Emergent Language in a Multi-Modal, Multi-Step Referential Game

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Abstract

Inspired by previous work on emergent language in referential games, we propose a novel multi-modal, multi-step referential game, where the sender and receiver have access to distinct modalities of an object, and their information exchange is bidirectional and of arbitrary duration. The multi-modal multi-step setting allows agents to develop an internal language significantly closer to natural language, in that they share a single set of messages, and that the length of the conversation may vary according to the difficulty of the task. We examine these properties empirically using a dataset consisting of images and textual descriptions of mammals, where the agents are tasked with identifying the correct object. Our experiments indicate that a robust and efficient communication protocol emerges, where gradual information exchange informs better predictions and higher communication bandwidth improves generalization.

1 Introduction

Recently, there has been a surge of work on neural network-based multi-agent systems that are capable of communicating with each other in order to solve a problem. Two distinct lines of research can be discerned. In the first one, communication is used as an essential tool for sharing information among multiple active agents in a reinforcement learning scenario [1][4]. Each of the active agents is, in addition to its traditional capability of interacting with the environment, able to communicate with other agents. A population of such agents is subsequently jointly tuned to reach a common goal. The main goal of this line of work is to use communication (which may be continuous) as a means to enhance learning in a difficult, sparse-reward environment.

The other line of research focuses more on investigating and analyzing the emergence of language in (cooperative) multi-agent referential games [5][7], where one agent (the sender) must communicate what it sees using some discrete emergent language, while the other agent (the receiver) is tasked with figuring out what the first agent saw. These lines of work are partially motivated by the idea that artificial language (and other manifestations of machine intelligence) can emerge through interacting with the world and/or other agents, which could then converge towards human language [8][11]. Lazaridou et al. [12] have recently proposed a basic version of this game, where there is only a single transmission of a message from the sender to the receiver, as a test bed for both inducing and analyzing a communication protocol between two neural network-based agents. A related approach to using a referential game with two agents is proposed by Andreas and Klein [13]. Jorge et al. [14] have more recently introduced a game similar to the setting above, but with multiple transmissions
of messages between the two agents. The sender is, however, strictly limited to sending single bit (yes/no) messages, and the number of exchanges is kept fixed.

These earlier works lack two fundamental aspects of human communication in solving cooperative games. First, human information exchange is bidirectional with symmetric communication abilities, and spans exchanges of arbitrary length. In other words, linguistic interaction is not one-way, and can take as long or short as it needs. Second, the information exchange emerges as a result of a disparity in knowledge or access to information, with the capability of bridging different modalities. For example, a human who has never seen a tiger but knows that it is a “big cat with stripes” would be able to identify one in a picture without effort. That is, humans can identify a previously unseen object from a textual description alone, while agents in previous interaction games have access to the same modality (a picture) and their shared language.

Based on these considerations, we extend the basic referential game used earlier in [12–14] into a multi-modal, multi-step referential game. Firstly, our two agents, the sender and receiver, are grounded in different modalities: one has access only to the visual modality, while the other has access only to textual information (multi-modal). The sender sees an image and communicates it to the receiver, whose job is to determine which object the sender refers to, while only having access to a set of textual descriptions. Secondly, communication is bidirectional and symmetrical, in that both the sender and receiver may send an arbitrary binary vector to each other. Furthermore, we allow the receiver to autonomously decide when to terminate a conversation, which leads to an adaptive-length conversation (multi-step). The multi-modal nature of our proposal enforces symmetric, high-bandwidth communication, as it is not enough for the agents to simply exchange the carbon copies of their modalities (e.g. communicating the value of an arbitrary pixel in an image) in order to solve the problem. The multi-step nature of our work allows us to train the agents to develop an efficient strategy of communication, implicitly encouraging a shorter conversation for simpler objects and a longer conversation for more complex objects.

We evaluate and analyze the proposed multi-modal, multi-step referential game by creating a new dataset consisting of images of mammals and their textual descriptions. The task is somewhat related to recently proposed multi-modal dialogue games, such as that of de Vries et al. [15], but then played by agents using their own emergent language. We build neural network-based sender and receiver, implementing techniques such as visual attention [16] and textual attention [17]. Each agent generates a multi-dimensional binary message at each time step, and the receiver decides whether to terminate the conversation. We train both agents jointly using policy gradient [18].

2 Multi-Modal, Multi-Step Referential Game

Game The proposed multi-modal, multi-step referential game is characterized by a tuple

\[ G = \langle S, O, O_S, O_R, s^* \rangle. \]

\( S \) is a set of all possible messages used for communication by both the sender and receiver. An analogy of \( S \) in natural languages would be a set of all possible sentences. Unlike Jorge et al. [14], we let \( S \) be shared between the two agents, which makes the proposed game a more realistic proxy to natural language conversations where two parties share a single vocabulary. In this paper, we define the set of symbols to be a set of \( d \)-dimensional binary vectors, which reminds us of a widely-used bag-of-words representation of a natural language sentence. That is, \( S = \{0, 1\}^d \).

\( O \) is a set of objects. \( O_S \) and \( O_R \) are the sets of two separate views, or modes, of the objects in \( O \), exposed to the sender and receiver, respectively. Due to the variability introduced by the choice of mode, the cardinalities of the latter two sets may differ, i.e., \( |O_S| \neq |O_R| \), and it is usual for the cardinalities of both \( O_S \) and \( O_R \) to be greater than or equal to that of \( O \), i.e., \( |O_S| \geq |O| \) and \( |O_R| \geq |O| \). In this paper, for instance, \( O \) is a set of select mammals, and \( O_S \) and \( O_R \) are, respectively, images and textual descriptions of those mammals: \( |O_S| \gg |O_R| = |O| \).

The ground-truth map between \( O_S \) and \( O_R \) is given as

\[ s^* : O_S \times O_R \rightarrow \{0, 1\}. \]

This function \( s^* \) is used to determine whether elements \( o_s \in O_S \) and \( o_r \in O_R \) belong to the same object in \( O \). It returns 1 when they do, and 0 otherwise. At the end of a conversation, the receiver selects an element from \( O_R \) as an answer, and \( s^* \) is used as a scorer of this particular conversation based on the sender’s object \( o_s \) and the receiver’s prediction \( o_r \).
Agents

The proposed game is played between two agents, sender $A_S$ and receiver $A_R$. A sender is a stochastic function that takes as input the sender’s view of an object $o_s \in O_S$ and the message $m_r \in S$ received from the receiver and outputs a binary message $m_s \in S$. That is,

$$A_S : O_S \times S \rightarrow S.$$ 

We constrain the sender to be memory-less in order to avoid a behavior where it can decide to make a series of messages on its own without consulting with the receiver.

Unlike the sender, it is necessary for the receiver to possess a memory in order to reason through a series of messages exchanges with the sender and make a final prediction. The receiver also has an option to determine whether to terminate the on-going conversation. We thus define the receiver as:

$$A_R : S \times \mathbb{R}^q \rightarrow \Xi \times O_R \times S \times \mathbb{R}^q,$$

where $\Xi = \{0, 1\}$ indicates whether to terminate the conversation. It receives the sender’s message $m_r \in S$ and its memory $h \in \mathbb{R}^q$ from the previous step, and stochastically outputs: (1) whether to terminate the conversation $s \in \{0, 1\}$, (2) its prediction $o_r \in O_R$ (if decided to terminate) and (3) a message $m_r \in S$ back to the sender (if decided not to terminate).

Play

Given $G$, one game instance is initiated by uniformly selecting an object $o$ from the object set $O$. Given the object $o$, the corresponding views $o_s \in O_S$ and $o_r \in O_R$ are sampled and given to the sender $A_S$ and receiver $A_R$, respectively. The memory of and the initial message from the receiver are learned as separate parameters.

At each time step $t \in \{1, \ldots, T_{\text{max}}\}$, the sender computes its message $m^t_s = A_S(o_s, m^{t-1}_r)$. This message is then transmitted to the receiver. The receiver updates its memory $h^t_r$, decides whether to terminate the conversation $s^t$, makes its prediction $o^t_r$, and creates a response $m^t_r : (s^t, o^t_r, m^t_r, h^t_r) = A_R(m^t_s, h^{t-1})$. If $s^t = 1$, the conversation terminates, and the receiver’s prediction $o^t_r$ is used to score this game instance, i.e., $s^t(o_s, o^t_r)$. Otherwise, this process repeats in the next time step: $t \leftarrow t + 1$.

3 Agents

Feedforward Sender

Let $o_s \in O_S$ be a $d^s$-dimensional real-valued vector, and $m_r \in S$ be a $d$-dimensional binary message. We build a sender $A_S$ as a feedforward neural network that outputs a $d$-dimensional factorized Bernoulli distribution. It first computes the hidden state $h_s$ by

$$h_s = f_s(o_s, m_r),$$

and computes $p(m_{s,j} = 1)$ for all $j = 1, \ldots, d$ as

$$p(m_{s,j} = 1) = \sigma(w^\top_{s,j} h_s + b_{s,j}),$$

where $\sigma$ is a sigmoid function, and $w_{s,j} \in \mathbb{R}^{\text{dim}(h_s)}$ and $b_{s,j} \in \mathbb{R}$ are the weight vector and bias, respectively. During training, we sample a sender’s message from this distribution, while during test time we take the most likely message, i.e., $m_{s,j} = \arg\max_{b \in \{0,1\}} p(m_{s,j} = b)$.

Attention-based Sender

When the view $o_s$ of an object is given as a set of vectors $\{o_s, \ldots, o_{s_n}\}$ rather than a single vector, we implement and test an attention mechanism from [17] [16]. For each vector in the set, we first compute the attention weight against the received message $m_r$ as

$$\alpha_j = \exp(f_{\text{att}}(o_{s,j}, m_r)) \sum_{j'=0}^n \exp(f_{\text{att}}(o_{s,j'}, m_r)),$$

and take the weighted-sum of the input vectors: $\tilde{o}_s = \sum_{j=1}^n \alpha_j o_{s,j}$. This weighted sum is used instead of $o_s$ as an input to $f_s$ in Eq. (1). Intuitively, this process of attention corresponds to selecting a subset of the sender’s view of an object according to a receiver’s query.

Recurrent Receiver

Let $o_r \in O_R$ be a $d^r$-dimensional real-valued vector, and $m_s \in S$ be a $d$-dimensional binary message received from the sender. A receiver $A_R$ is a recurrent neural network that first updates its memory by $h^t_r = f_r(m_s, h^{t-1}_r) \in \mathbb{R}^q$, where $f_r$ is a recurrent activation function. We use a gated recurrent unit [GRU, 19].
Given the updated memory vector $h_r^t$, the receiver first computes whether to terminate the conversation. This is done by outputting a stop probability, as in

$$p(s^t = 1) = \sigma(w_{r,s}^T h_r^t + b_{r,s}),$$

where $w_{r,s} \in \mathbb{R}^q$ and $b_{r,s} \in \mathbb{R}$ are the weight vector and bias, respectively. The receiver terminates the conversation ($s^t = 1$) by either sampling from or taking the most likely value of this distribution. If $s^t = 0$, the receiver computes the message distribution similarly to the sender as a $d$-dimensional factorized Bernoulli distribution:

$$p(m^t_{r,j} = 1) = \sigma(w_{r,j}^T \tanh(W_r^T h_r^t) + U_r^T \sum_{o_r \in O_R} p(o_r = 1) g_r(o_r) + c_r + b_{r,j}),$$

where $g_r: \mathbb{R}^{\text{dim}(o_r)} \to \mathbb{R}^q$ is a trainable function that embeds $o_r$ into a $q$-dimensional real-valued vector space. The second term inside the sigmoid function ensures that the message generated by the receiver takes into consideration the receiver’s current belief $p(o_r = 1)$ (see below) on which object the sender is viewing.

If $s^t = 1$ (terminate), the receiver instead computes its prediction by computing the distribution over all the elements in $O_R$:

$$p(o_r = 1) = \frac{\exp(g_r(o_r)^T h_r^t)}{\sum_{o_r \in O_R} \exp(g_r(o_r)^T h_r^t)}. \quad (2)$$

Again, $g_r(o_r)$ is the embedding of an object $o$ by the receiver’s view $o_r$, similarly to what was proposed by Larochelle et al. [20]. The receiver’s prediction is given by $\hat{o}_r = \arg \max_{o_r \in O_R} p(o_r = 1)$, and the entire prediction distribution is used to compute the cross-entropy loss.

**Attention-based Receiver**  Similarly to the sender, we can incorporate the attention mechanism to the receiver. This is done at the level of the embedding function $g_r$ by modifying it to take as input both the set of vectors $o_r = \{o_{r,1}, \ldots, o_{r,n}\}$ and the current memory vector $h_r^t$. Attention weights over the view vectors are computed against the memory vector, and their weighted sum $\hat{o}_r$, or its affine transformation to $\mathbb{R}^q$, is returned.

### 4 Training

Both the sender and receiver are jointly trained in order to maximize the score $s^*(o_s, \hat{o}_r)$. Our per-instance loss function $L_s^i$ is the sum of the classification loss $L^i_c$ and the reinforcement learning loss $L^i_B$. The classification loss is a usual cross-entropy loss defined as

$$L^i_c = \log p(o_s^* = 1),$$

where $o_s^* \in O_R$ is the view of the correct object. The reinforcement learning loss is defined as

$$L^i_B = \sum_{t=1}^T \left( (R - B_s(o_s, m_{r}^{t-1})) \sum_{j=1}^d \log p(m_{s,j}^t) + (R - B_r(m_{r}^t, h_r^{t-1}))(\log p(s^t) + \sum_{j=1}^d \log p(m_{r,j}^t)) \right),$$

where $R$ is a reward given by the ground-truth mapping $s^*$. This reinforcement learning loss corresponds to REINFORCE [18]. $B_s$ and $B_r$ are baseline estimators for the sender and receiver, respectively, and both of them are trained to predict the final reward $R$, as suggested by Mnih and Gregor [21]:

$$L^i_B = \sum_{t=1}^T (R - B_s(o_s, m_{r}^{t-1}))^2 + (R - B_r(m_{r}^t, h_r^{t-1}))^2.$$
The final per-instance loss can then be written as

\[
L_i = L^c_i + L^r_i - \sum_{t=1}^{T} (\lambda_s H(s^t) + \lambda_m \sum_{j=1}^{d} (H(m_{s,j}^t) + H(m_{r,j}^t))),
\]

where \(H\) is an entropy, and \(\lambda_s \geq 0\) and \(\lambda_m \geq 0\) are regularization coefficients. We minimize this loss by computing its gradient with respect to the parameters of both the sender and receiver and taking a step toward the opposite direction.

5 Experimental Settings

5.1 Data Collection and Preprocessing

We collect a new dataset consisting of images and textual descriptions of mammals. We crawl the nodes in the subtree of the “mammal” synset in WordNet [22]. For each node, we collect the word \(o\) and the corresponding textual description \(o_r\) in order to construct the object set \(O\) and the receiver’s view set \(O_R\). For each word \(o\), we query Flickr to retrieve as many as 650 images, after filtering out duplicates using dHash [23] and discarding any image with a category beyond the 398-th most frequent one, as classified by a pretrained ImageNet classifier [24]. These images form the sender’s view set \(O_S\).

We sample 70 mammals from the subtree and build three sets from the collected data. First, we keep a subset of sixty mammals for training (550 images per mammal) and set aside data for validation (50 images per mammal) and test (20 images per mammal). This constitutes the in-domain test, that measures how well the model does on mammals that it is familiar with. We use the remaining ten mammals to build an out-of-domain test set, which allows us to test the generalization ability of the sender and receiver to unseen objects, and thereby to determine whether the receiver indeed relies on the availability of a different mode from the sender.

In addition to the mammals, we build a second test set consisting of 10 different types of insects. To construct this transfer test, we uniformly select 100 images per insect at random from the ImageNet dataset [25], while the descriptions are collected from WordNet, similarly to the mammals. The test is meant to measure an extreme case of zero-shot generalization, to an entirely different category of objects (i.e., insects rather than mammals and images from ImageNet rather than Flickr).

**Image Processing** Instead of a raw image, we use features extracted by ResNet-34 [26]. With the attention-based sender, we use 64 \((8 \times 8)\) 512-dimensional feature vectors from the final convolutional layer. Otherwise, we use the 512-dimensional feature vector after average pooling those 64 vectors. We do not fine-tune the network.

**Text Processing** Each description is lowercased. Stopwords are filtered using the Stopwords Corpus included in NLTK [27] and each description is constrained to include at most one copy of any word. The average description length is 9.1 words with a standard deviation of 3.16. Because our dataset is relatively small, especially in the textual mode, we use pretrained 100-dimensional GloVe word embeddings [28]. With the attention-based receiver, we consider a set of such GloVe vectors as \(o_r\), and otherwise, the average of those vectors is used as the representation of a description.

5.2 Models and Training

**Feedforward Sender** When attention is not used, the sender is configured to have a single hidden layer with 256 \(\tanh\) units. The input \(o_s\) is constructed by concatenating the image vector, the receiver’s message vector and their point-wise difference and point-wise product. The attention-based sender uses a bilinear function for computing attention weights, followed by a single hidden layer with 256 rectified linear units.

**Recurrent Receiver** The receiver is a single hidden-layer recurrent neural network with 64 gated recurrent units. When the receiver is configured to use attention over the words in each description, we use a feedforward network with a single hidden layer of 64 rectified linear units.
**Baseline networks**  The baseline networks \( B_s \) and \( B_r \) are both feedforward networks with a single hidden layer of 500 rectified linear units each. The receiver’s baseline network takes as input the recurrent hidden state \( h_{t-1} \) but does not backpropagate the error gradient through the receiver.

**Training and Evaluation**  We train both the sender and receiver as well as associated baseline networks using RMSProp \([29]\) with learning rate set to \( 10^{-4} \) and minibatches of size 64 each. The coefficients for the entropy regularization, \( \lambda_i \) and \( \lambda_m \), are set to 0.08 and 0.01 respectively, based on the development set performance from the preliminary experiments. Each training run is early-stopped based on the development set accuracy. We evaluate each model on a test set by computing the accuracy@\( K \), where \( K \) is set to be 10% of the number of categories in each of three test sets. In order to avoid a trivial solution, the maximum length of any conversation is strictly capped at 10.

**Code**  The Sender and Receiver are implemented using Pytorch \([30]\) and are available on Github \([1]\).

### 6 Result and Analysis

We examine various aspects of the emergent communication protocol between agents. First, we test the hypothesis that multi-step communication leads to a gradual information exchange that informs a better prediction. Specifically, we analyze the effect of conversation length and how it relates to prediction confidence; and examine how a decision is reached. We then investigate the communication protocol and find that its distribution somewhat resembles that of natural language. Lastly, we explore properties of the architecture, and show how higher communication bandwidth improves generalization capability.

**Effect of Conversation Length**  We train a pair of agents with an adaptive conversation length in which the receiver may terminate the conversation early based on the stop probability. We set the maximum length of conversation to be 10. Once training is done, we inspect the accuracy per the conversation length by partitioning the test examples into length-based bins.

We present the accuracies against the conversation lengths (automatically determined by the receiver) in Fig. 1. We notice a clear trend with the in-domain test set that examples for which the conversations are shorter are better classified, indicating that they are easier. It is important to remember that the receiver’s stop probability is not artificially tied to the performance nor confidence of the receiver’s prediction, but is simply learned by playing the proposed game. A similar trend can be observed with the out-of-domain test set, however, to a lesser degree. This trend of longer conversation for more difficult objects is also found with humans in the game of 20 questions \([31]\).

**Conversation length and confidence**  With the agents trained with an adaptive conversation length, we can investigate how the uncertainty in communication, or message distributions, between the two agents and prediction by the receiver evolves. We plot the evolution of the entropy of the prediction distribution in Fig. 2(a) averaged per conversation length. We first notice that the conversation length, determined by the receiver on its own, correlates well with the prediction confidence (measured as negative entropy) of the receiver. Also, it is clear on the in-domain test set that the entropy almost monotonically decreases over the conversation, and the receiver terminates the conversation when the predictive entropy converges. This trend is however not apparent with the out-of-domain test set, which we attribute to the difficulty in zero-shot generalization.

In Fig. 2(b), we plot the entropies of the message distributions by the sender and receiver. We notice that the entropy decreases for the receiver, while it increases for the sender, as the conversation pro-

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1. https://github.com/nyu-dl/MultimodalGame
2. Accuracy scores in relation to the number of questions were obtained via personal communication.
This observation can be explained by the following conjecture. As the receiver accumulates information transmitted by the sender, a set of possible queries to send back to the sender shrinks, and consequently the entropy decreases. On the other hand, as the receiver’s message becomes more complicated, the number of ways in which the sender could answer the receiver’s query increases, thereby increasing the entropy of the sender’s message distribution. We notice a similar trend on the out-of-domain test set as well.

**Decision making over a conversation** A conversation, or a series of message exchanges, between the sender and receiver is conducted in order to distinguish among many different objects. The initial message from the sender would give a rough idea of the high-level category that an object belongs to. From there on, the conversation is an attempt at distinguishing different objects in that high-level category. In other words, objects in a single such cluster, which are visually similar due to the sender’s access to the visual mode of an object, are predicted at different time steps in the conversation.

We verify this hypothesis by visualizing how the predictive probabilities of the receiver evolve over a conversation. In Fig. 3 we show two example categories – kangaroo and wolf. As the conversation, which is the process of information gathering for the receiver, progresses, similar, but incorrect categories receive smaller probabilities than the correct one does. We notice a similar trend with all the other categories.

**Message Analysis: a binary message as a bag of words** As briefly mentioned in Sec. 2, where the proposed game is defined, the message set $S$ consists of all possible binary vectors, and they could be thought of as a bag-of-words representation of a sentence. That is, a $d$-dimensional binary message may be considered as an indicator vector of which of $d$ words from a vocabulary occur in a sentence. This perspective lets us conduct more fine-grained analysis on the language created by the agents.

Here we look at the word frequency. By considering each binary vector as a sentence, we aggregate all the sentences and count how frequently each bit occurs. This is shown in Fig. 4(a). Similarly to what we often observe in natural languages, we see that some bits are frequently used, while some others are only rarely used. Up to approximately 20-th bit, this frequency distribution follows Zipf’s
law similarly to most natural languages. The importance, or influence, of each bit toward the accuracy is approximately related to these frequencies, and we observe in Fig. 4(b) that up to 20 least-frequent bits can be dropped without sacrificing the accuracy too much. This is similar to a common practice in natural language processing, where a shortlist of only $K$-most frequent words is used.

**Effect of the message dimensionality** We then vary the dimensionality $d$ of each message to investigate the impact of the constraint on the communication channel, while keeping the conversation length adaptive. We generally expect a better accuracy with a higher bandwidth. More specifically, we expect the generalization to unseen categories (out-of-domain test) would improve as the information bandwidth of the communication channel increases. When the bandwidth is limited, the agents will be forced to create a communication protocol highly specialized for categories seen during training. On the other hand, the agents will learn to decompose structures underlying visual and textual modes of an object into more generalizable descriptions with a higher bandwidth channel.

The accuracies reported in Fig. 5 agree well with this conjecture. On the in-domain test set, we do not see significant improvement nor degradation as the message dimensionality changes. We observe however a strong correlation between the message dimensionality and the accuracy on the out-of-domain test set. With 32-dimensional messages, the agents were able to achieve up to 45% accuracy@7 on the out-of-domain test set which consists of 10 mammals not seen during training.

**Effect of Attention Mechanism** All the experiments so far have been run without attention mechanism. We train additional three pairs of agents with 32-dimensional message vectors; (1) attention-based sender, (2) attention-based receiver, and (3) attention-based sender and attention-based receiver.

On the in-domain test set, we are not able to observe any improvement from the attention mechanism on either of the agents. We did however notice that the attention mechanism (attention-based sender) significantly improves the accuracy on the transfer test set from 16.9% up to 27.4%. We conjecture that this is due to the fact that attention allows the agents to focus on the aspects of the objects (e.g. certain words in descriptions; or regions in images) that they are familiar with, which means that they are less susceptible to the noise introduced from being exposed to an entirely new category. We leave further analysis of the effect of the attention mechanism for future work.

**7 Conclusion**

In this paper, we have proposed a novel, multi-modal multi-step referential game, for building and analyzing communication-based neural agents. The design of the game enables more human-like communication between two agents, by allowing a variable-length conversation with a symmetric language. The conducted experiments and analyses reveal interesting properties of the communication protocol, or artificial language, that emerges from learning to play the proposed game. First, the sender and receiver are able to adjust the length of the conversation based on the difficulty of predicting the correct object. The length of the conversation is found to (negatively) correlate with the confidence of the receiver in making predictions. Second, the receiver gradually asks more specific questions as the conversation progresses. This results in an increase of entropy in the sender’s message distribution, as there are more ways to answer those highly specific questions. Furthermore, we observe a power-law distribution of messages in the emergent communication protocol that is similar to the types of distributions usually found in actual natural languages. Lastly, we observe that increasing the bandwidth of communication, measured in terms of the message dimensionality, allows for improved zero-shot generalization.

**Limitations** Despite the significant extension we have made to the basic referential game, the proposed multi-modal, multi-step game also exhibits a number of limitations. First, an emergent language from this game is not entirely symmetric as there is no constraint that prevents the two
agents from partitioning the message space. This could be addressed by having more than two agents interacting with each other while exchanging their roles, which we leave as future work. Second, the message set \( S \) consists of fixed-dimensional binary vectors. This choice effectively prevents other linguistic structures, such as syntax. Third, the proposed game, as well as any existing referential game, does not require any action, other than speaking. This is in contrast to the first line of research discussed earlier in Sec. 1 where communication happens among active agents. We anticipate a future research direction in which both of these approaches are combined.

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