The spontaneous emergence of discrete and compositional messages

Anonymous ACL submission

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), $c' = \text{shuffled}(c)$: 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.*
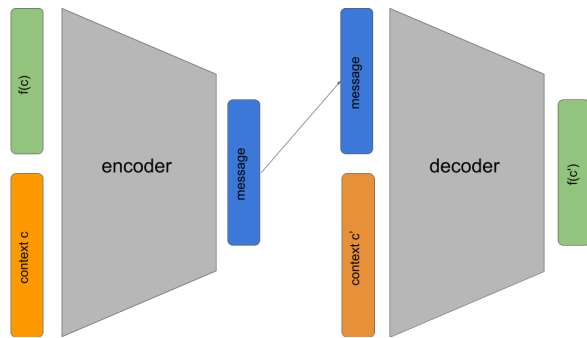

Figure 1: Model architecture caption *Do we really need this? It isn't super informative and might use too much space. I can also do something in TikZ if we think it's important and that this one is ugly.*

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 ($c' = \text{shuffled}(c)$). 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.

---

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

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.

4 Results

4.1 Communicative success

4.2 Discrete signals

4.3 Compositionality

5 Discussion

6 Conclusion

References

Rahma Chaabouni, Eugene Kharitonov, Emmanuel Dupoux, and Marco Baroni. 2019. Anti-efficient encoding in emergent communication. In *Proceedings of the 33rd Conference on Neural Information Processing Systems (NeurIPS 2019)*.

Xavier Glorot, Antoine Bordes, and Yoshua Bengio. 2011. Deep Sparse Rectifier Neural Networks. In *14th International Conference on Artificial Intelligence and Statistics (AISTATS)*, pages 315–323.

Serhii Havrylov and Ivan Titov. 2017. Emergence of Language with Multi-agent Games: Learning to Communicate with Sequences of Symbols. In *Proceedings of the 31st Conference on Neural Information Processing Systems (NeurIPS 2017)*.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A Method for Stochastic Optimization. In *International Conference of Learning Representations (ICLR)*.

Angeliki Lazaridou, Karl Moritz Hermann, Karl Tuyls, and Stephen Clark. 2018. Emergence of Linguistic Communication from Referential Games with Symbolic and Pixel Input. In *International Conference of Learning Representations (ICLR 2018)*.

Angeliki Lazaridou, Alexander Peysakhovich, and Marco Baroni. 2017. Multi-Agent Cooperation and the Emergence of (Natural) Language. In *International Conference of Learning Representations (ICLR2017)*.

Vinod Nair and Geoffrey E Hinton. 2010. Rectified Linear Units Improve Restricted Boltzmann Machines. In *Proceedings of the 27th International Conference on Machine Learning (ICML)*.

Brian Skyrms. 2010. *Signals: Evolution, Learning, and Information*. Oxford University Press.

Shane Steinert-Threlkeld. 2019. Paying Attention to Function Words. In *Emergent Communication Workshop @ NeurIPS 2018*.