# Learning to learn to communicate

**Abhinav Gupta***
MILA
abhinav.gupta@umontreal.ca

**Ryan Lowe***
Facebook AI Research
MILA
ryan.lowe@cs.mcgill.ca

**Jakob Foerster**
Facebook AI Research

**Douwe Kiela**
Facebook AI Research

**Joelle Pineau**
Facebook AI Research
MILA

## Abstract

How can we teach artificial agents to use human language flexibly to solve problems in a real-world environment? We have one example in nature of agents being able to solve this problem: human babies eventually learn to use human language to solve problems, and they are taught with an adult human-in-the-loop. Unfortunately, current machine learning methods (e.g. from deep reinforcement learning) are too data inefficient to learn language in this way [4]. An outstanding goal is finding an algorithm with a suitable 'language learning prior' that allows it to learn human language, while minimizing the number of required human interactions.

In this paper, we propose to learn such a prior in simulation, leveraging the increasing amount of available compute for machine learning experiments [1]. We call our approach Learning to Learn to Communicate (L2C). Specifically, in L2C we train a meta-learning agent in simulation to interact with populations of pre-trained agents, each with their own distinct communication protocol. Once the meta-learning agent is able to quickly adapt to each population of agents, it can be deployed in new populations unseen during training, including populations of humans. To show the promise of the L2C framework, we conduct some preliminary experiments in a Lewis signaling game [5], where we show that agents trained with L2C are able to learn a simple form of human language (represented by a hand-coded compositional language) in fewer iterations than randomly initialized agents.

**Keywords:** Meta-learning, emergent communication, language learning

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## 1 Introduction

Language is one of the most important aspects of human intelligence; it allows humans to coordinate and share knowledge with each other. We will want artificial agents to understand language as it is a natural means for us to specify their goals.

So how can we train agents to understand language? We adopt the functional view of language [18] that has recently gained popularity [9, 16]: agents understand language when they can use language to carry out tasks in the real world. One approach to training agents that can use language in their environment is via *emergent communication*, where researchers train randomly initialized agents to solve tasks requiring communication [8, 14]. An open question in emergent communication is how the resulting communication protocols can be transferred to learning human language. Existing approaches attempt to do this using auxiliary tasks, for example having agents predict the label of an image in English while simultaneously playing an image-based referential game [14]. While this works for learning the names of objects, it's unclear if simply using an auxiliary loss will scale to learning the English names of complex concepts, or learning to use English to interact in an grounded environment.

One approach that we know will work (eventually) for training language learning agents is using a human-in-the-loop, as this is how human babies acquire language. In other words, if we had a good enough model architecture and learning algorithm, the human-in-the-loop approach . However, recent work in this direction has concluded that current algorithms are too sample inefficient to effectively learn a language with compositional properties from humans [4]. Human guidance is expensive, and thus we would want such an algorithm to be as sample efficient as possible. An open problem is thus to create an algorithm or training procedure that results in increased sample-efficiency for language learning with a human-in-the-loop.

In this paper, we present the Learning to Learn to Communicate (L2C) framework, with the goal of training agents to quickly learn new (human) languages. The core idea behind L2C is to leverage the increasing amount of available compute for machine learning experiments [1] to learn a 'language learning prior' by training agents via meta-learning in simulation. Specifically, we train a meta-learning agent in simulation to interact with populations of pre-trained agents, each with their own distinct communication protocol. Once the meta-learning agent is able to quickly adapt to each population of agents, it can be deployed in new populations unseen during training, including populations of humans. The L2C framework has several advantages:

- The L2C framework permits for agents to learn language that is *grounded* in an environment, where agents can *interact* with the environment to (i.e. it is not limited to referential games).
- In contrast with work from the instruction following literature [2], agents can be trained via L2C to both *speak* (output language to help accomplish their goal) and *listen* (map from the language to a goal or sequence of actions).
- L2C can be easily combined with other methods for ; for example, neural architectures that bias towards learning compositional structure [3], or improved meta-learning algorithms.

To show the promise of the L2C framework, we provide some preliminary experiments in a Lewis signaling game [5]. Specifically, we show that agents trained with L2C are able to learn a simple form of human language (represented by a hand-coded compositional language) in fewer iterations than randomly initialized agents. These preliminary results suggest that L2C is a promising framework for training agents to learn human language from few human interactions.

## 2 Learning to learn to communicate

L2C is a training procedure that is composed of three main phases:

1. **Training agent populations:** Training populations of agents to solve some task (or set of tasks) in an environment, via emergent communication.
2. **Train meta-learner on agent populations:** We train a meta-learning agent to 'perform well' (i.e. achieve a high reward) on tasks in each of the training populations, after a small number of updates.
3. **Testing the meta-learner:** testing the meta-learning agent's ability to learn new languages, which could be both artificial (emerged languages unseen during training) or human.

A diagram giving an overview of the L2C framework is shown in Figure 1. Phase 1 can be achieved in any number of ways, either through supervised learning (using stochastic gradients) or via reinforcement learning (RL). Phases 2 and 3 follow the typical meta-learning set-up: to conserve space, we do not replicate a formal description of the meta-learning framework, but we direct interested readers to Section 2.1 of [7]. In our case, each 'task' involves a separate population of agents with its own emergent language. While meta-training can also be performed via supervised learning or RL, Phase 3 must be done using RL, as it involves interacting with humans which cannot be differentiated through. See Section 5 for a discussion of each of these phases in more detail.

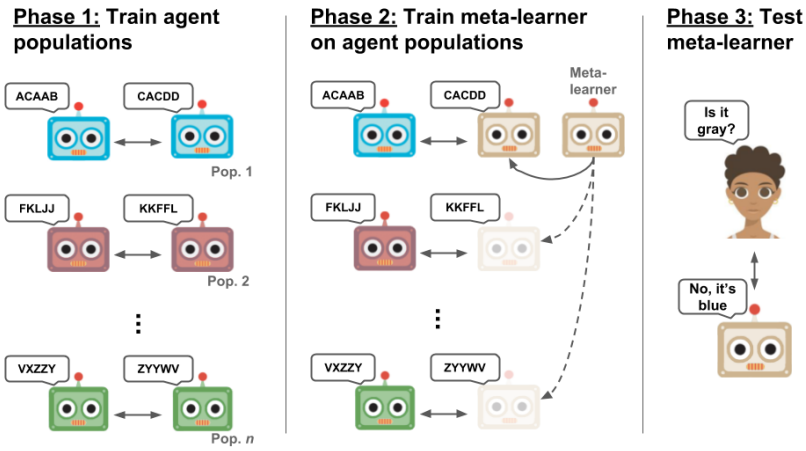



Figure 1: Diagram of the L2C framework. An advantage of L2C is that agents can be trained in an external environment (which *grounds* the language), where agents interact with the environment via actions and language. Thus, (in theory) L2C could be scaled to learn complicated grounded tasks involving language.

## 3 Problem set-up

**A speaker-listener game** We construct a referential game similar to the Task & Talk game from [12], except with a single turn. The game is cooperative and consists of 2 agents, a speaker and a listener. The speaker agent observes an object with a certain set of properties, and must describe the object to the listener using a sequence of words (represented by one-hot vectors). The listener then attempts to reconstruct the object. More specifically, the input space consists of $p$ *properties* (e.g. shape, color) and $t$ *types* per property (e.g. triangle, square). The speaker observes a symbolic representation of the input $x$, consisting of the concatenation of $p$ one-hot vectors, each of length $t$. The number of possible inputs scales as $t^p$. We also define the vocabulary size (length of each one-hot vector sent from the speaker to the listener) as $|V|$, and fix the number of words sent to be $w$.

**Approximating human language** To simulate a simplified form of human language on this task, we programatically generate a perfectly compositional language, by assigning each 'concept' (each type of each property) a unique symbol. In other words, to describe a blue shaded triangle, we create a language where the output description would be "blue, triangle, shaded", in some arbitrary order and without prepositions. By 'unique symbol', we mean that no two concepts are assigned the same word, even if they describe different properties. By generating this language programmatically, we avoid the need to have humans in the loop for testing, which allows us to iterate much more quickly. This is feasible because of the simplicity of our speaker-listener environment; we do not expect that generating these programmatic languages is practical when scaling to more complex environments.

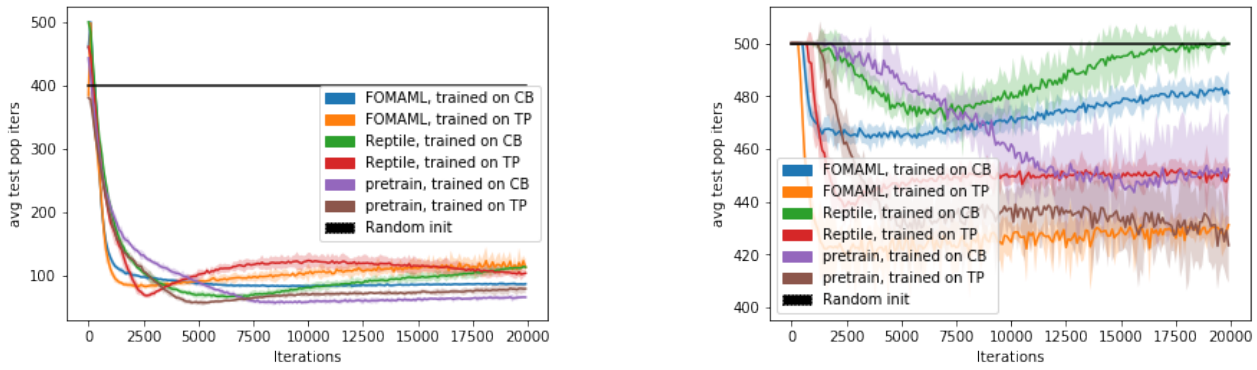
**Implementation details** The speaker and listener are parameterized by recurrent policies, both using an embedding layer of size 200 followed by an LSTM of size 200. The message produced by the speaker is a sequence of $p$ categorical random variables which are discretized using Gumbel-Softmax with an initial temperature $\tau = 1$. We set the vocabulary size to be equal to the total number of concepts $p * t$. In our initial experiments, we train our agents using Cross Entropy which is summed over each property $p$. We use the Adam optimizer [11] with a learning rate of 0.001. We first demonstrate the results with a meta-learning listener (a *meta-listener*), that learns from the different speakers of each training population.

## 4 Experiments

**Training agent populations** We first train encoder-decoder pairs to solve the game described in Section 3. We experiment with two different settings: a smaller game similar to [12] with $p = 3, t = 5$ (125 possible inputs), and a larger game with $p = 6, t = 10$ ($10^6$ possible inputs). We show the performance of our agents in Table 1, when trained on 80% of the available data, reserving 20% at random to test generalization. In both cases, agents trained with Gumbel-Softmax are able to achieve a low error on the training set when passing discrete vectors ($\tau = 0$). For the smaller game, the agents are able to fully memorize the training set, and thus do not generalize well to the test set. Interestingly however, when trained on a larger number of examples we find that the agents do learn a level of compositionality, and are able to generalize to unseen examples, which seems to contradict some recent findings on emergent languages [12].

| Game scenario | # populations trained | Avg. train % | Avg. test % | # populations test % $> 90\%$ |
|---|---|---|---|---|
| All $p = 3, t = 5$ | 20 | 44.2 | 2.5 | 0 |
| All $p = 6, t = 10$ | 20 | 72.5 | 67.2 | 12 |
| Select $p = 6, t = 10$ | 20 | 98.5 | 97.3 | 20 |

Table 1: Results from training speaker-listener pairs on the referential game. Performance is measured in terms of % accuracy in reconstructing the correct input, when passing discrete words ($\tau = 0$). The 'select $p = 6, t = 10$' refers to populations that were manually curated for their generalization performance, which we use to train our meta-learner.




(a) Generalization to learning 'human language' (CB).

(b) Generalization to learning unseen emerged languages (TP).

Figure 2: Performance of the meta-learner over the course of meta-training (horizontal axis) on 10 training populations. CB stands for the 'compositional bot' approximation to human language, whereas TP indicates the 'trained populations' in Section 4. The vertical axis measures the number of updates required to achieve 95% reconstruction performance on the test population. The agents trained with L2C (colored lines) perform better than a randomly initialized agent (black line). 95% confidence intervals shown, averaged over 5 seeds.

**Training the meta-learner** Our ultimate goal is to transfer to learning a human language in as few human interactions as possible. Thus, we measure success based on the number of samples required for the meta-learner to reach a certain performance level (95%) on a held-out test population, and we permit ourselves as much computation during pre-training as necessary. We compare the performance of several algorithms: a randomly initialized agent, an agent pre-trained on all populations that performs $n = 1$ update per population, the Reptile algorithm [17] that performs $n > 1$ updates per population, and a first-order variant of MAML [7]. In Figure 2 we find that each of the algorithms that uses L2C perform similarly, but significantly better than the randomly initialized baseline, which uses standard initialization schemes in Pytorch. Interestingly, agents generalize much better to the 'human' languages than other pre-trained languages, likely because the 'human' language is perfectly compositional.

## 5 Outstanding challenges, and moving forward

There are several immediate directions for future work: training the meta-agent via RL rather than supervised learning, and training the meta-agent as a joint speaker-listener (i.e. taking turns speaking and listening), as opposed to only speaking. We also want to scale L2C training to more complicated tasks involving grounded language learning, such as the Talk the Walk dataset [6], which involves two agents learning to navigate New York using language.

More broadly, there are still many challenges that remain for the L2C framework. In fact, there are unique problems that face each of the phases described in Section 2. In Phase 1, how do we know we can train agents to solve the tasks we want? Recent work has shown that learning emergent communication protocols is very difficult, even for simple tasks [15]. This is particularly true in the multi-agent reinforcement learning (RL) setting, where deciding on a communication protocol is difficult due to the non-stationary and high variance of the gradients [15]. This could be addressed in at least two ways: (1) by assuming the environment is differentiable, and backpropagating gradients using a stochastic differentiation procedure [10, 16], or (2) by 'seeding' each population with a small number of human demonstrations. Point (1) is feasible because we are training in simulation, and we have control over how we build that simulation — in short, it doesn't really matter *how* we get our trained agent populations, so long as they are useful for the meta-learner in Phase 2.

In Phase 2, the most pertinent question is: how can we be sure that a small number of updates is sufficient for a meta-agent to learn a language it has never seen before? The short answer is that it doesn't need to completely learn the language in only a few updates; rather it just needs to perform better on the language-task in the host population after a few updates,

in order to provide a useful training signal to the meta-learner. For instance, it has been shown that the model agnostic meta-learning (MAML) algorithm can perform well when multiple gradient steps are taken at test time, even if it is only trained with a single inner gradient step. Another way to improve the meta-learner performance is to provide a *dataset* of agent interactions for each population. In other words, rather than needing to meta-learner perform well after interacting with a population a few times, we'd like it to perform well after doing some supervised learning on this dataset of language, and after a few interactions. After all, we do have lots of available datasets of human language, and not using this seems like a waste. While we do not experiment with this yet in this paper, we are excited by this possibility, as algorithms have already been developed for combining meta-imitation learning and reinforcement learning in the robotics setting [13]. When incorporating supervised language datasets, we will need to show that L2C can outperform the most commonly used method for transfer learning, which is to simply pre-train via supervised learning on the dataset and fine-tune using RL on the task with humans.

Finally, in Phase 3, how do we know that the meta-learner will be able to generalize to learn a human language? This comes down to the similarity between the training populations and human language, and the diversity of the training populations. For instance, we expect certain properties like compositionality to be important in the training populations for transferring to human languages, which are inherently compositional. But the training languages may not need to be very close to human language; as a comparison, significant progress has been made in transferring robots from simulation the real world using *domain randomization*, i.e. by adding random image textures during training. Even though these image textures look nothing like the real world, it helps improve robustness of the learner, which allows it to generalize. Providing a detailed examination of the required properties of the trained population languages, such that a meta-learner is able to generalize to human language, is an important direction for future work.

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