COMPUTATIONAL LANGUAGE ACQUISITION WITH THEORY OF MIND

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ABSTRACT

Unlike current state-of-the-art language models, young children actively acquire language through interactions with their surrounding environment and caretakers. One mechanism that has been argued to be critical to language learning is the ability to infer the mental states of other agents in social environments, coined Theory of Mind (ToM) by Premack & Woodruff (1978). Drawing inspiration from the modern operationalized versions of ToM implemented in Rabinowitz et al. (2018) and Zhu et al. (2021), we build language-learning agents equipped with ToM, and measure its effects on the learning process.[1] We model ToM by giving the speaker agent an internal listener model that is trained alongside the speaker and using this ToM model to rerank potential utterances. We also experiment with varying task difficulty, with the hypothesis that stronger environmental pressures will promote the development of more complex language. We find that speakers trained with a ToM listener component have higher accuracies than those trained without in our image referential game setting. We also find that increasing task difficulty in the training process results in more fluent, higher-quality utterances in evaluation. This suggests the utility of incorporating ToM, as well as other insights from child language acquisition, into computational models thereof.

1 INTRODUCTION

Human languages are fundamentally shaped by social-communicative goals in the grounded world. Modern theories from developmental psychology often attribute humans' unique ability to quickly acquire and adapt language to their ability to ascribe mental states to other agents (Tomasello, 2005), an ability also known as Theory of Mind (ToM).

Some previous studies have attempted to perform computational modeling of ToM. For instance, ToM-like mechanisms have been demonstrated to allow models to better predict the behavior of a future agent (Rabinowitz et al., 2018), model agents' beliefs in a negotiation (Cao et al., 2018) or a cooperative game (Bard et al., 2020), or choose good utterances based on the listener's linguistic abilities (Zhu et al., 2021). However, the effects of ToM have not yet been studied in the higher-level context of computational language acquisition.

In this paper, we study how an *internal ToM mechanism* and *external environmental pressure* contribute to language learning. Specifically, we use the setting of image referential games consisting of a series of training episodes between a speaker, which represents a language learner (Zhu et al., 2022), and a listener, which represents a teacher who already speaks fluently. When presented with a set of images, one of which is the target referent, the speaker must learn to generate an English utterance that will direct the listener to successfully select this target. The speaker is rewarded for generating utterances that the listener uses to correctly guess the target image. Additionally, the speaker may be given feedback (in the form of a ground-truth image caption) depending on the confidence the listener has in the speaker's utterance. This setting provides an attractive test-bed because it makes it possible to test the utility of various reward signals or cognitively motivated model designs on the speaker's final learned language.

Within this setting, we seek to answer the following research questions:

[1] Code and data necessary to reproduce the experiments will be released upon publication.

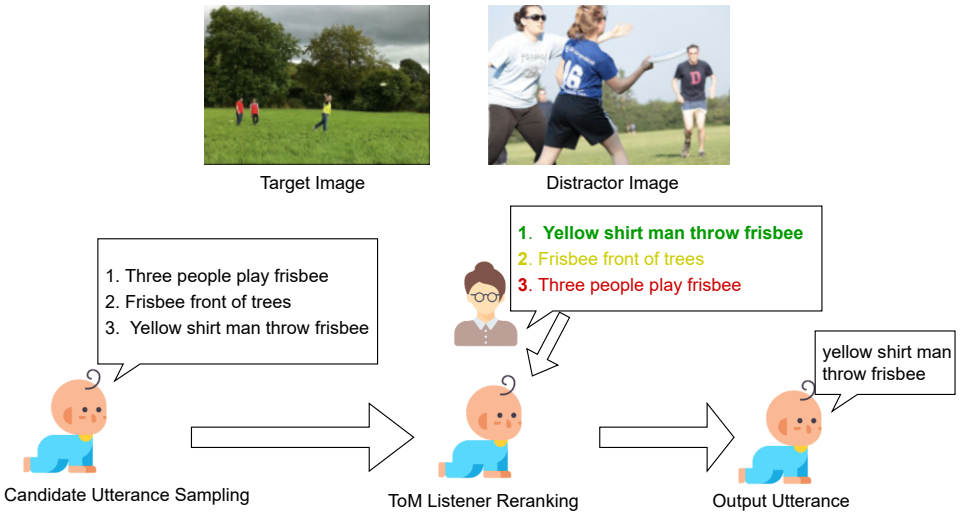

Figure 1: An example of how ToM is used by our speaker models in our implementation. The speaker first generates candidate utterances before reranking them according to the probability given to each target image, utterance pair by the internal ToM listener. It then selects either the highest-scoring or a random utterance from the candidate pool to output.

RQ1. Does the inclusion of ToM in language acquisition models improve the performance and learned language of said models? (*internal ToM mechanism*)

RQ2. How do our models' learned languages adapt to discriminate between more visually and semantically similar images? (*external environmental pressure*)

We study the impact of ToM (RQ1) by modeling an internal listener module within our speakers that aims to predict which utterances are most likely to result in the desired listener behavior. By incorporating the probabilities given to the target image by the ToM listener into the utterance reranking process, as shown in Fig. 1, we select for more pragmatic utterances sampled from the speaker's distribution. To study the impact of environmental pressure (RQ2) on our speakers, we create referential games with different difficulties by sampling distractors from different distributions. These distributions are based on the similarity between images calculated by various image representation models, including CLIP (Radford et al., 2021), RoBERTa (Liu et al., 2020), and TF-IDF variants.

In experiments, we answer the two research questions in the affirmative. (1) We find that speaker models including ToM components generally outperform those that do not in terms of fluency and final accuracy. (2) We also find that training with more visually and semantically similar distractor referents forces the speaker model to develop *longer, more fluent, and more precise* utterances to distinguish between potential referents. In other words, both ToM and environmental pressures have independent contributions to language acquisition in our setting. However, we still find significant gaps in performance between the language that our speaker model acquires and human captions, indicating that there is still room for improvement for this class of models. We hope our results hint at both better training methods for adapting language models and a deeper understanding of human language acquisition.

2 Image Referential Game Environment

Following Lazaridou et al. (2016); Lowe et al. (2019); Zhu et al. (2022), we consider image referential games with real world images, where a speaker and a listener collaborate on identifying a target image $x \in C$ among distractors randomly sampled from a set of candidates C. The identity of the target is known only to the speaker. The speaker generates an English-language utterance u that describes the target image, which is then passed to the listener. The listener will either select an image $\hat{x}$, in the case where they understand the utterance with a high enough probability or refuse to act, in the case where they do not. The listener can also determine whether or not to provide feedback (linguistic input in the form of the ground-truth caption of the target image) to the speaker.

Speaker training is motivated by a reward function that seeks to model the communicative goal of directing the listener to the correct referent. The speaker gets a positive reward of 1 if the listener chooses the target image and a penalty of -1 if the listener chooses the wrong target image. Additionally, a smaller penalty $w_{\texttt{noop}}$ is applied to the speaker if the listener chooses to not choose an image; this is done to penalize the speaker for generating unclear utterances.

2.1 Agent Formulation

We follow the speaker and listener formulations defined in Zhu et al. (2022). The speaker is a model $f : I \rightarrow \Sigma^*$ that generates utterances (sequences of tokens from its vocabulary) that correspond to a provided image. We define Σ^* as the speaker vocabulary and I as the set of candidate images.

The listener is defined on the same Σ^* and I. Given an utterance $\in \Sigma^*$ and an observation space $\in I^N$, where N is the number of candidate images, the listener will either return the index of its predicted image or $\texttt{noop}$, if it cannot predict an image. It may also return a feedback utterance from its vocabulary. We define it with the model $g : \Sigma^* \times I^N \rightarrow ([0, 1, \ldots N-1] \cup \texttt{noop}) \times \Sigma^*$.

2.2 Speaker Design

The speaker that we use is a captioning model composed of a pretrained ResNet (He et al., 2016) model and an LSTM-based utterance generation model. After generating an embedding vector of the target image using the ResNet model, the speaker autoregressively generates an utterance $u = \{u_i\}_{i=1}^{M}$ using the LSTM network:

$$\begin{aligned} &\pi(u_i \mid u_1, u_2, \ldots, u_{i-1}, x) \\ &\propto \exp(w_{u_i}^T \texttt{LSTM}(w_{u_1}, w_{u_2}, \ldots, w_{u_{i-1}}, h_0 = \texttt{ResNet}(x))), \end{aligned} \tag{1}$$

where $w_{u_i} \in \mathbb{R}^{d_w}$ is the word embedding of u_i. The speaker generates a sequence of tokens to either the maximum length, which is set to 20 in our experiments, or an end-of-sequence token. In our experiments, we use a vocabulary size of 200 to limit the size of the action space and to more realistically mimic the vocabulary of a language learner. This is done in practice by allowing the speaker to use the entire vocabulary, but adding a strong negative bias of -1000 to words outside of the most frequent 200 words in the ground truth captions.

2.3 Listener Design

Given a set of candidate images I_j ($j \in 1, 2 \ldots n+1$), where n is the number of distractors and an utterance u, the listener computes embeddings for each image, $L(I_j)$, for the utterance, $L(u)$. It then takes the dot product of each $L(I_j)$ with $L(u)$, and the softmax of the dot products to compute the probability $P(I_j|u) \propto \exp(L(I_j)L(u))$ of the utterance referring to image I_j for each image.

The listener also has a rule-based component to control when to give feedback in the form of the ground-truth caption $C(I_t)$. We introduce two new thresholds, θ_1 and θ_2. After the listener computes the most likely target image, $t = \arg\max P(I_j|u)$, and the probability given to this choice, $P_{\max} = \max P(I_j|u)$, it returns its choice $\hat{x}$ and feedback $f_{\texttt{listener}}$ according to the following logic:

$$(\hat{x}, f_{\texttt{listener}}) = \begin{cases} (\texttt{noop}, 0) & P_{\max} < \theta_1 \\ (t, C(I_t)) & \theta_1 < P_{\max} < \theta_2 \\ (t, 0) & P_{\max} > \theta_2 \end{cases} \tag{2}$$

This control strategy mimics a caregiver who only gives feedback when they understand what the language learner is referring to, but wants to direct it to generate higher-quality utterances. When the listener's confidence is very low, it will neither select a target image nor provide feedback, as the speaker utterance is too low-quality. Meanwhile, when the listener's confidence is very high, it will stop giving feedback, as further improvement is deemed unnecessary.

We use an LSTM-based model to learn embeddings of speaker utterances combined with a ResNet model to derive image features. Because we want our listener to at least model a competent user

of the language that the speaker is trying to acquire, some pretraining is required before initializing a listener in a new environment. The controller values θ_1, θ_2 and the ResNet parameters are set after preliminary experimentation on the dataset. However, the language network parameters are additionally trained with mini-batch stochastic gradient descent to optimize the network values

$$\theta_{\text{listener}} = \arg\max_{\theta} \mathbb{E}_{C \sim \mathcal{U}(I)^N} \frac{1}{N} \sum_{i=1}^{N} \log P_{\text{listener}}(i \mid U_i^*, C; \theta) \tag{3}$$

3 Speaker Training Process

3.1 Communicative Goals

We model communicative goals and learning from listener feedback as two separate learning objectives for our speaker network, which we combine with an adjustable coefficient λ. The communicative goal feedback is simply the reward (as defined in §2) averaged over each game in the episode. The space of possible output utterances is discrete and non-differentiable, so our speaker learns its policy π via the reinforcement learning method PPO (Schulman et al., 2017).

3.2 Learning from Feedback

We model the learning from feedback objective as the maximum likelihood of the listener feedback in the speaker models and optimize this continuous function with stochastic gradient descent.

$$\mathcal{O}_{LI} = \mathbb{E}_{x,C,u \sim \pi(u|x)} \log \pi(U^*_{f_{\text{listener}}(u,C)} \mid x, C) \tag{4}$$

We then combine the separate learning objectives for each task using a coefficient $\lambda \in [0, 1]$:

$$\mathcal{O}_{\text{joint}} = \lambda \mathcal{O}_{CG} + (1 - \lambda) \mathcal{O}_{LI} \tag{5}$$

Next, we introduce ToM Modeling, and an additional task objective, $\mathcal{O}_{ToM}$. This is a cross-entropy objective that represents how accurate the speaker's internal listener model is. Similar to the objective above, we combine these into a single learning objective for the entire speaker network.

4 Introducing ToM Modeling

We incorporate into the speaker architecture an LSTM-based ToM listener. This listener model is trained alongside of the rest of the speaker network to learn the "mental state" of the actual listener – the neural network parameters that allow it to best replicate the probabilities that the listener would assign to image-utterance pairs. It uses a similar architecture to the actual listener, combining its own learned sentence embeddings from an LSTM network with pretrained image embeddings using ResNet. In other words, our ToM listener seeks to learn the sentence embedding model θ_{ToM} that will maximize the probabilities assigned to the target image given an utterance.

$$\theta_{ToM} = \arg\max_{\theta} P_{ToM}(u_i | I_t) \propto \exp(\theta_{ToM}^T(u_i) \cdot ResNet(I_t)) \tag{6}$$

We introduce ToM into the speaker model by having our speaker sample candidate utterances and rerank them with the help of the ToM listener. Our ToM speaker first samples N candidate utterances $U = \{u^{(i)}\}_{i=1}^N$ from its distribution. Next, we generate a speaker and a listener score for each:

$$p_{\texttt{speaker}}(u^j) \propto \exp(w_{u_i^j}^T \texttt{LSTM}(w_{u_1^j}, w_{u_2^j}, \ldots, w_{u_i^j}) \texttt{ResNet}(x))) \tag{7}$$

$$P_{\texttt{ToM}}(I_t | u^i) \propto \exp(\texttt{LSTM}^T(u^i) \texttt{Resnet}(I_j)) \tag{8}$$

We then combine these scores using a listener weight hyperparameter w_l to get the overall score assigned to each utterance. Finally, we select the best utterance, u^b, as the argmax of this score:

$$u^b = \arg\max_U (P_{\texttt{ToM}}(I_t|u^j)^{w_l} \cdot p_{\texttt{speaker}}(u^j)) \tag{9}$$

We experiment with setting $w_l = 1$, weighing both the speaker and ToM listener input equally. We also set w_l to the arbitrarily high constant 1000. In this case, the listener score dominates, and our speaker essentially seeks to maximize $P_{\texttt{listener}}(I_t|u^i)$, which it approximates with the ToM listener score. Finally, we train models with $w_l = 0$ to isolate the effects of including a ToM listener from the effects of the new model architecture.

We also introduce a hyperparameter, σ, where the speaker outputs a random utterance with probability σ and the best utterance (the utterance with the highest score) with probability $1 - \sigma$. This randomization is done to promote early exploration by our speaker model, and can be set to linearly decay over time to a much smaller value σ_f.

By default, we begin with an untrained listener that will be trained to emulate the actual listener's outputs over time. To train the ToM listener, we introduce a third training objective in addition to $\mathcal{O}_{LI}$ and $\mathcal{O}_{CG}$, the ToM objective $\mathcal{O}_{ToM}$, defined as the cross-entropy loss between the distribution of the ToM listener and that of the speaker. Thus, we are training it to give higher probabilities to the intended target images based on the speaker's utterances. Formally,

$$\mathcal{O}_{ToM} = \begin{cases} -\sum_{0}^{i-1} \log P_{ToM}(w_{u^n}) & P_{\max} > \theta_1 \\ 0 & P_{\max} < \theta_1 \end{cases} \tag{10}$$

Note that this requires a choice to be made by the listener, so we mask out the case where the actual listener does not have a high enough confidence to choose one of the images by setting it to zero. This is done using the same parameter θ_1 and listener confidence $P_{\max}$ that were used to control feedback in 2. We add this to the joint learning objective previously defined in 5 to compute our combined objective for the ToM speaker system as a whole:

$$\mathcal{O}_{\text{joint}} = \lambda \mathcal{O}_{CG} + (1 - \lambda)\mathcal{O}_{LI} + \mathcal{O}_{ToM} \tag{11}$$

However, an untrained listener can introduce significant noise to the utterance generation process. To counteract this, we anneal the influence of the listener, by linearly increasing w_l from 0 to the final w_l value over a fixed number of steps. This allows our speaker to only begin using its ToM listener when the listener is at least somewhat capable.

5 Increasing Distractor Difficulty

Previous studies on human language acquisition have found that infants initially look at familiar objects when hearing semantically related labels for different objects, but adapt to more difficult tasks over time by learning more complex semantic representations of objects (Bergelson & Aslin, 2017a). We hypothesize that the usage of more similar distractor images might similarly force our speaker to generate more complex utterances due to the need to further distinguish between images. This motivated us to generate more similar distractor images in the training process in order to achieve such an effect. To do so, we computed a similarity rank between images based on visual and semantic similarity. Then, after selecting a "target" image in the training process, we sampled from images with high similarities to the target image to use as distractors during training.

We experiment with three options for calculating image/caption similarity:

- **Visual Cosine Similarity.** We compute the most visually similar images based on the cosine similarity of image embeddings from a pretrained ResNet model. For each image, we save a similarity ranking of the next 1000 most visually similar images, and then select distractors from this set during training whenever the original image is selected as a target.

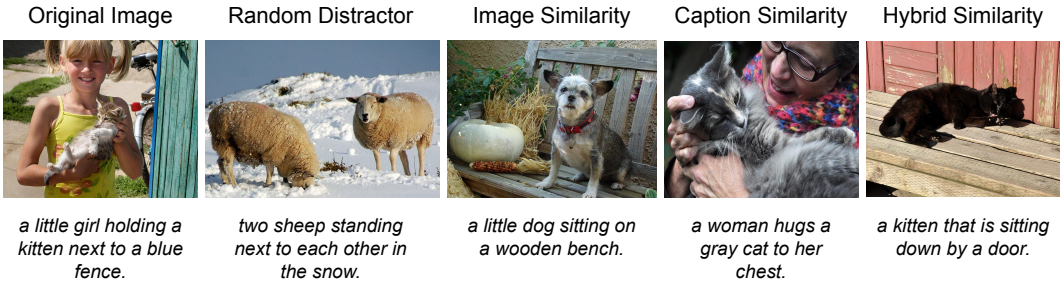

Figure 2: An example image-caption pair, and distractors ranked as similar by various similarity metrics. Here, Caption and Hybrid similarities are computed with TF-IDF - weighted RoBERTa embeddings.

- **Textual Cosine Similarity.** We calculate the textual similarity of captions by taking the cosine similarity of vector representations of the text. We experiment with both (1) dense vectors using embeddings calculated using either the pretrained RoBERTa or the pretrained CLIP mean pooled models from the sentence-transformers Python library (Reimers & Gurevych, 2019), and (2) sparse vectors using one-hot vectors of each word. We also experimented with weighting using term frequency – inverse document frequency (TF-IDF) to weight the vector for each token in our captions when computing caption similarity as a way to upweight rarer content words.
- **Visual+Textual Similarity.** In cases where both image and caption similarity were used, we added a caption weight parameter $w_c \in [0, 1]$ and used it to compute a weighted average of image and caption similarity. We hoped that using hybrid methods ($w_c = 0.5$) would capture distractors with both visual and semantic similarities.

Examples of a selection of the distractor difficulty settings are shown in Fig. 2.

6 Experimental Setup and Results

6.1 Experimental Setup

We focus on two main results: A speaker's ability to use language to correctly discriminate between the target and distractor images, as well as the quality of the language speakers use to do so.

To evaluate the former, we primarily consider average accuracy, or how often the listener selects the correct referent. We evaluate the quality of our speakers' learned languages using four sets of metrics: fluency, average length, part of speech distribution, and F1 score for salient parts of speech. We use a fluency score, first seen in Kann et al. (2018), that measures the grammatical quality of output utterances without considering the actual semantic content. This score is equivalent to the average gain in log probability when moving from a unigram model to a pretrained language model. Subtracting out the unigram model essentially prevents the individual token frequencies from affecting the fluency score.

$$\text{fluency} = \frac{1}{|u|}(\ln(p_M(u)) - \ln(p_U(u))) \tag{12}$$

We train a unigram model, p_U, and fine-tune GPT-2 large (Radford et al., 2019), p_M, on our training set.

We also consider part-of-speech statistics to evaluate utterance quality. Parts of speech for words in speaker utterances and ground-truth captions are tagged with spaCy (Honnibal et al., 2020). We use this to compute F1 scores between speaker utterances and ground-truth captions over each part of speech. This allows us to evaluate how effectively our speakers identify referents within the target image that a human captioner would consider salient. Higher F1 scores over a part of speech would suggest that a speaker is more capable of identifying concepts that fall under that part of speech.

Images and captions are drawn from the MS COCO dataset introduced in Lin et al. (2014). The train-val-test split given by the MS COCO 2017 dataset is extended to our experimental setup.

Base Speaker: A baseball player holding a holding umbrella.
Speaker Trained on Hard Distractors: A baseball player holding a bat on a field.
ToM Speaker Trained on Hard Distractors: A group of men are playing baseball outside.

Figure 3: Examples of output utterances generated by various speaker models. Here, the "Hard Distractors" referenced are hybrid metrics computed with CLIP embeddings. Both training on more difficult distractors and training with ToM leads to more accurate, fluent utterances.

Table 1: Performance and language features of various ToM speakers.

Model		Performance			POS F1				Average
ToM Weight	Distractors	Acc	Return	Fluency	ADJ	ADP	NOUN	VERB	Length
Baseline (No ToM)	Easy	0.81	0.59	1.50	0.16	0.52	0.41	0.38	8.97
Baseline (No ToM)	Hard	0.81	0.57	1.87	0.24	0.58	0.46	0.45	9.78
Gold Standard	N/A	0.92	0.84	2.52	1.00	1.00	1.00	1.00	10.79
Zero	Hard	0.83	0.61	1.99	0.22	0.64	0.49	0.47	10.21
Normal	Hard	0.78	0.50	2.04	0.21	0.62	0.45	0.44	10.37
High	**Hard**	**0.86**	**0.69**	**2.22**	**0.22**	**0.66**	**0.52**	**0.48**	**10.65**
Zero	Easy	0.85	0.66	1.73	0.21	0.57	0.48	0.49	9.51
Normal	Easy	0.84	0.65	1.89	0.21	0.62	0.49	0.48	9.96
High	**Easy**	**0.88**	**0.74**	**2.00**	**0.22**	**0.64**	**0.51**	**0.49**	**10.31**

6.2 Effects of ToM

We train models equipped with ToM listeners with normal weight (i.e. equally weighting the speaker and the listener scores when reranking output utterances) and with high weight (where the listener weight is set arbitrarily to 1000 and the speaker essentially optimizes for $P(I_t|u^i)$). In order to isolate the effects of using a ToM listener from the effects of modifying the utterance selection process, we also train a model equipped with a ToM listener that it does not give any weight to. Additionally, we train a model without any ToM component for comparison. We do this for both easy and hard distractors, where the hard distractors were those that were chosen by the hybrid similarity between visual and semantic (CLIP) features outlined in 5. Finally, we give the listener the ground-truth captions over the test set to compute gold-standard metrics of accuracy, return, and fluency.

We find significant performance improvements in Table 1 when speaker models are trained to rerank utterances solely by ToM listener score. Such "high-weight ToM" speaker models achieve accuracy gains of 3.0% and 3.1% on easy and hard distractors, respectively. This suggests that the inclusion of a sufficiently influential ToM reranker during the speaker training process improves speaker performance, although the relative gains appear to be much higher when training on easy distractors. However, we find that speaker models that rerank utterances using a combined speaker-ToM score generally fail to outperform models that do not use their ToM listener in training.

We also find that the usage of a highly-weighted ToM listener leads to significant fluency gains when training on both easy (15.6% relative increase in fluency score) and hard (11.6%) distractors. We also see limited fluency gains when using a normally weighted ToM listener, as well as longer and more complex utterances when using normally or highly weighted ToM listeners. However, these effects are more subtle, and in the case of the normally weighted ToM listener, seem to have little effect on model performance during evaluation. Generally, though, we may conclude that usage of a highly influential ToM listener during the training process leads to significant gains in accuracy and

Table 2: Performance and language features of speakers trained on different distractors

Model	Performance			POS F1				Average
Distractors	Acc	Return	Fluency	ADJ	ADP	NOUN	VERB	Length
Base	0.81	0.59	1.50	0.16	0.52	0.41	0.38	8.97
Gold Standard	0.92	0.84	2.52	1.00	1.00	1.00	1.00	10.79
Image	0.80	0.55	2.09	0.19	0.61	0.45	0.49	10.33
Caption CLIP	0.83	0.61	1.87	0.18	0.57	0.46	0.43	9.56
Caption RoBERTa	0.83	0.60	1.93	0.20	0.60	0.48	0.47	10.06
Caption RoBERTa TFIDF	0.86	0.70	2.01	0.19	0.62	0.49	0.48	10.04
Caption TFIDF	0.83	0.65	2.05	0.21	0.63	0.46	0.45	10.30
Hybrid CLIP	0.81	0.57	1.87	0.24	0.58	0.46	0.45	9.78
Hybrid RoBERTa	0.83	0.60	1.94	0.20	0.61	0.48	0.47	10.09
Hybrid RoBERTa TFIDF	0.84	0.67	2.09	0.20	0.65	0.48	0.46	10.29
Hybrid TFIDF	0.85	0.68	2.19	0.20	0.62	0.49	0.47	10.18

utterance fluency. We are also able to observe the improvement in utterance quality from using ToM qualitatively. As seen in one representative example in Fig. 3, our ToM Speaker is able to identify two elements that clearly distinguish the target image from the distractors (i.e. that there are multiple men and that they are playing baseball) while generating a fluent output utterance.

These qualitative and quantitative results provide the first computational evidence that ToM can play an important role in language acquisition, similarly to how it has been hypothesized to play a critical role in human language acquisition.

6.3 Effects of Distractor Difficulty

As shown in Table 2, we generally find significant improvements in language quality in models trained on more difficult distractors. The largest gains are those seen in the fluency score, where difficult distractors achieve gains ranging between 25% to 46%. We also find that models trained on more difficult distractors use more similar vocabulary to the ground-truth captions, as measured by F1 score in the ground-truth captions and utterances produced. This is significantly higher over adpositions, nouns, and verbs on models trained with more difficult distractors. Finally, all speakers trained on difficult distractors generate more complex utterances compared to the base speaker, with utterances that are at least one word longer on average. This supports our hypothesis that when confronted with increased environmental pressure, the speaker adapts by becoming more precise, fluent, and complex with its language. These can be seen qualitatively in one representative example in Fig. 3, which shows that a speaker trained on hard distractors is able to generate more fluent utterances that more precisely describe the image (in this example, correctly identifying an object in the image as a baseball bat, as opposed to an umbrella).

We find smaller differences between the language of models trained with various types of hard distractors. Speaker models trained with visually similar distractors achieve the highest fluency, at 2.094, and form the longest utterances. They also have more precise verb selection, as measured by F1. Speakers trained on distractors that were selected with RoBERTa caption similarity, both hybrid and caption, achieved high noun F1 scores of 0.49 compared to 0.41 for the base speaker model, indicating that semantically similar distractors in training may be better for identifying salient nouns.

We find that training on more difficult distractors does not consistently improve model performance when evaluating on easier distractors. This suggests some disconnect between a language's fluency and its suitability to the image referential game environment. However, speakers that train on more semantically similar distractors still achieve between 0 to 5 percent higher accuracy than the base speaker when evaluating on easier distractors, indicating some benefits to performance when training on these types of harder distractors.

7 RELATED WORK

Parallels in Human Language Acquisition. The concept of learning language through repeated exposure to referents is a popular model within the psychology community. Smith & Yu (2008) found that infants resolve the uncertainty of determining which referent in a scene a word refers to by statistical learning over many word-scene pairings. Yu & Ballard (2007) incorporated a social element into such models by considering "social-cognitive" capacities, such as attention reading, that act as a form of ToM. Yu & Smith (2012) studied the social impact that caregivers play in early language acquisition using head-mounted cameras, finding that caregiver feedback during moments where a referent was visually dominant directly led to language learning in the infant. Bergelson & Aslin (2017b) found that the home learning environment was essential to shaping infant language acquisition, and that both infants and older children were more capable of distinguishing between semantically unrelated images ("easy" distractors) than semantically similar images ("hard" distractors).

Pragmatic Modelling. We draw inspiration from previous work investigating the usage of pragmatics in referential games. Andreas & Klein (2016) found success in using pragmatic models to jointly train neural speaker and listener models to play a referential game that involved describing contrasting scenes. Here, the speaker already knows how the listener will respond to certain utterances; in contrast, our language learners must model this information with ToM. Nematzadeh et al. (2018) created a new dataset to evaluate question answering models' ability to keep track of inconsistent beliefs about the world. They found that state-of-the-art neural models do not have this ability, indicating that they cannot solve tasks with ToM. Moreno et al. (2021) used a more advanced model structure, recursive deep generative models, to approximate agents' beliefs in multi-agent systems and show that this leads to improved performance on Partially Observable Markov Games. Bao et al. (2022) considered how to use the Rational Speech Act framework to learn disparities between speaker and listener worldviews.

Emergent Language. Lazaridou & Baroni (2020) surveyed recent progress in emergent language from multi-agent communication, claiming that further progress can help deep networks become more interactive and interpretible. Chaabouni et al. (2022) analyzed the effects of task difficulty in emergent communication problems, although they did so by varying the number of distractors rather than distractor similarity. They found that doing so has a strictly negative impact on model performance. Mu & Goodman (2021) attempted to improve interpretability of learned languages in referential games by forcing speakers to communicate over sets of objects representing abstract visual concepts, and analyzed the compositionality of the ensuing emergent languages.

8 CONCLUSION AND FUTURE WORK

In this paper, we extend an existing computational framework that models the language acquisition process in an image referential game environment. Most notably, we add a ToM component to our speaker models, allowing our speakers to pragmatically rerank candidate utterances with an internal listener model. We also experiment with increasing distractor difficulty by upweighting more semantically and visually similar distractor images. We find that incorporating ToM into our speaker models leads to improvements in speaker performance. We also find that incorporating harder distractors leads to the development of more complex and fluent languages.

Future work could measure the similarity of the learning process between human learners and our computational models, and whether the changes implemented in this paper result in a more human-like learning process. Further work could also consider the implications of more dynamic distractor difficulty adjustment or curriculum design, as well as different variants of training scheduling for the ToM listener. Finally, the role of the listener in influencing the acquired language can be studied by varying the skill and architecture of the listener. We encourage the machine learning and psychological modelling communities to consider the further incorporation of ToM into language learning simulations, as this could drive the development of more pragmatically-aware models.

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