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Focus on What's Informative and Ignore What's not: Communication Strategies in a Referential Game

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Abstract

Research in multi-agent cooperation has shown that artificial agents are able to learn to play a simple referential game while developing a shared lexicon. This lexicon is not easy to analyze, as it does not show many properties of a natural language. In a simple referential game with two neural network-based agents, we analyze the object-symbol mapping trying to understand what kind of strategy was used to develop the emergent language. We see that, when the environment is uniformly distributed, the agents rely on a random subset of features to describe the objects. When we modify the objects making one feature non-uniformly distributed, the agents realize it is less informative and start to ignore it, and, surprisingly, they make a better use of the remaining features. This interesting result suggests that more natural, less uniformly distributed environments might aid in spurring the emergence of better-behaved languages.

1 Introduction

Recent work on language emergence in a multi-agent setup showed that the interaction between agents performing a cooperative task while exchanging discrete symbols can lead to the development of a successful communication system [4, 2, 15, 3]. This language protocol is fundamental to solve the task, since lack of communication results in performance decrease [13].

One of the simplest configurations is the setup where two artificial agents play a referential game [12, 6, 1]. An agent receives a target object, and it must communicate about it to another, which is then tasked to recognize the target in an array of similar items. The set of all distinct messages exchanged by the agents is their communication protocol. The emergent protocol is strictly dependent on the distribution of items used in the game. In fact, when the agents interact while playing the game, the language gets grounded in the environment represented by the objects. Ideally, as it is the case for natural language, we would like to see an emergent protocol that reflects the structure of the environment. For instance, when using messages of 3 symbols, if the target object is a red, full, square and its generated description is *qry*, *q* could refer to the fact the object is red, *r* could be related to its texture being full and *y* could communicate that the object to be described is a square, and this would suffice to discriminate it among set of similar items. Similar results have indeed been found in experiments on artificial language evolution with human subjects [11, 17].

However, analyzing agents language is not trivial, as it does not necessarily possess properties of natural language such as consistency or compositionality. Different works have proposed a qualitative analysis of the object-message mapping performed by the agents [4], others have performed an analysis of the purity of learned symbols with regards to clustered items [12].

In this work our goal is to understand if the agents develop a communication strategy that focus on describing salient features of the objects. We study the symbol-object mapping in a simple referential game, and how such association changes when the objects in the environment have different statistical properties, trying to assess how much information is shared between the object and the emergent protocol. Borrowing from information theory, mutual information (MI) has been used to asses form-to-meaning mapping in natural [16] as well as emergent quantifies how many bits of information can we obtain about a distribution by observing a different one. Using mutual information between object and message distribution, we show that when the environment is uniformly distributed, the agents communicate about an arbitrary subset of the features of the objects. When instead an environment where some features are less informative than others is used, the agents learn to ignore those uninformative features, while adapting to better use a subset of the remaining ones.

2 Experimental Setup

Two agents, a sender and a receiver, cooperate in a referential game where the sender has to describe a discrete-valued target vector to the receiver, that must distinguish it from a distractor (random baseline performance is consequently at 50%).

Data In order to test form-to-meaning mapping variations with objects having different distributions, we generate two sets of 5-dimensional discrete vectors. In one, the feature vectors are uniformly distributed, in the other one feature has a highly skewed value distribution. In the first configuration (uniform environment) each value of the 5 features can be between 1 and 4, each with probability 0.25. In the second configuration (skewed environment), the first feature takes value 1 with probability 0.75, value 2 with probability 0.15, and values 3 and 4 with 0.05 probability. This leads to configurations with $4^5 = 1024$ distinct vectors each. We randomly sampled target-distractor pairs to generate training, validation and testing partitions (128K, 16K and 4K pairs, respectively). The test data was used to asses the generalization capabilities of the agents on unseen pairs.

Game and Network Architectures The sender and receiver agents are parametrized with two Vanilla RNNs. The sender linearly transforms the target vector and feeds it into its RNN. Through the Gumbel-Softmax trick [14, 7], it then generates a message that is passed to the receiver. The receiver processes the message through its own RNN generating an internal representation of the target description. It linearly processes the pair of vectors it is fed (where target/distractor order is randomized), and it computes a similarity score through a dot product between each element in the pair and the message representation. The highest score is then used to recognize the target. Both sender and receiver RNNs are single-layer networks with 50 hidden units and embed the messages into vectors of dimensionality of 10. For the reparametrization through the Gumbel-softmax, temperature τ is kept fixed at 1.

Training and hyperparameter search We train the agents to optimize the cross entropy loss using backpropagation and the Adam optimizer [10]. Vocabulary was fixed to 1100, which in our setup ensures that the agent could in principle develop a one-to-one mapping between input vectors and symbols. The agents were trained for 50 epochs (after which, they had always converged). We conducted an hyperparameter search varying batch size (32, 64, 128, 256, 512) and sender and receiver learning rates (from 0.01, until 0.0001). We cross-validated the top 20 performing models with 5 different initialization seeds, using the uniform data-set. The best performing model uses batches of size 64, with both sender and receiver trained with a learning rate of 0.001 and an accuracy of 99.04%. For both the uniform and skewed data-sets experiments, we will report results averaged 1,000 runs (10 data-set initialization seeds times 100 network initialization seeds). A small number of runs did not complete. All experiments were performed using the EGG toolkit [8].

Mutual information as a measure of form-to-meaning mapping We want to measure to what extent the sender is referring to each feature of the target vector. We measure the consistency in

feature-symbol mapping as the mutual information between each feature distribution and the symbol protocol distribution as follows [9, 5]:

$$I(m; v_i) = H(v_i) - H(v_i|m) \tag{1}$$

where $H(v_i)$ is the entropy of feature i in the target vectors and $H(v_i|m)$ is the entropy of the conditional distribution of the i -th feature given the messages. MI is a positive metric, and in our setup it is upper bounded by the first term of the difference in eq. 1, $H(v_i)$. This corresponds to a value of 2 in the uniform data configuration, where each feature in the target vector can equiprobably take a value between 1 and 4. In the skewed setup, MI is bounded to 2 for features 2, 3 and 4, and to value of 1.15 for the non-uniform feature. A high feature-protocol MI implies the agents are consistently using symbols to denote the values of the feature. A low value can be interpreted as the agents ignoring the feature when describing the vector.

3 Results

Uniform Environment Averaged accuracy and MI results are reported in Table 1. While showing good performance, the agents do not reach perfect accuracy, suggesting that they are not making full use of the feature space. Indeed, although MI has similar average values across features, we constantly observed that, in each run, three of them had a higher MI compared to the remaining two, in line with our hypothesis that the agents rely on an arbitrary subset of features to describe the target vector. In this way, they pay a small accuracy cost in exchange for lower protocol complexity. In the uniform setup, the choice of the feature subset is arbitrary. We looked next at whether we can influence it by making a feature less informative than the others.

Data	Acc.	Unique Msgs	H(msgs)	Unique Target Vectors	H(targets)
U	98.61%	50	5.46	1005	9.80
S	98.52%	46	5.35	772	8.96

Data	Mutual Information				
	Feat 1	Feat 2	Feat 3	Feat 4	Feat 5
U	0.62±0.40	0.61±0.41	0.61±0.41	0.60±0.40	0.60±0.41
S	0.07±0.06	0.84±0.41	0.84±0.42	0.82±0.41	0.76±0.42

Table 1: Top: results of the experiments performed with the uniform data distribution (U) and with the skewed one (S). Unique target vectors and unique msgs represent the distinct input vector count seen by the sender and the unique symbols count produced, respectively. H(msgs) is the entropy of the emergent protocol, the higher the value the more the message distribution approaches a uniform one. H(vectors) is the entropy of the target vectors. Bottom: mutual information and standard deviation between each target vector feature and and the message distribution.

Skewed Environment Results are also presented in Table 1. We see that accuracy is comparable in both uniform and non-uniform conditions. The unique target vectors are less in the skewed configuration than in the uniform one. We also found a lower entropy in this configuration as having a non-uniform feature makes sampling the same object more likely. The number of unique messages produced, as well as their entropy, is only very slightly lower in the skewed configuration (8% less message for 30% less target vectors), making us think that messages are used effectively. Similarly to the uniform environment, also in the the skewed configuration we see close average values of MI across all the uniform features, although, again, in specific runs 3 arbitrary features would have particularly high MIs. We confirm that making one feature in the environment non-uniform leads the agents to ignore it (MI value of 0.07). More surprisingly, we see higher average MI values for the remaining features compared to the uniform simulation (features 2, 3 and 4 show a 30% MI increase, feature 5 a 26% increase). This suggests that making one feature less informative has led the agents to make a better use of the other features, compared to when they have to choose from a larger set of equally informative ones.

4 Conclusion and future work

In order to understand agents' communicative strategy and how it relates to salient features of the items in the environment, we presented quantitative evidence of the relation between objects in the environment and the language protocol developed. Using the referential game setting and tools from information theory we showed that the agents rely on an arbitrary subset of the input features to describe target objects. We also discovered that if we assign a more skewed distribution to a feature of the environment, they learn to ignore it, as it is less informative in terms of trying to discriminate a target among similar items. Moreover, with this non-uniform distribution, the agents adapt to make a better use of the remaining ones. As future work, we plan first of all to understand how consistent this effect is, what causes it, and under which natural distributions it is more likely to emerge. We want moreover to extend the analysis to games using variable length messages, studying how form-to-meaning mapping might relate to language properties like compositionality. Another direction will be to analyze the mapping in richer environments having a greater number of objects and dimensions. We believe that a better understanding of the object-symbol mapping as well as of the related strategies used to develop the emergent protocol will be useful to design better environments to test neural artificial agents and enforce the emergence of a more human-like language protocol.

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