Unified Pragmatic Models for Generating and Following Instructions

Daniel Fried  Jacob Andreas  Dan Klein
Computer Science Division
University of California, Berkeley
{dfried,jda,klein}@cs.berkeley.edu

Abstract

We extend models for both following and generating natural language instructions by adding an explicit pragmatic layer. These pragmatics-enabled models explicitly reason about why speakers produce certain instructions, and about how listeners will react upon hearing them. Given learned base listener and speaker models, we build a pragmatic listener that uses the base speaker to reason counterfactually about alternative action descriptions, and a pragmatic speaker that uses the base listener to simulate the interpretation of candidate instruction sequences. Evaluation of language generation and interpretation in the SAIL navigation and SCONE instruction following datasets shows that the pragmatic inference procedure improves state-of-the-art listener models (at correctly interpreting human instructions) and speaker models (at producing instructions correctly interpretable by humans) in diverse settings.

1 Introduction

How should speakers and listeners reason about each other when they communicate? The core concepts of computational pragmatics have been studied by a long line of work in natural language processing and cognitive science – specifically that speaker and listener agents operate within a cooperative game-theoretic context and that there are advantages to reasoning about each other’s intents and actions within that context. In this paper, we present a technique for layering this type of explicit inference on top of models for instruction interpretation and instruction generation tasks. We investigate a range of current data sets for both tasks, showing that pragmatic behavior arises naturally from this inference procedure, giving rise to state-of-the-art results in a variety of domains.

Consider the example shown in Figure 1a, in which a speaker agent must describe a route to a target position in a hallway. A conventional learned instruction-generating model produces a true description of the route (walk forward four times). However, the pragmatic speaker we propose in this paper, which is capable of reasoning about the listener, chooses to also include additional information (the intersection with the bare concrete hall), to reduce potential ambiguity and increase the odds that the listener reaches the correct destination.

This same reasoning procedure also allows a listener agent to overcome ambiguity in instructions by reasoning counterfactually about the speaker (Figure 1b). Given the command walk along the blue carpet and you pass two objects, a conventional learned instruction-following model is willing to consider all paths that pass two objects, and ultimately arrives at an unintended final position. But a pragmatic listener which reasons about the
speaker can infer that the long path would have been more easily described as *go to the sofa*, and thus that the shorter path is probably intended. In these two examples, which are produced by the system we describe in this paper, a unified reasoning process (choose the output sequence which is most preferred by an embedded model of the other agent) produces pragmatic behavior for both speakers and listeners.

The application of models with explicit pragmatic reasoning abilities has so far been largely restricted to simple *reference games*, in which the listener’s only task is to select the right item from among a small set of candidate referents given a single short utterance from the speaker. But as the example shows, there are real-world instruction following and generation tasks with complex, structured action spaces that might also benefit from pragmatic modeling. Moreover, approaches that learn to map directly between human-annotated instructions and action sequences are ultimately limited by the effectiveness of the humans themselves. The promise of pragmatic modeling is that we can use these same annotations to build a model with a different (and perhaps even better) mechanism for interpreting and generating instructions.

Our experimental evaluation focuses on four instruction-following domains which have been studied using both semantic parsers and attentional neural models. We investigate the closely related tasks of instruction following and instruction generation, and show that incorporating an explicit model of pragmatics into a state-of-the-art approach helps in both cases. Reasoning about the human listener allows a speaker model to produce directions that are easier for humans to interpret correctly in all domains (with absolute gains in accuracy ranging from 12% to 46%). Similarly, reasoning about the human speaker improves the accuracy of the listener models in interpreting directions in most domains (with gains in accuracy of up to 10%). In all cases, the resulting systems are competitive with, and in many cases exceed, results from past state-of-the-art systems for these tasks.

2 Related Work

The approach in this paper builds upon long lines of work in both pragmatic models for reference games and instruction following.

**Pragmatics** Our approach to pragmatics falls under the broad class of rational speech acts models (Frank and Goodman, 2012), in which the interaction between speakers and listeners is modeled as a probabilistic process with Bayesian actors (Goodman and Stuhlmüller, 2013). Alternative formulations (e.g. with best-response rather than probabilistic dynamics) are also possible (Golland et al., 2010). Inference in these models is challenging even when the space of listener actions is extremely simple (Smith et al., 2013), and one of our goals in the present work is to show how this inference problem can be solved even in much richer action spaces than previously considered in computational pragmatics. This family of pragmatic models captures a number of important linguistic phenomena, especially those involving conversational implicature (Monroe and Potts, 2015); we note that many other topics studied under the broad heading of “pragmatics”, including presupposition and indexicality, require different machinery.

Much recent work on pragmatic models, especially models of speakers, focuses on the referring expression generation or “contrastive captioning” task introduced by Kazemzadeh et al. (2014). In this family are approaches that model the listener at training time (Mao et al., 2015), at evaluation time (Andreas and Klein, 2016; Monroe et al., 2017) or both (Yu et al., 2017b; Luo and Shakhnarovich, 2017).

Other conditional sequence rescoring models that are structurally similar but motivated by concerns other than pragmatics include Li et al. (2016) and Yu et al. (2017a). Lewis et al. (2017) perform a similar inference procedure for a competitive negotiation task. The language learning model of Wang et al. (2016) also features a structured output space and uses pragmatics to improve online predictions for a semantic parsing model. Our approach in this paper performs both generation and interpretation, and does not require a structured model of the domain.

**Instruction following** Work on instruction following tasks includes models that parse commands into structured representations processed by a rich execution model (Tellex et al., 2011; Chen, 2012; Artzi and Zettlemoyer, 2013; Guu et al., 2017), and models that map directly from instructions to a policy over primitive actions (Branavan et al., 2009), possibly mediated by an
Figure 2: (a) Rational pragmatic models embed base listeners and speakers. Potential candidate sequences are drawn from one model, and then the other scores each candidate to simulate whether it produces the desired pragmatic behavior. (b) The base listener and speaker are neural sequence-to-sequence models which are largely symmetric to each other. Each produces a representation of its input sequence (a description, for the listener; a route with associated environmental percepts, for the listener) using an LSTM encoder. The output sequence is generated by an LSTM decoder attending to the encoded input.

We use a model similar to Mei et al. (2016) as our base listener in this paper, evaluating on the SAIL navigation task (MacMahon et al., 2006) as they did, as well as the SCONE context-dependent execution domains (Long et al., 2016).

Instruction generation

A line of work has also investigated the instruction generation task, in particular for navigational directions. The GIVE shared tasks (Byron et al., 2009; Koller et al., 2010; Striegnitz et al., 2011) have produced a large number of interactive direction-giving systems, both rule-based and learned. The work most immediately related to the generation task in this paper is that of Daniele et al. (2017), which also focuses on the SAIL dataset but requires substantial additional structured annotation for training, while both our base and pragmatic speaker models learn directly from strings and action sequences.

Older work has studied the properties of effective human strategies for generating navigational directions (Anderson et al., 1991). Instructions of this kind can be used to extract templates for generation (Look, 2008; Dale et al., 2005), while here we focus on the more challenging problem of learning to generate new instructions from scratch. Like our pragmatic speaker model, Goeddel and Olson (2012) also reason about listener behavior when generating navigational instructions, but rely on rule-based models for interpretation.

3 Tasks

Consider the instruction following and instruction generation tasks shown in Figure 1, where an agent must produce or interpret directions about a structured world context (e.g. *walk along the blue carpet and you pass two objects*).

In the instruction following task, a listener agent begins in a world state, for example in Figure 1, an initial map location and orientation. The agent is then tasked with following a sequence of direction sentences $d_1\ldots d_K$ produced by humans. At each time $t$ the agent receives a percept $y_t$, which is a feature-based representation of the current world state, and chooses an action $a_t$ (e.g. move forward, or turn). The agent succeeds if it is able to reach the correct final state described by the directions.

In the instruction generation task, the agent receives a sequence of actions $a_1, \ldots, a_T$ along with the world state $y_1, \ldots, y_T$ at each action, and must generate a sequence of direction sentences $d_1, \ldots, d_K$ describing the actions. The agent succeeds if a human listener is able to correctly follow those directions to the intended final state.

4 Pragmatic instruction following

As a foundation for pragmatic reasoning models, we assume that we have *base* listener and speaker models to map directions to routes and vice-versa. The base listener, $L_0$, gives a probability distribution over sequences of actions, conditioned on a representation of the directions and environment as seen before each action: $P_{L_0}(a_{1:T}|d_{1:K}, y_{1:T})$. Similarly, the base speaker, $S_0$, defines a distribution over possible descriptions conditioned on a representation of the actions and environment: $P_{S_0}(d_{1:K}|a_{1:T}, y_{1:T})$.

Our pragmatic inference procedure requires these base models to produce candidate outputs from a given input (actions from descriptions, for the listener; descriptions from actions, for the speaker), and calculate the probability of a fixed...
output given an input, but is otherwise agnostic to the form of the models. We use standard sequence-to-sequence models with attention for both the base listener and speaker, with differences in architecture tailored to the various settings. Both the base listener and speaker models are described in section 5.

4.1 Models

Using these base models as self-contained modules, we derive a rational speaker and rational listener that reason pragmatically with embedded instances of these base models (Figure 2a). When describing a route, a rational speaker $S_1$ should choose a description that has a high chance of causing the listening agent, modeled by the embedded base listener $L_0$, to follow the given route:

$$S_1(a_{1:T}) = \arg\max_{d_{1:T}} P_{L_0}(a_{1:T}|d_{1:T}, y_{1:T}) \quad (1)$$

(noting that, in all settings we explore here, the percepts $y_{1:T}$ are completely determined by the route $a_{1:T}$).

Conversely, a rational listener $L_1$ should follow a description by choosing a route which has high probability of having caused the speaker, modeled by $S_0$, to produce the description:

$$L_1(d_{1:T}) = \arg\max_{a_{1:T}} P_{S_0}(d_{1:T}|a_{1:T}, y_{1:T}) \quad (2)$$

These optimization problems are intractable to solve for general base listener and speaker agents, including the sequence-to-sequence models we use, as they involve choosing an input from a combinatorially large space of possible sequences to maximize the probability of a fixed output sequence. We instead follow a simple approximate inference procedure, detailed in section 4.2.

We consider also incorporating the scores of the base model used to produce the candidates. For example, we define a combined rational speaker, denoted $S_0 \cdot S_1$, that selects the candidate that maximizes a weighted product of probabilities under both the base listener and the base speaker:

$$\max_{d_{1:T}} P_{L_0}(a_{1:T}|d_{1:T}, y_{1:T})\lambda$$

$$\times P_{S_0}(d_{1:T}|a_{1:T}, y_{1:T})^{1-\lambda} \quad (3)$$

for a fixed interpolation hyperparameter $\lambda \in [0, 1]$. There are several motivations for this combination with the base speaker score. First, as argued by Monroe et al. (2017), we would expect varying degrees of base and reasoned interpretation in human speech acts. Second, we want the descriptions produced by the model to be fluent descriptions of the route. Since the base models are trained discriminatively, maximizing the probability of output sequences for a fixed conditioning input sequence, their scoring behaviors for fixed outputs paired with inputs dissimilar to those seen in the training set may be poorly calibrated, for example when conditioning on ungrammatical descriptions. Incorporating the scores of the base model used to produce the candidates (Figure 2a) aims to prevent this behavior.

To define rational listeners, we use the symmetric formulation: first, draw route candidates from $L_0$. For $L_1$, choose the route that achieves the highest probability under $S_0$; and for the combination model $L_0 \cdot L_1$ choose the route with the highest weighted combination of $S_0$ and $L_0$ (parallelizing equation 3).

4.2 Inference

As in past work (Smith et al., 2013; Andreas and Klein, 2016; Monroe et al., 2017), we employ a simple approximation to the optimization problems in equations 1, 2, and 3: use the base models to generate reasonable (if not necessarily pragmatic) candidates, and rescore them to find ones that are likely to produce the desired pragmatic behavior.

In the case of the rational speaker $S_1$, we use the base speaker $S_0$ to draw a set of $n$ candidate descriptions $w_{1:K_1}^{(1)} \ldots w_{1:K_n}^{(n)}$ for the route $a_{1:T}$, $y_{1:T}$, using beam search as described below. We then find the score of each description under $P_{L_0}$ (using it as the input sequence for the observed output route we want the rational speaker to describe), or a weighted combination of $P_{L_0}$ and the original candidate score $P_{S_0}$, and choose the description $w_{1:K_1}^{(j)}$ with the largest score, approximately solving the maximizations in equations 1 or 3, respectively. We do the same for the rational listener: draw candidates from the base listener, and rescore them using the base speaker.

To obtain candidates that are high-scoring under the combination of models in the base ensemble, we perform standard beam search, using all models in lock-step. At every timestep of the beam search, each possible extension of an output sequence is scored using the product of the exten-
sion’s conditional probabilities across all models in the ensemble.

As the rational speaker must produce long output sequences (multiple sentences), we interleave the speaker and listener in inference, determining each output sentence sequentially. We obtain a list of candidate direction sentences from the base speaker for the current sub-sequence of actions, choosing the top-scoring direction under the listener model (which may also condition on the directions which have been output previously), and then moving on to the next sub-sequence of actions.

We might expect varying performance of the rational models depending on the tradeoff between having candidates that have high scores under the base models, versus having a more diverse list to give the rescoring model a wider latitude. This led us to experiment with sampling from the base models to produce these candidate lists, as was done in previous work (Andreas and Klein, 2016; Monroe et al., 2017). In early experiments, however, we found better performance with beam search in the rational models, and use it in all results reported here.

5 Base model details

Given this high-level framework, all that remains is to describe the base models $L_0$ and $S_0$. In all our experiments we implement these as sequence-to-sequence models that map directions to actions (for the listener) or actions to directions (for the speaker), additionally conditioning on the world state at each time step.

5.1 Base listener

The base listener, $L_0$, directly represents the probability of a route as a sequence of actions, conditioned on the direction sentences $d_{1:K}$ and the percepts $y_{1:T}$ received at each step so far along the route:

$$p_{L_0}(a_{1:T}|d_{1:K}, y_{1:T}) = \prod_{t=1}^{T} p(a_t|a_{1:t-1}, y_{1:t}, d_{1:K})$$

We use a sequence-to-sequence model with attention and monotonic alignments between direction sentences and sub-sequences of actions. In the case of the SAIL domain, this reduces to the model of Mei et al. (2016) (illustrated in green in Figure 2b for a single sentence and its associated actions).

**Encoder** Each direction sentence is encoded separately with a bidirectional LSTM (Hochreiter and Schmidhuber, 1997); the LSTM’s hidden states are reset for each sentence. We obtain a representation for each word in each sentence by concatenating the vectors output by the forward and backward LSTMs at the word’s position.

**Decoder** We generate actions incrementally using an LSTM decoder. We use monotonic alignment between the direction sentences and subsequences of actions; at each time step the decoder either produces an action for the current sentence $w_{1:M}$ or moves on to the next sentence.

At time step $t$, the decoder takes as input i) a learned embedded representation vector, $e_t$, of the world state $y_t$ and ii) a context vector, $z_t$, which is a representation produced by an attention mechanism over the current sentence (see below). These inputs are then combined again with the decoder output vector, $d_t$, to produce a distribution over possible actions (including choosing to stop producing actions for this sentence):

$$q_t = W_l(e_t + W_d d_t + W_z z_t)$$
$$p(a_t|a_{1:t-1}, y_{1:t}, w_{1:M}) = \text{softmax}(q_t)$$

for learned parameter matrices $W_l, W_d$ and $W_z$.

**Attention mechanism** The context vector $z_t$ which is used as one of the inputs to the decoder cell at time $t$ represents the sequence of directions as a linear combination of the concatenation of two vectors at each position $k$ for the current sentence: i) the one-hot vector for the word, $w_k$ and ii) the bidirectional LSTM-encoded vector, $h_k$. The weights for the linear combination are determined using an attention mechanism (Bahdanau et al., 2015):

$$z_t = \sum_{k=1}^{K} \alpha_{t,k} \begin{bmatrix} w_k \\ h_k \end{bmatrix}$$
$$\alpha_t = \text{softmax} \left( v^T \tanh \left( W_a d_{t-1} + W_e \begin{bmatrix} w_k \\ h_k \end{bmatrix} \right) \right)$$

where $W_a, W_e, v$ are parameters to be learned, and $\alpha_{t,k}$ gives the weight from the $k$th component of the vector produced in the softmax operation.

**Domain specifics** For SAIL, following Mei et al. (2016), we reset the decoder’s hidden state when moving on to a new sentence. We use the alignments between sentences and route segments.
annotated by Chen and Mooney (2011), which were also used in previous work (Artzi and Zettlemoyer, 2013; Artzi et al., 2014; Mei et al., 2016).

For the SCONE domains, which have a larger space of possible outputs and more complex perceptual observations than SAIL, we extend the decoder by: i) decomposing the actions so that the model first chooses an action type and then chooses arguments for it, ii) using a separate attention mechanism for each step in the action decomposition and iii) representing actions with state-dependent embeddings. See Appendix A for details. The domains are constructed so that each sentence is associated with a single (non-decomposed) action; this provides our alignment.

5.2 Base speaker

While previous work (Daniele et al., 2017) has relied on more structured approaches, we construct our base speaker model $S_0$ using largely the same sequence-to-sequence machinery as above. $S_0$ (illustrated in orange in Figure 2b) encodes a sequence of actions and world states, and then runs a decoder to output a description. This relies on the sequence-to-sequence model to do both content selection (e.g. choosing which landmarks in the world to refer to) as well as surface realization.

**Encoder** We concatenate an embedding for each action $a_t$ with an embedded representation $e_t$ of the world context for the current state, as in the base listener. We then run a bidirectional LSTM for the speaker encoder over these concatenated vectors, giving an output vector $h_t$ for each position $t$ in the input route sequence.

**Decoder** Directions are produced one word at a time:

$$P_{S_0}(w_{1:T} | a_{1:T}, y_{1:T}) = \prod_{k=1}^{K} p(w_k | w_{1:k-1}, a_{1:T}, y_{1:T})$$

As in the listener, we use a monotonic alignment between direction sentences and subsequences of actions; at each step the decoder either produces a word or determines to move onto the next subsequence of actions.

At each time step the LSTM decoder takes as input: i) a context vector $z_k$ produced by an attention mechanism over the encoded sequence of actions and world states and ii) a one-hot vector encoding the last word $w_{k-1}$ produced by the decoder. Using these two inputs it produces an output vector $d_k$. The decoder’s output $d_k$ is combined again with the context vector to produce a distribution over words from the vocabulary:

$$p(w_k | w_{1:k-1}, a_{1:T}, y_{1:T}) = \text{softmax}(W_z z_k + W_d d_k)$$

where $W_z$ and $W_d$ are parameter matrices to be learned. The LSTM decoder state is reset at the beginning of each new sentence.

**Attention mechanism** We use the same structure for the attention mechanism to produce the context vector $z_k$ as in the base listener, but with the concatenation of input actions, embedded percepts, and encoded inputs $[a_t, e_t, h_t]$ taking the place of $[w_k, h_k]$ in the attention mechanism.

**Domain specifics** In SAIL, for comparison to the generation system of Daniele et al. (2017) which did not use segmented routes, we train a route segmenter for use at test time. We also represent routes using a collapsed representation of action sequences. In the SCONE domains, we i) use the same context-dependent action embeddings used in the listener, and ii) don’t require an attention mechanism, since only a single action is used to produce a given sentence within the sequence of direction sentences. See Appendix A for more details.

5.3 Training

The base listener and speaker models are trained independently to maximize the conditional likelihoods of the actions–directions pairs in the training sets. See Appendix A for details on the optimization, LSTM variant, and hyperparameters.

We use ensembles for the base listener $L_0$ and base speaker $S_0$, where each ensemble consists of 10 models trained from separate random initializations. This follows the experimental setup of Mei et al. (2016) for the SAIL base listener.

6 Experiments

We evaluate speaker and listener agents on both the following and generation tasks in four domains. For all these domains, we compare the rational listener and speaker against the base listener and speaker, respectively, as well as against past state-of-the-art results for these datasets when available. Finally, we examine pragmatic inference from a model combination perspective, comparing the pragmatic reranking procedure to sim-
ply ensembling a larger number of base speakers or listeners.

Our first domain is the SAIL corpus of virtual environments and navigational directions (MacMahon et al., 2006; Chen and Mooney, 2011), where an agent navigates through a two-dimensional map consisting of a number of intersections connected by segments of hallway in a grid (Figure 1 shows a portion of one of these hallways). Some of the intersections contain objects, such as chairs and stools, from a fixed discrete set, and each section of hallway has patterned walls and floor.

In the three SCONE domains (Long et al., 2016), the agent is presented with a number of manipulable objects with various properties, such as colored beakers which it can combine, drain, and mix. These domains were designed to elicit a variety of context-dependent language phenomena, including ellipsis and coreference (Long et al., 2016) which we might expect a model of pragmatics to help resolve (Potts, 2011).

For all the following experiments, we use beam search for the base models, with the same beam sizes used to produce candidate lists for the rational systems. We tune the weight \( \lambda \) in the combined rational agents \( (L_0 \cdot L_1) \) or \( S_0 \cdot S_1 \) to maximize accuracy (for listener models) or BLEU (for speaker models) on the domain’s development data.

### 6.1 Instruction following

We evaluate our listener models by their accuracy in carrying out human instructions: whether the system was able to reach the final world state which the human was tasked with guiding them to.

#### SAIL

We follow standard cross-validation evaluation for the instruction following task on the SAIL dataset (Artzi and Zettlemoyer, 2013; Artzi et al., 2014; Mei et al., 2016). Table 1 shows gains from using the rational listener \( L_0 \cdot L_1 \) over the base listener \( L_0 \) in the single- and multi-sentence settings. We also report the best accuracies from past work. We see that the largest relative gains come in the multi-sentence setting, where handling ambiguity is potentially more important to avoid compounding errors. The rational model improves on the published results of Mei et al. (2016), and while it is still below the systems of Artzi and Zettlemoyer (2013) and Artzi et al. (2014), which use additional supervision in the form of hand-annotated seed lexicons and logical domain representations, it approaches their results in the single-sentence setting.

#### SCONE

In the SCONE domains, past work has trained listener models with weak supervision. In training, a sequence of 5 instructions corresponding to 5 actions is given, but only the world states at the beginning and end of the action sequence are provided to the model. To use a consistent model and training procedure across domains, we train listener and speaker models using the intermediate world states as well. As in the SAIL domain, this allows maximum likelihood training of the listener and speaker models without searching over latent actions. The evaluation method is the same as in past work on SCONE: models are provided with an initial world state and a sequence of 5 instructions.

- Past work has differed in the handling of undetermined orientations in the routes, which occur in the first state for multi-sentence routes and the first segment of their corresponding single-sentence routes. For comparison to both types of past work, we train and evaluate listeners in two settings: Abs, which sets these undetermined starting orientations to be a fixed absolute orientation, and Rel, where an undetermined starting orientation is set to be a 90 degree rotation relative to the orientation for the next state in the true route.
- The evaluation method is the same as in past work on SCONE: models are provided with an initial world state and a sequence of 5 instructions.
a red guy appears on the far left then to orange’s other side

Figure 3: Action traces produced for a partial description sequence in the Scene domain. The base listener moves the red figure to a position that is a marginal, but valid, interpretation of the directions. The rational listener correctly produces the action sequence the directions were intended to describe.

instructions to carry out, and are evaluated on their accuracy in reaching the intended final world state.

Our results are reported in Table 2. We see gains from the rational system $L_0 \cdot L_1$ in both the Alchemy and Scene domains.

The pragmatic inference procedure allows correcting errors or overly-literal interpretations from the base listener. An example is shown in Figure 3. The base listener (left) interprets \textit{then to orange’s other side} incorrectly, while the rational listener discounts this interpretation (it could be better described by, for example \textit{to the left of blue}) and produces the action the descriptions were meant to describe (right). To the extent that human annotators already account for pragmatic effects when generating instructions, examples like these suggest that our model’s explicit reasoning is able to capture interpretation behavior that the base sequence-to-sequence listener model is unable to model.

6.2 Instruction generation

As our primary evaluation for the instruction generation task, we had Mechanical Turk workers carry out directions produced by the speaker models (and by other humans) in a simulated version of each domain. For SAIL, we use the simulator released by Daniele et al. (2017) which was used in their human evaluation results, and we construct simulators for the three SCONE domains. In all settings, we take a sample of 50 action sequences from the domain’s test set (using the same sample as Daniele et al. (2017) for SAIL), and have three separate subjects attempt to follow the systems’ directions for the action sequence.

Table 3 gives the average accuracy of subjects in reaching the intended final world state across all instances, for each domain. The “human” row reports accuracy at following the dataset’s reference directions, which were produced by humans. The directions produced by the base speaker $S_0$ are often much harder to follow than those produced by humans (e.g. 29.3% of $S_0$’s directions are correctly interpretable for Alchemy, vs. 83.3% of human directions). However, we see substantial gains from the rational speaker $S_0 \cdot S_1$ over $S_0$ in all cases (with absolute gains in accuracy ranging from 12.4% to 46.0%), and the average accuracy of humans at following the rational speaker’s directions is substantially higher than for directions from other humans in the Tangrams domain. In the SAIL evaluation, we also include the directions produced by the system of Daniele et al. (2017) (DBW), and find that the rational speaker’s directions are followable to comparable accuracy.

We also compare the directions produced by the systems to the reference instructions given by humans in the dataset, using 4-gram BLEU (Papineni et al., 2002) in Table 4. Consistent with past work (Krahmer and Theune, 2010), we find that BLEU score is a poor indicator of whether the directions can be correctly followed.

Qualitatively, the rational inference procedure is most successful in fixing ambiguities in the base speaker model’s descriptions. Figure 4 gives a

Table 3: Test accuracy of humans at following the outputs of the speaker systems (as well as other humans) for the SAIL dataset and SCONE domains.

Table 4: Gains in how easy the directions are to follow are not always associated with a gain in BLEU. Corpus-level 4-gram BLEU comparing outputs of the speaker systems to human-produced directions on the SAIL dataset and SCONE domains, compared to gains in accuracy when asking humans to carry out a sample of the systems’ directions (see Table 3).
Figure 4: Descriptions produced for a partial action sequence in the Tangrams domain. Neither the human nor base speaker $S_0$ correctly specifies where to add the shape in the second step, while the rational speaker $S_0 \cdot S_1$ does.

typical example of this for the last few steps in a Tangrams instance. The base speaker correctly describes that the shape should be added back, but does not specify where to add it, which could lead a listener to add it in the same position it was deleted. The human speaker also makes this mistake in their description. This speaks to the difficulty of describing complex actions pragmatically even for humans in the Tangrams domain. The ability of the pragmatic speaker to produce directions that are easier to follow than humans’ in this domain (Table 3) shows that the pragmatic model can generate something different (and in fact better in some cases) than the training data.

6.3 Pragmatics as model combination

Finally, our rational models can be viewed as pragmatically-motivated model combinations, searching with listener or speaker models and reranking using a combination of scores from both. It is conceivable that a rational listener that uses $n$ ensembled base listeners and $n$ base speakers is simply comparable to using an ensemble of $2n$ base listeners. We want to verify that the pragmatics effect results from more than simple ensembling of this type.

Fixing the total number of models to 10 for the speaker experiments and 20 for the listener experiments (since inference in the speaker models is more expensive), we find that the rational models still outperform the base listeners and speakers, while using the same total number of models in each setting. For the listener, there are still gains from pragmatics but they are smaller in most domains: the accuracy gains are 70.1 to 72.0%, 71.9 to 72.7%, 69.1 to 69.6%, and 68.5 to 71.6% for Alchemy, Scene, Tangrams, and SAIL single-sentence Rel, respectively. For the speaker, the gains are still substantial: from 30.7 to 74.7%, 32.0 to 66.0%, 58.7 to 92.7%, and 61.9 to 73.4%, for Alchemy, Scene, Tangrams, and SAIL, respectively.4

7 Conclusion

We have demonstrated that a simple procedure for pragmatic inference, with a unified treatment for speakers and listeners, obtains improvements for instruction following as well as instruction generation in multiple settings. The inference procedure is capable of reasoning about sequential, interdependent actions in non-trivial world contexts. As the pragmatic procedure places few requirements on the base models that it uses to reason, we are able to embed a listener model that is already state-of-the-art for single-sentence instructions alongside a similarly structured speaker model.

We find that pragmatics improves upon the performance of the base models for both tasks, in most cases substantially. While this is perhaps unsurprising for the generation task, which has been discussed from a pragmatic perspective in a variety of recent work in NLP, it is encouraging that pragmatic reasoning can also improve performance for a grounded listening task with complex, structured output spaces. This suggests that future work may continue to find benefits from pragmatic inference in realistic interpretation tasks, aiding understanding of language by reasoning about the agent that produced it.

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4The base interpretation accuracies are slightly different than in Table 3, despite being produced by the same system, since we reran experiments to control as much as possible for time variation in the pool of Mechanical Turk workers.
References

Anne H. Anderson, Miles Bader, Ellen Gurman Bard, Elizabeth Boyle, Gwyneth Doherty, Simon Garrod, Stephen Isard, Jacqueline Kowtko, Jan McAllister, Jim Miller, et al. 1991. The HCRC map task corpus. *Language and speech* 34(4):351–366.

Jacob Andreas and Dan Klein. 2015. Alignment-based compositional semantics for instruction following. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*.

Jacob Andreas and Dan Klein. 2016. Reasoning about pragmatics with neural listeners and speakers. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*.

Yoav Artzi, Dipanjan Das, and Slav Petrov. 2014. Learning compact lexicons for CCG semantic parsing. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics.

Yoav Artzi and Luke Zettlemoyer. 2013. Weakly supervised learning of semantic parsers for mapping instructions to actions. *Transactions of the Association for Computational Linguistics* 1(1):49–62.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. *International Conference on Learning Representations*.

S.R.K. Branavan, Harr Chen, Luke S. Zettlemoyer, and Regina Barzilay. 2009. Reinforcement learning for mapping instructions to actions. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, pages 82–90.

Donna Byron, Alexander Koller, Kristina Striegnitz, Justine Cassell, Robert Dale, Johanna Moore, and Jon Oberlander. 2009. Report on the first NLG challenge on generating instructions in virtual environments (GIVE). In *Proceedings of the 12th European workshop on natural language generation*. Association for Computational Linguistics, pages 165–173.

David L. Chen. 2012. Fast online lexicon learning for grounded language acquisition. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics*. pages 430–439.

David L. Chen and Raymond J. Mooney. 2011. Learning to interpret natural language navigation instructions from observations. In *Proceedings of the Meeting of the Association for the Advancement of Artificial Intelligence*, volume 2, pages 1–2.

Robert Dale, Sabine Geldof, and Jean-Philippe Prost. 2005. Using natural language generation in automatic route. *Journal of Research and practice in Information Technology* 37(1):89.

Andrea F. Daniele, Mohit Bansal, and Matthew R. Walter. 2017. Navigational instruction generation as inverse reinforcement learning with neural machine translation. *Proceedings of Human-Robot Interaction*.

Michael C Frank and Noah D Goodman. 2012. Predicting pragmatic reasoning in language games. *Science* 336(6084):998–998.

Yarin Gal and Zoubin Ghahramani. 2016. A theoretically grounded application of dropout in recurrent neural networks. In *Advances in Neural Information Processing Systems 29 (NIPS)*.

Xavier Glorot and Yoshua Bengio. 2010. Understanding the difficulty of training deep feedforward neural networks. In *AISTATS*. volume 9, pages 249–256.

Robert Goeddel and Edwin Olson. 2012. Dart: A particle-based method for generating easy-to-follow directions. In *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*. IEEE, pages 1213–1219.

Dave Golland, Percy Liang, and Dan Klein. 2010. A game-theoretic approach to generating spatial descriptions. In *Proceedings of the 2010 conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, pages 410–419.

Noah D Goodman and Andreas Stuhlmüller. 2013. Knowledge and implicature: Modeling language understanding as social cognition. *Topics in cognitive science* 5(1):173–184.

Klaus Greff, Rupesh K Srivastava, Jan Koutník, Bas R Steunebrink, and Jürgen Schmidhuber. 2016. Lstm: A search space odyssey. *IEEE transactions on neural networks and learning systems*.

Kelvin Guu, Panupong Pasupat, Evan Zheran Liu, and Percy Liang. 2017. From language to programs: Bridging reinforcement learning and maximum marginal likelihood. In *Association for Computational Linguistics (ACL)*.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation* 9(8):1735–1780.

Sahar Kazemzadeh, Vicente Ordonez, Mark Matten, and Tamara L Berg. 2014. ReferItGame: Referring to objects in photographs of natural scenes. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*. pages 787–798.

Diederik Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. *International Conference on Learning Representations*.

Alexander Koller, Kristina Striegnitz, Andrew Gargett, Donna Byron, Justine Cassell, Robert Dale, Johanna Moore, and Jon Oberlander. 2010. Report on the second NLG challenge on generating instructions in
virtual environments (GIVE-2). In *Proceedings of the 6th international natural language generation conference*. Association for Computational Linguistics, pages 243–250.

Emiel Krahmer and Mariët Theune, editors. 2010. *Empirical Methods in Natural Language Generation: Data-oriented Methods and Empirical Evaluation*. Springer-Verlag, Berlin, Heidelberg.

Mike Lewis, Denis Yarats, Yann N Dauphin, Devi Parikh, and Dhruv Batra. 2017. Deal or no deal? end-to-end learning for negotiation dialogues. In *Empirical Methods in Natural Language Processing (EMNLP)*.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016. A diversity-promoting objective function for neural conversation models. In *Proceedings of the Annual Meeting of the North American Chapter of the Association for Computational Linguistics*.

Reginald Long, Panupong Pasupat, and Percy Liang. 2016. Simpler context-dependent logical forms via model projections. In *Association for Computational Linguistics (ACL)*.

Gary Wai Keung Look. 2008. Cognitively-inspired direction giving.

Ruotian Luo and Gregory Shakhnarovich. 2017. Comprehension-guided referring expressions. *arXiv preprint arXiv:1701.03439*.

Matt MacMahon, Brian Stankiewicz, and Benjamin Kuipers. 2006. Walk the talk: Connecting language, knowledge, and action in route instructions. *Proceedings of the Meeting of the Association for the Advancement of Artificial Intelligence* 2(6):4.

Junhua Mao, Jonathan Huang, Alexander Toshev, Oana Camburu, Alan Yuille, and Kevin Murphy. 2015. Generation and comprehension of unambiguous object descriptions. *arXiv preprint arXiv:1511.02283*.

Hongyuan Mei, Mohit Bansal, and Matthew Walter. 2016. Listen, attend, and walk: Neural mapping of navigational instructions to action sequences. In *Proceedings of the Meeting of the Association for the Advancement of Artificial Intelligence*.

Will Monroe, Robert X.D. Hawkins, Noah D. Goodman, and Christopher Potts. 2017. Colors in context: A pragmatic neural model for grounded language understanding. *Transactions of the Association for Computational Linguistics*.

Will Monroe and Christopher Potts. 2015. Learning in the Rational Speech Acts model. In *Proceedings of 20th Amsterdam Colloquium*. ILLC, Amsterdam.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting on association for computational linguistics*. Association for Computational Linguistics, pages 311–318.

Christopher Potts. 2011. *Pragmatics*, Oxford University Press.

Nathaniel J Smith, Noah Goodman, and Michael Frank. 2013. Learning and using language via recursive pragmatic reasoning about other agents. In *Advances in Neural Information Processing Systems*. pages 3039–3047.

Kristina Striegnitz, Alexandre Denis, Andrew Gargett, Konstantina Garoufi, Alexander Koller, and Mariët Theune. 2011. Report on the second second challenge on generating instructions in virtual environments GIVE-2.5. In *Proceedings of the 13th European workshop on natural language generation*. Association for Computational Linguistics, pages 270–279.

Stefanie Tellex, Thomas Kollar, Steven Dickerson, Matthew R. Walter, Ashis Gopal Banerjee, Seth Teller, and Nicholas Roy. 2011. Understanding natural language commands for robotic navigation and mobile manipulation. In *Proceedings of the National Conference on Artificial Intelligence*.

Sida I. Wang, Percy Liang, and Christopher D. Manning. 2016. Learning language games through interaction. In *Association for Computational Linguistics (ACL)*.

Lei Yu, Phil Blunsom, Chris Dyer, Edward Grefenstette, and Tomas Kocisky. 2017a. The neural noisy channel. *International Conference on Learning Representations*.

Licheng Yu, Hao Tan, Mohit Bansal, and Tamara L. Berg. 2017b. A joint speaker-listener-reinforcer model for referring expressions. In *Computer Vision and Pattern Recognition*.
the log probability for action \( a \) type and relevant arguments), and then normalized sum of its factors’ log probabilities – the action \( b \) \( q \) where \( IX \) the action \( M \) \( the state vector corresponding to the 5th beaker in \( rather than needing to learn to select the region of \( relevant features from the state embeddings \( e.g. \) \( A.1 SCONE listener details \)

We decompose actions in each of the three SCONE domains, separately predicting the action type and the arguments specific to that the action. Action types and arguments are listed in the first two columns of Table 5. A distribution over the possible action types and possible options for each argument is predicted at every time-step. For example, Alchemy’s actions involve predicting the action type, a potential source beaker index \( i \) and target beaker index \( j \), and potential amount to drain \( a \). All action types and arguments are predicted using separate softmax layers and attention mechanisms.

We also obtain state-specific embeddings of actions, to make it easier for the model to learn relevant features from the state embeddings \( e.g. \) rather than needing to learn to select the region of the state vector corresponding to the 5th beaker in the action Mix(5) in Alchemy, this action’s contextual embedding encodes the current content of the 5th beaker). We incorporate these embeddings into computation of the action probabilities using a bilinear bonus score:

\[
b(a) = q^\top W_q a + w_a^\top a
\]

where \( q \) is the concatenation of all \( q_t \) vectors for the factors, and \( W_q \) and \( w_a \) are a parameter matrix and vector. This bonus score \( b(a) \) is added to the log probability for action \( a \) (computed as the sum of its factors’ log probabilities – the action type and relevant arguments), and then normalized using a softmax to produce a distribution over all un-factored actions.

A.2 SAIL speaker details

Since our speaker model operates on segmented action sequences, we train a route segmenter on the training data and then predict segmentations for the test data. This provides a closer comparison to the generation system of Daniele et al. (2017) which did not use segmented routes. The route segmenter runs a bidirectional LSTM over the concatenated state and action embeddings (as in the speaker encoder), then uses a logistic regression layer to classify whether the route should be split at each possible position. We also collapse consecutive sequences of forward movement actions into a single action token, which we found helped prevent counting errors (such as outputting move forward three when the correct route moved forward four steps).

A.3 SCONE speaker details

We use a one-hot representation of the factors in each action \( a_t \), as well as the action’s contextual embedding (as described in A.1) as input to the SCONE speaker encoder at time \( t \) (along with the representation \( e_t \) of the world state, as in SAIL). Since SCONE uses a monotonic, one-to-one alignment between actions and direction sentences, the decoder does not use a learned attention mechanism but fixes the contextual representation \( z_k \) to be the encoder vector at the action corresponding to the sentence currently being generated.

A.4 Training details

We optimize model parameters using ADAM (Kingma and Ba, 2015) with default hyperparameters and the initialization scheme of Glorot and
Bengio (2010). The LSTM cell in both the listener and the follower use coupled input and forget gates, and peephole connections to the cell state (Greff et al., 2016). We also apply the LSTM variational dropout scheme of Gal and Ghahramani (2016), using the same dropout rate for inputs, outputs, and recurrent connections. See Table 6 for hyperparameters. We perform early stopping using the evaluation metric (accuracy for the listener and BLEU score for the speaker) on the development set.

A.5 Computing BLEU for SAIL

To compute BLEU in the SAIL experiments, as the speaker models may choose produce a different number of sentences for each route than in the true description, we obtain a single sequence of words from a multi-sentence description produced for a route by concatenating the sentences, separated by end-of-sentence tokens. We then calculate corpus-level 4-gram BLEU between all these sequences in the test set and the true multi-sentence descriptions (concatenated in the same way).