Structural Inductive Biases in Emergent Communication

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Abstract

In order to communicate, humans flatten a complex representation of ideas and their attributes into a single word or a sentence. We investigate the impact of representation learning in artificial agents by developing graph referential games. We empirically show that agents parametrized by graph neural networks develop a more compositional language compared to bag-of-words and sequence models, which allows them to systematically generalize to new combinations of familiar features.

Keywords: emergent communication; graph neural networks; language compositionality

Introduction

Human language is characterized by the ability to generate a potentially infinite number of sentences from a finite set of words. In principle, humans can use this ability to express and understand complex hierarchical and relational concepts, such as kinship relations and logical deduction chains. Existing multi-agent communication systems fail to compositionally generalize even on constrained symbolic data [Kottur et al., 2017]. For instance, if a person knows the meaning of utterances such as 'red circle' and 'blue square', she can easily understand the utterance 'red square' even if she has not encountered this particular combination of shape and color in the past. This type of generalization capacity is referred to as *compositionality* [Smith et al., 2003, Andreas, 2019, Baroni, 2020] or *systematic generalization* [Bahdanau et al., 2019].

The ability to represent complex concepts and the relationships between them in the manner of a mental graph was found to be one of the key factors behind knowledge generalization and prolonged learning in humans [Bellmund et al., 2018]. Through communication, humans flatten the non-Euclidean representation of ideas into a sequence of words. Advances in graph representation learning [Kipf and Welling, 2017] and sequence decoding [Sutskever et al., 2014, Cho et al., 2014] provide the means for simulating this *graph linearization* process in the artificial agents.

In *emergent communication* studies, learning agents develop a communication protocol from scratch through solving a

shared task, most commonly a *referential game* [Lazaridou et al., 2018, Guo et al., 2020]. Modelling communication as an interactive, goal-driven problem mitigates some of the issues observed in supervised training, such as sample inefficiency and memorizing superficial signals rather than discovering the real factors of variation in the data [Lake et al., 2017, Baroni, 2020].

In this work, we analyze the effect of varying the input representation and the corresponding representation learning method on compositional generalization in referential games. Given the recent resurgence of strong structural bias in neural networks, we evaluate the hypothesis that graph representations encourage compositional generalization [Battaglia et al., 2018] in emergent communication.

Related work

In prior work using referential games, input data is represented as sequences and bags-of-words [Lazaridou et al., 2018, Bouchacourt and Baroni, 2018] with few instances of using images as input [Lazaridou et al., 2018, Evtimova et al., 2018] and one instance of using graph encoders without a sequence decoder [Słowik et al., 2020, Gupta et al., 2020]. Notably, more information in the input does not necessarily lead to a more compositional language or higher generalization as shown in [Lazaridou et al., 2018]. Battaglia et al. [2018] claim that graph representations induce stronger compositional generalization across a variety of reasoning and classification tasks. Recent work in relational reasoning [Sinha et al., 2019] supports this claim.

Environment

Referential games

A referential game involves two agents of fixed roles: the *speaker* and the *listener*. The speaker has access to the input data (*target*), which the listener cannot directly observe. The speaker sends a message describing the target and the listener learns to recognize the target based on the message. In the referential games studied in this work, the listener receives the message and a set consisting of the target and *distractors*,

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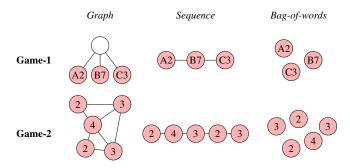


Figure 1: Structural biases in the input. Baselines of sequences and bags-of-words are constructed similarly as in the existing work on emergent communication [Kottur et al., 2017, Lazaridou et al., 2018].

new objects sampled without replacement from the target data distribution. The agents are rewarded if and only if the receiver recognizes the target, and not for the messages sent. In the existing work, target and distractors are represented as bags-of-words, sequences or images. See the **Training** section for details on training.

Graph referential games

We extend existing referential games by developing graph referential games: *Game-1* and *Game-2*. We include corresponding representations of a lower degree of structure in order to study the effect of varying the input representation (Figure 1).

Game-1: hierarchy of concepts and properties In this game, we construct a tree from a vector of $[p_1, p_2, ..., p_n]$ (which we will refer to as *perceptual dimensions*) where n corresponds to the number of properties and $p_1, p_2, ..., p_n$ denote the number of possible types per property. Each tree has the same number of properties n and they only differ in the property values. Formally, each tree is an undirected graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$ where \mathcal{V} is the set of all nodes representing unique properties along with a 'central' node, and \mathcal{E} is the set of edges. The central node corresponds to a conceptually more abstract representation of the input, which is initially empty and then learned by a graph agent based on the object properties. The node features consist of a concatenation of the property encoding and the type encoding (represented as one-hot vectors).

Game-2: relational concepts In this game, we evaluate the graph agents using arbitrary undirected graphs of varying edges. Such graphs can be used to represent relations between arbitrary entities, e.g. connections between users of a social media platform. In Game-2, each undirected graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$ is defined over the set of nodes \mathcal{V} and the set of edges \mathcal{E} . In a given instance of the game, $|\mathcal{V}|$ is fixed for all targets and distractors. The number of edges varies across the graphs. We add a self-loop to each node to include its own features in the

node representation aggregated through message passing. We use node degrees converted to one-hot vectors as the initial node features.

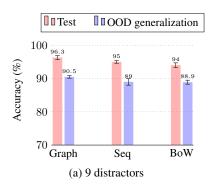
Baseline agents In each instance of the game, the speaker is parametrized by an encoder-decoder architecture and the listener is implemented as a classifier over the set consisting of the target and distractors. We use generic Bag-of-Words2Sequence and Sequence2Sequence (Seq2Seq) [Sutskever et al., 2014] models over the node features as baseline speakers, and corresponding classifiers as listeners.

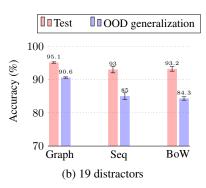
Graph agents In order to handle graph input, the speaker and the listener are parametrized using a graph encoder. The speaker additionally uses a sequence decoder to generate a message. The graph encoder first generates node embeddings for each node, and then it uses them to construct an embedding of the entire graph. The sequence decoder takes the graph embedding as input and generates a message. A graph encoder consists of a node representation learning method and a graph pooling method. Node representations are computed for each node v_i through neighborhood aggregation that follows the general formula $h_{v_i}^{(l+1)} = \text{ReLU}\left(\sum_{j \in N_i} h_{v_j}^{(l)} W^{(l)}\right)$, where l corresponds to the layer index, h_{v_i} are the features of the node v_i , W refers to the weight matrix, and N_i denotes the neighborhood of the node v_i . We compare a Graph Convolutional Network (GCN) [Kipf and Welling, 2017]) with GraphSAGE [Hamilton et al., 2017], an extension of GCN which allows modifying the trainable aggregation function beyond a simple convolution. A graph embedding is obtained through a linear transformation of the node features. A graph embedding vector in our graph-to-sequence implementation of the speaker corresponds to the context vector in the Seq2Seq implementation. Similarly as in Seq2Seq architectures, the sequence decoder in graph-to-sequence outputs a probability distribution over the whole vocabulary for a fixed message length which is then discretized to produce the message.

Training

The speaker produces a softmax distribution over the vocabulary V, where V refers to the finite set of all distinct words that can be used in the sequence generated by the speaker. Similar to [Sukhbaatar et al., 2016, Mordatch and Abbeel, 2018], we use the 'straight through' version of Gumbel-Softmax [Jang et al., 2017, Maddison et al., 2017] during training to make the message discrete and propagate the gradients through the non-differentiable communication channel. At test time, we take the argmax over the whole vocabulary.

In our graph referential games, the listener receives the discretized message m sent by the speaker along with the set of distractors K and the target graph d^* . The listener then outputs a softmax distribution over the |K|+1 embeddings representing each graph. The speaker f_{θ} and the listener g_{ϕ} are parametrized using graph neural networks. We formally





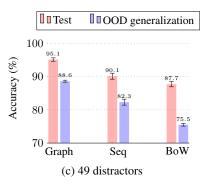


Figure 2: Standard test accuracy (Test) and out-of-domain (OOD) generalization in Game-2. Number of nodes, message length and vocabulary size are equal to 25. We report mean and standard deviation of three runs.

define it as follows:

$$m(d^*) = exttt{Gumbel-Softmax}(f_{ heta}(d^*))$$
 $o(m,\{K,d^*\}) = g_{f \phi}(m,\{K,d^*\})$

We used Deep Graph Library [Wang et al., 2019], EGG [Kharitonov et al., 2019] and PyTorch [Paszke et al., 2019] to build graph referential games. We generate 40000 train samples, 5000 validation samples and 5000 test samples in each game.

Experiments & Analysis

We investigate three questions:

- What is the effect of data representation and the corresponding representation learning models on the compositionality of the emerged language (**Topographic similarity**)?
- What is the effect of structural biases on the ability to generalize to previously unseen combinations of familiar features (Out-of-domain generalization)?
- Can the listener identify the target if it receives a distorted message? (Do agents rely on the communication channel in solving the game?).

Qualitative analysis

| Sample input data | Data representation | | |
|-------------------|---------------------|----------|---------|
| | Bag-of-words | Sequence | Graph |
| A2 B4 C6 | [1 4 4] | [5 1 3] | [7 1 4] |
| A2 B4 C5 | $[1\ 0\ 0]$ | [8 3 2] | [472] |
| A2 B2 C6 | [6 4 1] | [9 9 1] | [9 4 1] |
| A5 B4 C6 | [8 8 9] | [3 5 2] | [6 6 1] |

Table 1: Qualitative samples of messages.

In Table 1, we show sample messages generated in Game-1. Similarly as in Figure 1, we represent input properties using capital letters and property types using numbers. We see that

in the messages generated by a Graph2Seq model varying one input property (e.g. replacing C6 with C5) changes only one symbol in the message (the speaker replaces the word 1 with 2 in the utterance). In Seq2Seq, changing one symbol leads to a change of two symbols on average in the transmitted messages. In the example, the vocabulary size is 10 with message of fixed length 3 and the perceptual dimensions being [10,6,8]. When using larger input in Game-1, we experimented with the message length-to-vocabulary size trade-off (details in the **Hyperparameters** section) and we found that longer messages are less compositional. In Game-2 (Figure 2), the speaker learns to describe 25 properties in 25 words. We found that for messages of the length 25, sample messages are difficult to interpret qualitatively, as all representations lead to languages that are order invariant with respect to words (see Table 1).

Topographic similarity

We use *topographic similarity* as a measure of language compositionality, following a common practice in the domain of referential games [Lazaridou et al., 2018, Li and Bowling, 2019]. We compute a negative Spearman correlation between all the possible pairs of target objects and the corresponding pairs of emerged messages. We use cosine similarity in the input space and Levenshtein distance in the message space. For graph representations we concatenate the node features in the same order as in sequences and bags-of-words for a fair comparison.

Figure 3 shows topographic similarity (TS) of all three data representations in Game-1. All representations lead to positive values of TS, which implies that there is a positive correlation between the input features and the messages emerging in the game. On average, graph representations lead to a more compositional language (measured by greater TS) than bag-of-words and sequence representations. This effect is observed for instances of Game-1 with different numbers of distractors (19, 29, 49). We hypothesize that in more difficult communication scenarios (e.g., if the number of distractors increases), structured representations are needed for emergence of a compositional language.

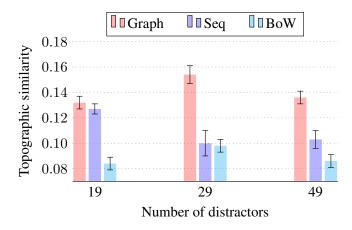


Figure 3: Topographic similarity in Game-1 with perceptual dimensions [10, 6, 8, 9, 10], a message length of size 3, and a vocabulary size of 50. We report mean and standard deviation across five random seeds.

Out-of-domain generalization

In Game-2, we compare sequences, bag-of-words and graph representations in terms of test accuracy (using a 60% / 20% / 20% train/valid/test split) and *compositional generalization* (OOD generalization). In evaluating OOD generalization, the agent sees an unseen graph/sequence/bag-of-words with a new combination of seen features. Intuitively, the agents only learn a "red dotted circle", "blue dotted square", "yellow dashed star" during training, and at test time we check if they can correctly identify the target: "red dashed square". Since both the target and distractors are new to the agents, both agents are tested for their ability to disentangle input properties.

We investigated test accuracy and OOD generalization for an increasing number of distractors (9, 19, 49). Accuracy of a random guess in these games is, respectively, 10%, 5% and 2%. Consequently, the game becomes significantly more complex as the number of distractors increases. Figure 2 shows the effect of structural priors on test accuracy and compositional generalization. Graph representations consistently lead to a better generalization to new combinations of familiar features, and this effect increases with the complexity of the game. Since for each representation we use generic agents of a comparable expression power, we hypothesize that graph representations lead to a more compositional language, especially in more difficult communication scenarios.

Do agents rely on the communication channel in solving the game?

We analyzed whether the communication channel is crucial in learning to recognize the target among distractors. Figure 4 shows the results of this analysis over the entire set of targets and messages developed by graph learning agents. We show the results for messages in the form of $\{m_1, m_2, m_3\}$ (message length ml = 3, m_i corresponds to individual symbols in the message, i = 1, 2, 3) and vocabulary size vs = 10. In each subplot, the title corresponds to the symbol m_1 in the original

message developed through playing the game. The dark bar corresponds to the number of correctly classified samples given the original message (also included in the subplot title, e.g. Symbol 0: 39.2%). We generate the remaining results by replacing the first symbol m_1 in the messages with each of the remaining symbols from the vocabulary. The rest of the message (symbols m_2 and m_3) remains fixed.

We observe that in all emerged messages distorting 1/3 of the symbols leads to a decrease in test accuracy. In all cases, the highest test accuracy is dependent on the target encoding produced by the graph speaker through playing the game.

Ablation studies on Graph Neural Networks

GraphSAGE learns aggregator functions that can induce the embedding of a new node given its features and the neigborhood, without re-training on the entire graph. The GraphSAGE encoders are thus able to learn dynamic graphs. In this paper, we experiment with commonly used 'mean', 'pool' and 'gcn' aggregator types.

Pooling methods: In order to compute the graph embedding, we experimented with the standard graph pooling methods: mean, sum and max functions. We found that the sum pooling gave a significant boost in performance, and thus we use sum pooling throughout the experiments presented in this paper.

Encoder networks: We also experimented with two popular graph neural networks to compute the graph encoding, namely GraphConv and SAGEConv. We did not find a significant difference in performance between the two models.

Aggregator types: Another axis of variation is the aggregator type used in GraphSAGE and we found that the effect of all types- 'mean', 'pool' and 'gcn' is the same across both games.

Hyperparameters

In this work, we studied generic architectures and the main axis of variation was the degree of structure in the input representation and the corresponding representation learning method. In the experiments reported in this paper, we used the a range of hyperparameters listed below (bold indicates the ones used for the charts above) that were manually tuned using accuracy as the selection criterion:

• Number of distractors: 1, 2, 4, 9, 19, 29, 49

• Vocab Size of the message: **10**, **25**, **50**, 100

• Max length of the message: 3, 4, 5, 10, 25

• Number of layers in Graph NN: 1, 2, 3

• Size of the hidden layer: 100, 200

• Size of the message embedding: **50**, 100

• Learning Rate: 0.01, **0.001**

• Gumbel-Softmax temperature: 1.0

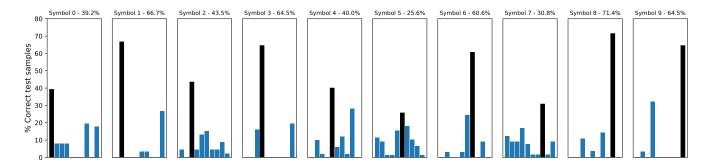


Figure 4: Robustness of the communication protocol. We use trained agents and emerged messages from Game-1 with perceptual dimensions [10, 6, 8], a message length of size 3, and a vocabulary size of 10.

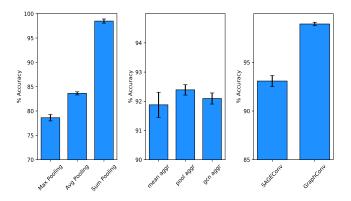


Figure 5: Ablation studies on different parameters of Graph Neural Network. The y-axis represent the test accuracy. All the runs are averaged across three different random seeds and standard error bars are shown.

For more details, please refer to the codebase. We used Nvidia V100 and Titan RTX GPUs for running our experiments. On average, the models were trained for 3-5 days depending on the #distractors and the type of data representation used with Graph2Sequence models taking the longest and Bag2Sequence models the shortest time.

Conclusion and future work

We analyzed the effect of structural inductive biases (bags-of-words, sequences, graphs) on compositional generalization in referential games. We found that graph representations induce a stronger compositional prior measured by topographic similarity and out-of-domain generalization. Graph agents learn messages that lead to the highest accuracy in solving the task. Given the advancements in using graphs in natural language processing [Vaswani et al., 2017], a future direction could be to train graph speakers to generate sentences closer to natural language [Lowe et al., 2020].

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