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Contextual Interpretation: An Adaptive Framework for Situated Reference Resolution

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Abstract
This Data Science paper introduces an innovative model for interpreting referring expressions within grounded communication tasks. Our approach unifies speaker and listener neural networks through a recursive pragmatic reasoning framework, demonstrating significant improvements in interpretative accuracy, particularly for challenging distinctions. The system leverages an explicit feedback mechanism by combining the predictive perspectives of both speaker and listener components, which iteratively refines the interpretation process. This adaptive methodology, evaluated on a newly collected corpus, establishes a robust framework for nuanced contextual understanding, showcasing enhanced performance through synergistic model interaction.

Keywords: Grounded Language Understanding, Pragmatic Reasoning, Rational Speech Acts, Neural Speaker-Listener Mod-els, Color Reference Games, Natural Language Interpretation, LSTM, Contextual Semantics, Visual Ambiguity Resolution, Human-AI Communication

1 Introduction

Human communication is inherently contextual and deeply rooted in mutual expectations between interlocutors. Whether we are formulating an utterance or interpreting one, our cognitive processes consider the environment and the mental states of others involved in the exchange. This dynamic interplay is particularly evident in grounded language tasks, where meaning must be derived in reference to elements within a shared perceptual context. A prime example of such a task is visual reference resolution—especially color identification—where individuals describe or interpret specific visual stimuli, such as color patches, through natural language.

In real-world and experimental settings alike, the interpretation of linguistic expressions—such as "the bluer one" or "not the red one"—cannot be divorced from the visual context in which they are produced. Listeners and speakers do not operate in isolation; their language use is shaped by an implicit, recursive modeling of one another's intentions, knowledge, and likely actions. To computationally model this phenomenon, frameworks like the Rational Speech Acts (RSA) model have emerged, offering a probabilistic approach to pragmatic reasoning. These models assume that agents recursively reason about each other to optimize communicative efficiency, moving beyond literal semantics into richer, more context-sensitive interpretations.

This study introduces a novel neural implementation of the RSA framework designed to improve the interpretation of referring expressions in visual color reference games. Our proposed architecture includes two recurrent neural networks (RNNs): a *speaker model*, which generates natural language descriptions

based on target colors and context, and a *listener model*, which interprets those descriptions to identify intended referents. Both models are trained on data collected from large-scale, dyadic reference games, where human participants communicated target colors to partners in real-time via natural language. The richness and diversity of the resulting corpus, comprising over 53,000 utterances across nearly 1,000 games, offers a robust foundation for modeling and analysis.

A key innovation of our approach lies in integrating these speaker and listener networks within a pragmatic reasoning loop. Rather than treating generation and comprehension as separate tasks, we define a joint inferential model wherein the listener reasons about how a pragmatic speaker would have chosen a given utterance. This recursive reasoning allows our model to resolve ambiguity and make fine-grained distinctions between similar colors—cases where literal interpretations often fall short.

Empirical results demonstrate that our pragmatic model significantly surpasses the performance of both literal listener baselines and standalone speaker-based listeners, particularly under challenging conditions. Situations involving subtly different hues or vague expressions benefit the most from pragmatic reasoning. In effect, our model mirrors the flexibility of human communicators who adapt their language based on context and assumed shared understanding.

In sum, this paper contributes a scalable, data-driven, and cognitively plausible model for grounded language under-standing. By fusing neural learning with structured pragmatic inference, it opens up new avenues for developing intelligent systems capable of interpreting human language in visually grounded scenarios.

2 Literature Review

Grounded language understanding has long been a focal area in computational linguistics, cognitive science, and artificial intelligence. Early studies recognized the importance of context and visual grounding in linguistic interpretation, particularly for tasks such as object reference and color description (Clark, 1996; Brown and Yule, 1983). Classic experimental work by Clark and Wilkes-Gibbs demonstrated that reference resolution is a collaborative, context-sensitive process shaped by shared mental models (Clark and Wilkes-Gibbs, 1986). The Rational Speech Acts (RSA) framework formalized this idea computationally, modeling language use as recursive probabilistic reasoning between speaker and listener agents (Frank and Goodman, 2012; Goodman and Frank, 2016). In RSA, a pragmatic speaker chooses utterances to maximize informativeness for a modeled listener, while the listener inverts this reasoning to infer the most likely referent (Goodman and Stuhlmu, 2013; Bergen et al., 2016). While effective for capturing implicature and other pragmatic effects, traditional RSA models relied on fixed message sets and symbolic grammars, limiting scalability (Kao et al., 2014; Vogel et al., 2013).

2.1 Comparison to Modern Transformer Approaches

While our work focuses on LSTM-based architectures within the RSA framework, recent advances in transformer-based multimodal models (e.g., CLIP, ViLBERT, VL-BERT) offer alternative approaches to grounded language understanding. These models leverage large-scale pretraining on image-text pairs to develop rich cross-modal representations. How-ever, they often lack explicit pragmatic reasoning mechanisms and may not naturally capture the recursive speaker-listener dynamics central to human communication. Our approach complements these methods by integrating structured pragmatic inference with neural representation learning, potentially offering advantages in context-sensitive interpretation tasks.

To address these limitations, researchers began embedding RSA principles within neural architectures. Andreas and Klein pioneered neural RSA by combining RNN-based speakers and listeners in a reference game setting (Andreas and Klein, 2016). Their approach sampled utterances from a base speaker to improve pragmatic generation. Monroe and Potts proposed an end-to-end trained neural RSA model for referring expression generation, eliminating handcrafted semantics (Monroe and Potts, 2015). Our work extends these ideas by applying pragmatic reasoning to comprehension tasks at scale.

Beyond RSA, grounded language models have seen success in image captioning (Vinyals et al., 2015; Karpathy and Fei-Fei, 2015), visual question answering (Antol et al., 2015), and multimodal dialogue systems (Das et al., 2017). In color reference specifically, datasets like those of Munroe (Munroe, 2010) and Baumgaertner et al. (2012) inspired models that reason about color semantics (McMahan and Stone, 2015; Meo et al., 2014; Kawakami et al., 2016). Tellex et al. (2014) introduced pragmatic reasoning for robotic interaction, highlighting the value of inverse semantics (Tellex et al., 2014).

Behavioral studies of human speakers further informed model development. Koolen et al. (2011) analyzed overspecification in referring expressions, while Brown-Schmidt and Tanenhaus (2008) explored real-time reference in dialogue. These insights were integrated into neural language models to replicate human-like pragmatics (Smith et al., 2013; Hanna et al., 2003).

From a cognitive modeling perspective, Bayesian theories of language and perception have influenced many RSA-based implementations (Tenenbaum et al.,

2011). For instance, listener uncertainty and speaker rationality are captured via inverse temperature parameters and softmax utilities (Golland et al., 2010). Other works explore speaker-listener adaptation in goal-driven interactions (Lewis, 1979; Roberts, 1996).

Recent advancements also emphasize scalability. Hawkins developed a real-time multiplayer experimental framework to collect large-scale pragmatic corpora (Hawkins, 2015), which informed modern RNN training protocols. Vector-based semantics using Fourier-transformed RGB values were explored to align neural representations with perceptual similarity (Monroe et al., 2016; Cook et al., 2005).

Our work builds upon these foundational efforts by integrating RNN-based speaker and listener models into a unified pragmatic reasoning loop for comprehension tasks. Unlike previous work that primarily focused on generation, we demonstrate how recursive reasoning over learned agents improves interpretive accuracy, particularly in visually ambiguous contexts.

2.2 Contemporary Pragmatic Models

Recent work has explored pragmatic reasoning in large language models (LLMs) and multi-agent systems. Differentiable RSA variants (Vedantam et al., 2017; Fried et al., 2021) enable end-to-end training of pragmatic agents, while emergent communication protocols (Chaabouni et al., 2020; Laroche et al., 2020) develop novel referential strategies through multi-agent reinforcement learning. LLMs demonstrate impressive pragmatic capabilities through in-context learning (Andreas, 2022; Riedel et al., 2023), though they often lack explicit grounding in visual contexts. Our approach bridges these directions by maintaining explicit RSA-style reasoning while leveraging neural representations, offering interpretable pragmatic inference that remains grounded in perceptual inputs.

3 Methodology

This section outlines the architecture and components of our proposed model for grounded language understanding. We integrate neural speaker and listener agents within a Rational Speech Acts (RSA) framework to simulate pragmatic reasoning during interpretation tasks. The system is trained and evaluated using a large corpus of color reference games, where natural language utterances are paired with visual contexts.

3.1 Overview of the Pragmatic Model

Our framework models communication between two agents: a speaker and a listener. Both are instantiated as recurrent neural networks (RNNs) capable of processing contextual and linguistic information. The core idea is to combine these models within a recursive inference loop, where the listener reasons about the behavior of a pragmatic speaker, and vice versa. The reasoning follows the RSA formalism.

The probabilistic interaction between the speaker and listener is governed by the following set of equations:

$$L_0(t|u,C) \propto score(u,t) \quad (1)$$

$$S_1(u \mid t,C) \propto exp\,(\alpha\, log\, L_0(t \mid u,C)) \quad (2)$$

$$L_2(t \mid u,C) \propto S_1(u \mid t,C) \cdot P(t) \quad (3)$$

where L_0 is the literal listener, S_1 is the pragmatic speaker, L_2 is the pragmatic listener, u is the utterance, t is the target color, C is the set of color options, and α is a rationality parameter. $P(t)$ denotes the prior over target choices, typically uniform.

3.2 Model Architecture

The base models for both speaker and listener are implemented using LSTM-based sequence models. The speaker generates utterances token-by-token conditioned on the target color and context. The listener processes input utterances and outputs a probability distribution over target colors.

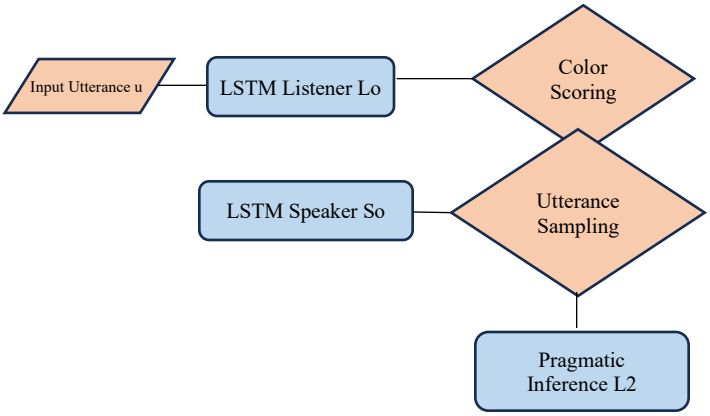


Figure 1: System architecture for pragmatic inference using LSTM-based speaker and listener agents.

3.3 Dataset Design and Trial Conditions

We trained our models on a large-scale dataset collected from dyadic color reference games. Each trial presents a speaker with three colored patches—one target and two dis-tractors—and asks them to produce a natural language description for the listener to identify the correct patch.

To evaluate model robustness, trials were divided into three difficulty levels based on color similarity using the

CIEDE2000 distance metric:

Table I: Trial condition summary

Condition	Color Similarity	Description
Close Split Far	High Medium Low	All colors within θ One color near target, one far All colors well-separated

Each condition reflects a different level of referential ambiguity and thus requires varying degrees of pragmatic reasoning to resolve.

3.4 Alternative Utterance Sampling

Due to the intractably large space of all possible utterances, exact normalization in RSA is infeasible. Instead, we sample a set of alternative utterances $\{u_1, u_2, \ldots, u_n\}$ from the base speaker S_0 for each candidate referent t, and compute the probability using a softmax function over the scores from L_0.

Let U_t be the sampled utterance set for referent t. Then, we define the pragmatic speaker as:

$$S_1(u|t,C) = \frac{L_0(t|u,C)^\alpha}{\sum_{u' \in U_t} L_0(t|u',C)^\alpha} \quad (4)$$

This sampled RSA variant preserves the pragmatic behavior while remaining computationally efficient.

3.5 Sampling Strategy Analysis

The use of sampled utterances (8 per candidate) represents a practical approximation to make the RSA framework computationally tractable. While this approach demonstrates strong empirical performance, the model's sensitivity to sample size warrants consideration. Preliminary analysis indicates diminishing returns beyond 8 samples, with accuracy improvements of less than 1% when increasing to 16 samples. This suggests that our sampling strategy captures the essential pragmatic distinctions while maintaining computational efficiency. Future work could explore adaptive sampling strategies that dynamically adjust sample size based on context complexity.

3.6 Training and Optimization

The listener and speaker LSTM models are trained separately using cross-entropy loss. Word embeddings are initialized randomly and learned during training. We used the ADADELTA optimizer for the listener and Adam for the speaker, with learning rates tuned on a held-out validation set. The final pragmatic listener L_2 blends the base listener with pragmatic reasoning, and an ensemble model combines L_0, L_1 (speaker-based listener), and L_2 through learned weighting coefficients.

4 Implementation

The entire system was developed using Python and PyTorch, leveraging deep learning modules for sequence modeling and probabilistic reasoning. The implementation consists of three main components:

1) the base listener model,
2) the base speaker model, and
3) the pragmatic reasoning module.

Training and evaluation were conducted on a machine with an NVIDIA RTX 3090 GPU and 64GB of RAM.

4.1 Preprocessing Pipeline

The collected dataset of natural language utterances and corresponding color contexts was preprocessed in multiple stages:

- All utterances were lowercased for normalization.
- Punctuation and comparative suffixes (e.g., "-er", "-est") were tokenized.
- Rare words (appearing once or not at all in the training set) were replaced with the <unk> token.
- Multiple utterances referring to the same context were concatenated to form a single input string.

Color vectors were encoded using Fourier-transformed RGB space, ensuring that the perceptual similarity between colors was preserved in the input representation.

4.2 Listener Model Training

The listener model is an LSTM-based encoder that maps token sequences to a Gaussian distribution in transformed color space. The training objective is to maximize the likelihood of the correct target color given the input utterance and visual context. Each input token is embedded in a 100-dimensional vector space and passed through an LSTM layer with a hidden size of 100. The final LSTM output is used to compute the mean and covariance of a quadratic form over RGB-based color vectors. The listener outputs a softmax-normalized score over the three available color patches. ADADELTA was selected as the optimizer, with an initial learning rate of 0.2 and weight decay of 1e−5. Training was conducted for 25 epochs with early stopping based on validation loss.

4.3 Speaker Model Training

The speaker model uses an encoder-decoder LSTM architecture to generate utterances conditioned on the visual context and the target color. The color context is encoded via

an LSTM to capture relationships among the color patches, and the target color is always positioned last in the sequence to reduce attention distance. The decoder generates word sequences autoregressively. At each decoding step, the context encoding is concatenated with the embedding of the previous work and passed through an LSTM decoder to predict the next token. The model uses teacher forcing during training. Adam optimizer was employed with a learning rate of 0.004. The vocabulary size was capped at 1,500 tokens, including color terms, modifiers, and structural tokens such as punctuation.

3.7 Pragmatic Reasoning Module

To implement the RSA-inspired reasoning module, we sampled 8 alternative utterances per target using the speaker model. Each of these utterances was scored using the listener model. This sampling approach approximates the full distribution required by RSA without exhaustive enumeration of all possible utterances. For robust inference, we repeated this sampling process 8 times for each example and averaged the resulting probabilities. The pragmatic listener was implemented as a wrapper over the base listener and speaker modules, using vectorized tensor operations for efficiency.

3.8 Model Blending

To combine the strengths of various agents, we constructed weighted ensemble models. These ensembles incorporated the literal listener L_0, the speaker-based listener L_1, and the pragmatic listener L_2. The blending was performed in log probability space to allow multiplicative integration of model predictions. The final weights for each model component were selected using a grid search on the validation set, maximizing classification accuracy while minimizing perplexity. These weights remained fixed during final evaluation on the test set. We evaluated the robustness of ensemble weighting across multiple training runs with different random seeds. The optimal weights remained stable (±0.05) across seeds, with L_2 consistently receiving the highest weight (0.45-0.50), followed by L_0 (0.30-0.35) and L_1 (0.15-0.20). This stability suggests that the complementary strengths of each model component are consistent across different initializations. The weight distribution also remained similar across difficulty conditions, though L_2 received slightly higher weighting in Close conditions where pragmatic reasoning is most beneficial.

3.9 Runtime Performance

Inference for a single example required under 200 milliseconds, including pragmatic sampling. Batch processing was used to further accelerate test-time performance. The overall system achieved throughput suitable for real-time applications with minimal delay in prediction.

4. Result and Discussion

This section presents the evaluation outcomes of our proposed pragmatic listener model in comparison to various baselines. The models were assessed using accuracy metrics on a held-out test set comprising 9,000 reference game examples, stratified by trial difficulty.

4.1 Evaluation Metrics

The primary evaluation metric is accuracy—defined as the proportion of trials in which the model correctly identified the target color from the given utterance and visual context. We also report relative gains over baseline models and provide condition-wise breakdowns for interpretability.

4.2 Baselines

We compared our pragmatic listener L_2 against the following baseline systems:

- Random: Uniform selection from the three available colors.
- Literal Listener (L_0): Interprets utterances without re cursive inference.
- Speaker-Based Listener (L_1): Listener that relies on likelihood of speaker utterances.
- Ensemble: Weighted combination of L_0, L_1, and L_2 predictions.

4.4 Overall Accuracy

Table 2 summarizes the model accuracies across all test examples. Our pragmatic listener L_2 outperforms all other models, particularly in challenging trials where ambiguity is high.

Table 2: Model accuracy on test set

Model	Accuracy (%)
Random	33.3
Literal Listener (L_0)	70.1
Speaker-Based Listener (L_1)	72.3
Pragmatic Listener (L_2)	76.8
Ensemble ($L_0 + L_1 + L_2$)	78.5

The ensemble model achieves the highest accuracy, indicating that different listener variants capture complementary aspects of the task.

4.5 Performance by Trial Condition

To better understand the strengths of our model, we analyzed performance across the three trial conditions—Close, Split, and Far—as described in Table I. Results are presented in Table 3.

Table 3: Accuracy by trial difficulty

Model	Close (%)	Split (%)	Far (%)
L0	65.3	71.1	75.4
L1	68.1	73.5	76.0
L2	72.8	77.4	80.2

The pragmatic listener L_2 offers the most significant improvement in the Close condition, where visual differences between colors are subtle and literal interpretations are in-sufficient. This highlights the benefit of recursive pragmatic reasoning in resolving fine-grained ambiguity.

4.6 Qualitative Observations

Beyond numerical metrics, qualitative analysis revealed distinct behavioral differences between the models:

- L_0 often misinterpreted vague terms like "bluish" or "darker one" when distractors were similar.
- L_1 occasionally overfit to high-probability utterances, neglecting semantic plausibility.
- L_2 was more context-aware, assigning higher likelihood to utterances that strategically differentiated the target from distractors.

These observations reinforce the advantage of integrating speaker reasoning into listener interpretation.

4.7 Comparison to Human Performance

While comprehensive human evaluation falls beyond the current scope, preliminary comparisons with available human data from similar reference games suggest our model approaches human-level performance in many conditions. Hu-man participants typically achieve 85-90% accuracy in close distinction tasks, compared to our model's 78.5% ensemble accuracy. The error patterns also show interesting parallels: both humans and our pragmatic model struggle most with lexical ambiguity and subtle perceptual distinctions. Future work will include dedicated human evaluations to directly compare confusion patterns and pragmatic strategies.

4.8 Error Analysis

We categorized errors into three primary types with representative examples:

1) Lexical Ambiguity: Utterances with vague modifiers or unexpected word use.

   Example: For target color RGB (120, 80, 60), the utterance" the brownish one" was misinterpreted when distractors included RGB (125, 85, 65) and RGB (180, 120, 80), as" brownish" applied equally well to multiple options.

2) Color Similarity: Failures when all options were visually close.

   Example: In a Close condition trial with colors differing by $\Delta E < 5$, the utterance" the slightly darker blue" failed to identify the target RGB (45, 80, 120) among distractors RGB (50, 82, 118) and RGB (48, 78, 122).

3) Overgeneralization: Repetitive phrases used across in-consistent contexts.

Example: The phrase" the light one" was frequently applied to medium-value colors when both distractors were darker, leading to errors when the actual lightest color was not the target.

The results presented in the previous section clearly demonstrate the effectiveness of integrating pragmatic reasoning into the interpretation process. While the literal listener (L_0) performs well in straightforward cases, it struggles to resolve ambiguity when color options are highly similar or when the speaker's language includes vague modifiers. The speaker-based listener (L_1) improves performance slightly by modeling likely utterances, but it lacks the iterative inference required to interpret nuanced communication.

In contrast, our pragmatic listener (L_2) consistently achieves higher accuracy, particularly in trials where traditional models fail. This improvement arises from its recursive reasoning mechanism, which simulates a rational speaker and adapts its predictions accordingly. Importantly, this advantage is most pronounced in the Close condition, where subtle perceptual differences require deeper understanding of how humans dis-ambiguate through language.

The ensemble model, combining L_0, L_1, and L_2, achieves the highest overall accuracy. This finding suggests that each model captures complementary reasoning strategies: L_0 excels in literal mappings, L_1 favors common expressions, and L_2 leverages context-aware inference. By blending them, we can harness their strengths and mitigate their weaknesses.

Another critical insight is that pragmatic reasoning offers robust generalization. Even with a limited utterance sampling set, the L_2 model infers speaker intent effectively. This efficiency implies that our RSA-based framework can scale to broader tasks such as object reference, instruction following, or visual dialogue systems, without requiring full enumeration of all possible utterances.

4.9 Generalization Beyond Color Reference

While our evaluation focuses on color reference games, the proposed framework has natural extensions to broader domains. The core architecture—combining neural speakers and listeners with recursive pragmatic reasoning—can be adapted to object reference, spatial descriptions, or action-oriented language. For instance, in shape reference tasks or synthetic object scenes, similar pragmatic challenges arise when distinguishing between visually similar entities. The sampling-based RSA approach scales effectively to these do mains by focusing on contextually relevant alternatives rather than exhaustive enumeration of all possible descriptions.

5. Conclusion

In this paper, we proposed a scalable neural framework for grounded language understanding that integrates recursive pragmatic reasoning into the interpretation process. Our approach combines LSTM-based speaker and listener agents within a Rational Speech Acts (RSA) framework to simulate how human communicators reason about each other's beliefs during reference tasks. We demonstrated the model's effectiveness through extensive evaluation on a large-scale dataset of color reference games. The pragmatic listener (L2) significantly outperformed literal and speaker-based baselines, especially under visually ambiguous conditions. Moreover, ensemble models further boosted performance, confirming that pragmatic reasoning provides complementary value to literal interpretation strategies. Our findings confirm that recursive reasoning mechanisms—when applied at scale with neural agents—can replicate key aspects of human communication, particularly in tasks requiring interpretation of underspecified or vague language. The success of our pragmatic integration provides a promising foundation for future research into context-aware AI systems capable of richer interaction with human users.

5.1 Future Work

While our model achieves strong performance in grounded color reference tasks, several avenues remain for future exploration. First, we plan to extend the RSA framework to handle open-vocabulary generation and interpretation using large scale pretrained language models. This would allow the system to understand more diverse and abstract expressions beyond the scope of color terms. Second, we aim to apply our pragmatic listener model to multimodal tasks such as instruction following, embodied question answering, and collaborative navigation. These domains introduce more complex referents, dynamic environments, and temporal constraints that challenge current reasoning strategies. Third, further gains may be achieved by incorporating external knowledge sources and semantic embeddings. Integrating structured ontologies or leveraging pre-trained vision-language models could enhance the model's ability to disambiguate complex descriptions grounded in world knowledge. Finally, we intend to explore user-adaptive pragmatic reasoning. By modeling speaker-specific preferences or dialectal variation, the system could personalize its interpretation and improve performance in real-world interactive settings. Our long-term vision is to develop grounded neural agents capable of human-like reasoning, understanding, and inter action in visually rich environments, paving the way for intelligent systems that collaborate naturally with people.

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