# The spontaneous emergence of discrete and compositional messages

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## Abstract

blah blah blah


## 1 Introduction

In a signalling game, artificial agents communicate to achieve a common goal: a sender sees some piece of information and produces a message, this message is then sent to a receiver that must take some action. If the action is appropriate, the whole communication stream, and in particular the choice of the message, is reinforced. For instance, in a referential game, sender and receiver see a set of objects, and the sender must send a message to the receiver, so that the receiver can pick up the right object, as determined in advance for the sender, but unbeknownst to the receiver.

## 2 Function Games

We here introduce a general communication game setting, which we call Function Games. Our games contain three basic components: (i) a set of contexts $C$, (i) a set of actions $A$, (ii) a family of functions $F$, from contexts to actions. One play of a Function Game game runs as follows:

1. Nature chooses $f \in F$ and a context $c \in C$.
2. Sender sees the context $c$ and $f(c)$. I like f(c) here, but f is a bit more appropriate. What do you all think?
3. Sender sends a message $m$ to Receiver.
4. Receiver sees *a possibly different* context $c'$ and the message $m$ and chooses an action $a'$.
5. Both are 'rewarded' iff $a' = f(c')$.

Two concrete interpretations will be helpful in illustrating the various components.

**Generalized referential games.** A reference game is one in which Sender tries to get Receiver to pick the correct object out of a given set (Skyrms, 2010; Lazaridou et al., 2017, 2018; Havrylov and Titov, 2017; Chaabouni et al., 2019). Here, contexts are sets of objects (i.e. an $m \times n$ matrix, with $m$ objects represented by $n$ features). Normally (though we will drop this assumption later), $c' = \texttt{shuffled}(c)$: Sender and Receiver see the same objects, but in a different arrangement. Actions are the objects, and the functions $f \in F$ are *choice functions*: $f(c) \in c$ for every context $c$.

**Belief update games.** Contexts can represent possible belief states for the agents. Letting $A = C$, the functions will then be 'belief update' functions, representing e.g. how to update an agent's beliefs in the light of learning a new piece of information.

What should we cite here? Something from dynamic semantics?

## 3 Experiment

Because we are interested in the simultaneous emergence both of discrete signals and of compositional messages, we use a Function Game called the Extremity Game designed to incentivize compositionality (Steinert-Threlkeld, 2019). This is a generalized referential game, where objects are represented as $n$-dimensional vectors, with each value corresponding to the degree to which it has a gradable property. For instance, objects could be shaded circles, with two values, one for their diameter and one for their darkness. For the functions, we set $F = \{\arg\min_i, \arg\max_i : 0 \leq i < n\}$. These may incentivize the emergence of communication protocols with messages like 'small + EST' and 'dark + EST'.

### 3.1 Model

Our model resembles an encoder-decoder architecture, with the Sender encoding the context/target pair into a message, and the Receiver decoding the message (together with its context $c'$) into an action. Both the encoder and decoder are multi-layer perceptrons with two hidden layers of size 64 and rectified linear (ReLU) activation (Nair and Hinton, 2010; Glorot et al., 2011). Figure 1 depicts this architecture. I gleaned this from the code; please correct if I'm wrong.

### 3.2 Game Parameters

In our experiments, we manipulated the following parameters of the Extremity Game:

- Context strictness. In *strict* contexts, every object is the $\arg\max$ or $\arg\max$ of exactly one dimension. This means that there is a one-to-one (and onto) correspondence between $F$ and $A = C$.[1] In *non-strict* contexts, no such restriction is imposed.

  We considered strict contexts with Nur: add number 10 objects (5 dimensions) and non-strict contexts with Nur: add objects.

- Context identity. In the *shared* setting, Receiver sees a shuffled version of Sender's context ($c' = \texttt{shuffled}(c)$). In the *non-shared* setting, Receiver's context $c'$ is entirely distinct from Sender's. This may incentivize compositional messages, since Sender cannot rely on the raw properties of the target object in communication.

- Object size: in all experiments, objects had 5 dimensions. Verify that this is correct

- Latent space (message) dimension: in all experiments, the latent space had 2 dimension.

For each setting of the above parameters, we ran 20 trials with different random seeds.

### 3.3 Training Details

As mentioned earlier, by using a continuous latent space, the entire model, including the communication channel, is differentiable and so can be trained end-to-end using backpropagation to compute gradients. We used the Adam optimizer (Kingma and Ba, 2015) with learning rate 0.001, $\beta_1 = 0.9$, and $\beta_2 = 0.999$. I gleaned this from the code; please correct if I'm wrong. Can move to an Appendix if need space.

Code and data will be made available once the paper can be de-anonymized.

[1]These are the contexts used in (?).

## 4 Results

### 4.1 Communicative success

### 4.2 Discrete signals

### 4.3 Compositionality

## 5 Discussion

## 6 Conclusion

## References

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Here be a graphic of our model.

Figure 1: Model architecture caption