig\_blue)$.

6 Human Studies

We conduct an user study to evaluate how well a naive end-user interacts with a pragmatic program synthesizer ($L_1$) versus a non-pragmatic one ($L_0$). We hypothesized that to the extent that the pragmatic models capture computational principles of communication, humans should be able to communicate with them efficiently and intuitively, even if the form of communication is new to them.

6.1 Methods

Subjects. Subjects ($N = 55$) were recruited on Amazon Mechanical Turk and paid $2.75 for 20 minutes. Subjects gave informed consent. Seven responses were omitted for failing to answer an instruction quiz. The remaining subjects ($N=48$) (26 M, 22 F), (Age = 40.9 +/- 12.1 (mean/SD)) were included. The study was approved by our institution’s Institutional Review Board.

\[[code]: https://github.com/evanthebouncy/program_synthesis_pragmatics\]
Stimuli. Stimuli were 10 representative renderings of program sampled from the DSL, capturing different concepts such as stripes vs checkered colour patterns and solid vs hollow ring shapes.

The communication task. The subjects were told they are communicating with two robots, either white ($L_0$) or blue ($L_1$). The subjects were given a stimuli (a rendering), and were asked to make a robot recreate this pattern by providing the robots with few, strategically placed symbols on a scratch grid (set of examples). Each time the subject places a symbol, the robot guesses the most likely program given the examples, and display its guess as a rendering as feedback to the subject. The subject may proceed to the next task if the pattern is successfully recreated. See Figure 6.1.

Procedure. First, the subjects read the instructions followed by a quiz. Subjects who failed the quiz twice proceeded with the experiment, but their responses were omitted. Next, the subjects practice with selecting and placing symbols. Subjects proceed with the communication task presented in two blocks, one with white robot $L_0$ and one with blue robot $L_1$, in random order between subjects. Each block contains 10 trials of the 10 stimuli, also in random order. In the end of the experiment subjects fill a survey: which robot was easier, and free-form feedback about their communication strategies.

6.2 Results

Behaviour Analysis. We first compared the mean number of symbols subjects used to communicate with each robot. A paired t-test was significant ($t = 12.877, df = 47, p < .0001$), with a mean difference of 2.8 moves, and a 95% confidence interval (2.35, 3.22). The numbers of symbols used for both robots by subjects is shown in Figure 5 (a).

A linear regression model for the mean number of symbols used as a dependent variable, and robot, trial as independent variables, was significant (adjusted $R^2 = 0.95, p < .0001, F(3, 16) = 134.8$), with significant coefficients for robot ($p < .0001$), and trial ($p < .0001$). The regression equation is given by: $\text{symbols} = 6.1 + 2.23 \times \text{robot} - 0.14 \times \text{trial} + 0.1 \times (\text{robot} : \text{trial})$, where robot = \{0 - blue, 1 - white\}, and trial is the order in which the stimulus was shown to subjects. This concludes that subjects’ communication with robots became more efficient over time. The interaction between the variables was small but not significant ($p = .06$), suggests that this communication improvement might have been driven by the pragmatic listener (blue robot) (Figure 5(b)).

A significant majority of subjects (77%, $\chi^2 = 26.042, p < .0001, df = 1$) reported that the blue($L_1$) robot was easier. This was true regardless of which robot they saw first (Figure 5(c)).

Communication Efficiency Analysis. Next, we compare communication efficiency between different speaker-listener pairs. We consider 3 speakers: S0 (a random speaker that uses any consistent examples, as a lower bound), S1 (the pragmatic speaker that $L_1$ was expecting, as an upper bound), and human. We consider two listeners: L0 and L1. We first measure the probability of successful
communication, $P(L(S(h)) = h)$, as a function of numbers of symbols used by sampling from the speaker and listener distributions (Figure 6 (a)). We find that both human and S1 communicate better with an informative listener L1 rather than L0. We then measure the mean number of symbols required for successful communication between a speaker-listener pair (Figure 6 (b)). A one-way ANOVA testing the effect of speaker-listener pair on number of symbols used was significant ($F(4, 45) = 66, p < .0001$), with significant multiple comparisons between means given by Tukey test for the following pairs: S0-L0 vs human-L0 ($p < .0001, d = 8.4$), S1-L0 vs human-L0 ($p = .004, d = 3.5$) and human-L0 vs human-L1 ($p = .3, d = 2.8$). There were no significant differences between S1-L1 vs human-L1 ($p = .2$) and between S1-L1 vs S1-L0 ($p = .6$). This means that human communication is significantly more efficient compared to the uninformative speaker (S0), and for the pragmatic listener, human efficiency is indistinguishable from the pragmatic speaker (S1). Further, compared to the pragmatic model S1, humans were significantly less efficient when communicating with the literal listener L0. This suggests that humans intuitively assume that a listener is pragmatic, and find communication difficult when this assumption is violated. This may have implications when engineering systems that do few-shot learning from human demonstration.

Figure 6: (a) probability of successful communication as a function of symbols used (up to 10). (b) mean number of moves for speaker-listener pair, error bars indicate 95% confidence intervals.

7 Looking Forward

In this work, we show that it is possible to obtain a pragmatic program synthesis system by building the principles of pragmatic communication into the synthesis algorithm rather than having it train on actual human interaction data. However, interaction data is still valuable, and we believe much benefit could be gained by building a system that can learn and adjust to a human communicator interactively. It is also interesting to see whether version space algebra approaches would scale to more complex

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5 instead of picking the top-1 program
6 taking the top-1 program from the listeners instead of sampling
program synthesis domains, and whether we can use a neural network to cheaply approximate the more computationally-intensive $L_1$ listener. In general, we believe interactive learning systems are a prime target of future research: not only do we desire machines that learn from massive data, but also machine intelligence which can acquire knowledge from pedagogy and communication.

**Broader Impact**

We hope that naive end-users would benefit from this research, as we aim for a more natural interaction between human and machine. This would democratize computation to allow broader access to computers by non-programmers, so that we may work along-side the machines rather than being replaced by them. We believe that one can also better assess the properties of a machine learning system (such as safety) through communication as well as through dissection of its architectures (looking at its neurons firing while showing it different stimuli). One potential risk is that it may become more complicated to prove and verify whether an AI system is working as intended in a complex communication setting, which can lead to errors.

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