Emergent Communication in a Multi-modal, Multi-step Referential Game

NYU

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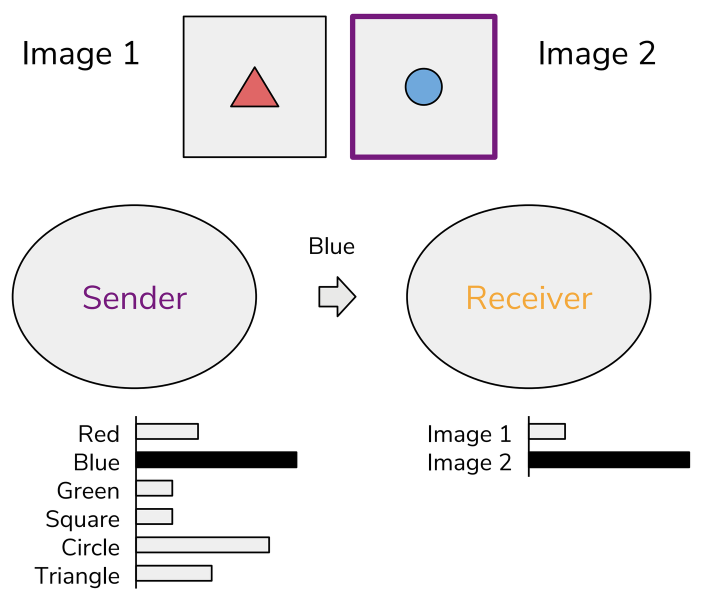
Overview

This works presents a novel referential game where the Sender and Receiver are grounded in two separate modalities, have an adaptive conversation length, and learn a communication protocol.

We find that the agents vary conversation length according to the difficulty of the task and gradual information exchange informs better predictions.

Referential Games

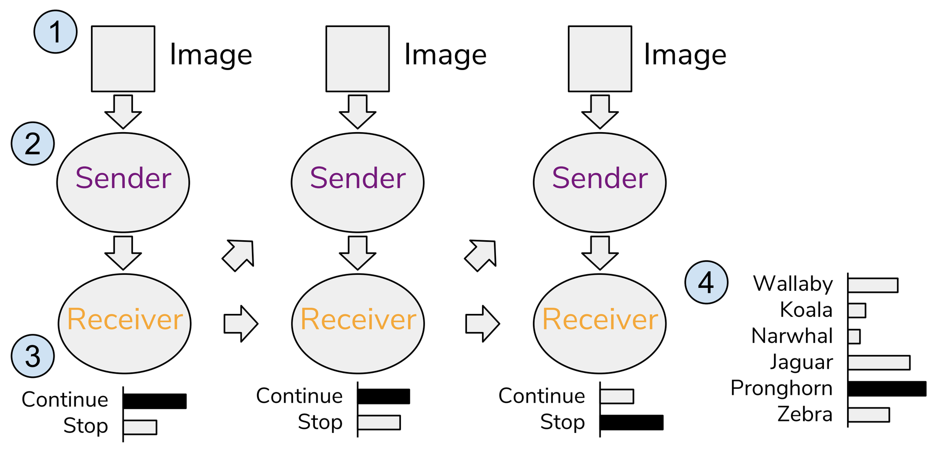


An example Referential Game where both agents see the images, the Sender knows the target image, and it may send one message to the Receiver [Lazaridou et al., 2017].

Other setups have been studied such as one where the Sender and Receiver have a conversation of fixed length, the Receiver may send a single discrete token from a small vocabulary, and the Sender may only answer yes or no [Jorge et al., 2016].

Paper (arXiv)
1705.10369

This Work



1. The image features are extracted using a pre-trained network.
2. The Sender incorporates the image and the Receiver's message (if it's available) to generate a message for the Receiver.
3. The Receiver incorporates the class descriptors, the Sender's message, and its own hidden state to generate a message for the Sender.
4. When the conversation terminates, the Receiver predicts the image's most likely class.

Per-Instance Loss:

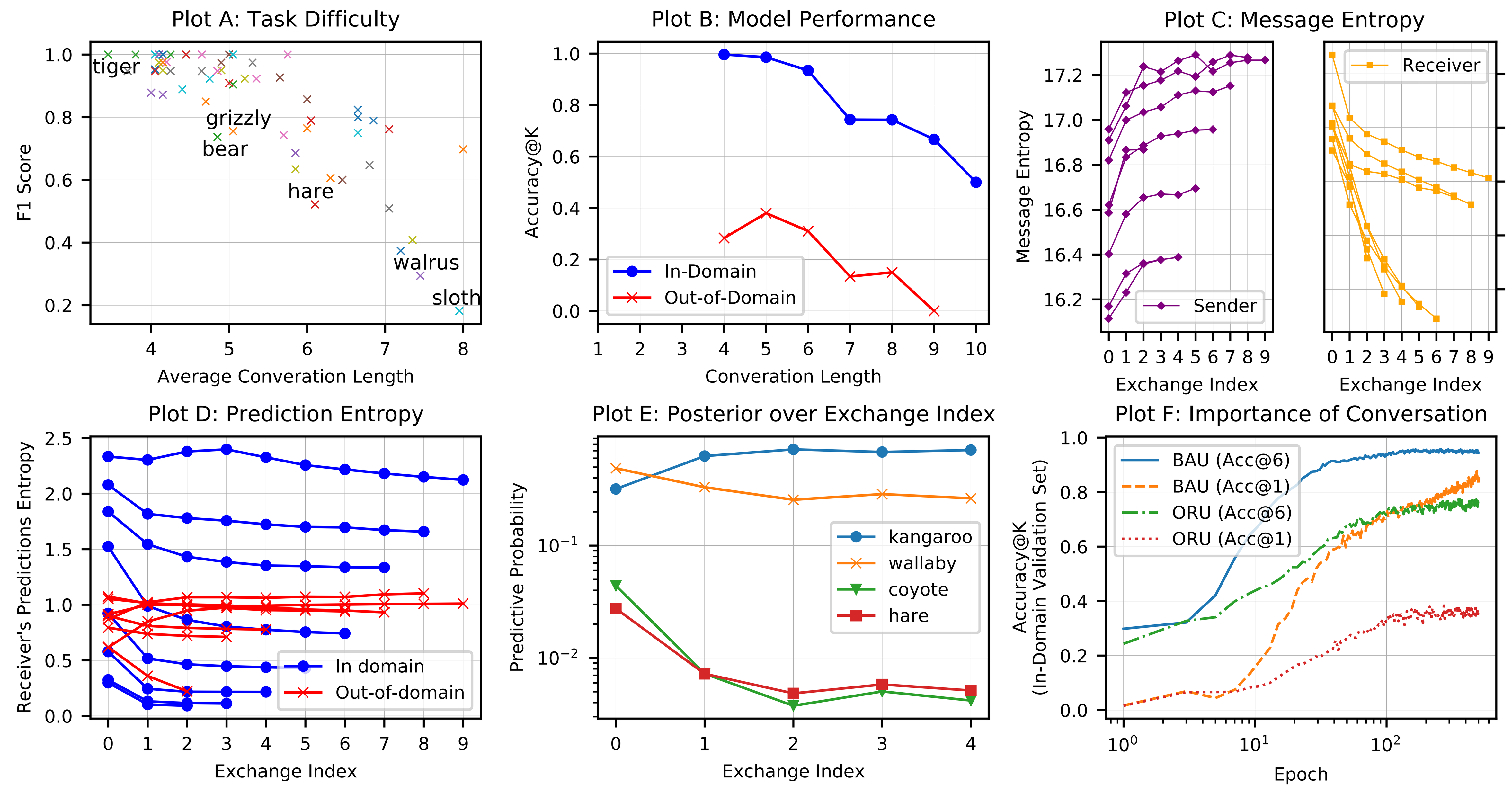
$$L^i = L^i_c + L^i_r - H^i_{stop,sen,rec}$$

- L^i_c is the classification loss.
- L^i_r is the reinforcement learning loss.
- $H^i_{stop,sen,rec}$ is the entropy regularization on the Sender's messages, the Receiver's messages, and the Receiver's stop-bit.

Experimental Setup

In-Domain: 60 mammals with 550 images per mammal for training, 50 validation, and 20 test.
Out-of-Domain: 10 mammals with 20 images.
Transfer: 10 insects with 100 images.

Results



Analysis

- There's a significant negative relationship between class difficulty and the average conversation length [Plot A].
- Examples for which conversations are shorter are better classified [Plot B].
- As the conversation progress, the Receiver's messages become more specific [Plot C right] and the Sender's messages become less certain [Plot C left].
- The conversation length correlates well with the Receiver's prediction confidence [Plot D].
- As the Receiver gathers more information, similar but incorrect categories receive smaller probabilities than the correct one [Plot E].
- The learned protocol was more effective when communication was bidirectional [Plot F].

References

[Jorge et al., 2016] Jorge, E., Kågebäck, M., and Gustavsson, E. (2016). Learning to play guess who? and inventing a grounded language as a consequence. In *Deep Reinforcement Learning Workshop at NIPS*.

[Lazaridou et al., 2017] Lazaridou, A., Peysakhovich, A., and Baroni, M. (2017). Multi-agent cooperation and the emergence of (natural) language. In *Proceedings of ICLR*.

Code (Github)
nyu-dl/MultimodalGame