**Emergent Communication under Different Agent Populations: Investigating the Impact of Role Alteration on Language Generalizability**

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Github code for this paper:

https://github.com/WeitaoKe/Emergent\_Communication\_Experiments

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**Abstract**

Communication game simulates the early stage of language evolution, which may provide insights into the nature of human languages. Role alteration, or agents’ ability to switch between the roles of speaker and listener, is an important consideration when setting up players of a communication game. Adopting a referential game framework, the experiments conducted by the author covered in this paper aim to investigate the effect of role alteration on language generalizability under different agent population designs. The novelty of the experiment design lies in not only the explorational inquiry on the impact of role alteration but also the use of DualRole LSTM as the method to implement agent symmetry. The result shows that despite its effect being insignificant under a static agent population, role alteration creates a more generalizable language protocol than non-alteration design under a specific dynamic population design proposed in the paper.

**Introduction**

The language simulation not only provides insights into the linguistic essence of natural human languages, but also has implications related to various fields of study, such as anthropology, cognitive science, and artificial intelligence. For example, a phenomenon that plays an important role in cognitive processing cultural evolution, iterated learning (acquisition of behavior from another individual), can also be studied in the context of multi-agent simulation (Kirby et al., 2014). Also, the emergent communication formed in a simulation can achieve complex goals by simple protocol (Mordatch & Abbeel, 2018), which can be potentially applied to improve the efficiency of models in some machine learning settings. These potential implications are all achieved by conducting communication simulation, which necessitates the careful design of an effective communication game.

In a communication game, there are several players (or just two) known as agents, which are usually implemented with neural networks. Although sometimes agents may share a common architecture (sometimes not, as agents play different roles), each agent has independent memory and knowledge, stored as the weights and biases of their neural network. These agents interact with each other in some form and transfer information to each other to complete their task, with each agent’s task depending on its role. The channel between two interacting agents through which the information is transmitted is known as the communication channel. Agents are rewarded according to their performance on the task and update their memory and knowledge after each task, or each turn of interaction is completed. Most of the time, they utilize the updated memory (weights and biases of the network) for the next round. Usually, the training, or the simulation, is done when the agent’s overall reward plateaus.

In the background literature review part, this paper will review different methods of implementing communication games, aiming to address previous works with various game designs, individual agent designs, and measurements and properties of emergent communication protocol. In the subsequent sections, the innovative objectives, methodology, results, and implications of the experiments designed by the author will be introduced.

**Background Literature Review**

**Task & Game Designs**

Emergent communication simulations focus on how an effective communication system is formed during task-oriented interactions between agents, who can adjust their communication strategy and update their knowledge based on some reward design. Different game designs address different aspects and functions of language. The referential game, deriving from the renowned Lewis’ signaling game (Lewis, 1969), involves the roles of sender and receiver transmitting messages between each other to clarify and distinguish different referents (Goldman et al., 2007; Lazaridou et al., 2016; Evtimova et al., 2017). In the classical setting, the agent who completes the task (reconstructing or identifying the target image) solely relies on the unidirectional information channel from the other agent holding the target referent, while an example of an atypical variant of the game may involve agents each having a partition of the image of the target object and bi-directionally communicating to figure out the whole picture (Graesser et al., 2019).

Going beyond the referencing power of language, another version of the communication game is the negotiation game that explores the bargaining functions of language under the context of multi-agent communication simulation. A study proves the effectiveness of linguistic communications compared to making mere numerical proposals and observes interesting phenomena including the natural specialization of agents (Cao et al., 2018). Efforts have also been made to explore various spatial coordination games, exemplified by the innovative design of various traffic coordination games (e.g., Sukhbaatarand & Fergus, 2016) navigation games (e.g., Yu et al., 2022, Kajić et al., 2020), investigating the emergence of directive signals or reference for directions, such as "up", "left", "stop", etc. Some games attempt to incorporate various modes of communication and task objectives, such as the one that combines cooperative and adversarial environments (Lowe et al., 2017).

**Agent Designs in Simulation**

**Individual agent design.** The most important consideration of individual design is the reward design. By altering the reward and loss function for agent individuals, agents can be trained to serve different interests and pursue different goals. For example, in a social sequential dilemma setting (Leibo et al., 2017) where the individual's short-term benefit conflicts with the collective long-term interest, agents can communicate to coordinate for the common good when we introduce additional rewards for social influence (Jaques et al., 2019) or inequality aversion (Hughes et al., 2018). Reward design can also make agents hostile or pro-social (Ruland et al., 2023), or even have a preference for the communication system itself (Luna et al., 2020), favoring a simpler version of communication as required by the least-effort rule (Grice et al., 1975; Levinson, 2000; Haiman 1983). Other than the reward design, memory constraint is also hypothesized to have an impact on the emergent communication system (Galke, Ram, & Raviv, 2022) since the memory needed for an agent to learn a language with compositional structure is not as large as the memory needed for memorizing the whole dataset (Resnick et al., 2019).

**Agent population design** One topic of population design is about how agents are drawn to communicate. An agent may only communicate with only a limited set of agents of the whole population. In some special settings, agents are “nodes” connected by “edges” of communications channels, forming an entire “graph”, and in each turn, an “edge” is randomly picked so that the pair of agents connected by this channel interacts (e.g., Graesser, Cho, & Kiela, 2019). Another aspect of population design is agent replacement. Mostly, the replacement represents generation turnover, which simulates the reproduction in natural-world language evolution. Martin Nowak (Nowak & Krakauer, 1999) proposed mathematical frameworks that specify how language is transmitted across generations. The replacement of agents encourages cultural transmission, which is crucial to cultural evolution and has a positive impact on the compositionality of the emergent language (Cogswell et al., 2019). A study on Language Transmission Simulators further explores the combination of cultural evolution and architecture evolution by not only periodically replacing agents with newly-initialized ones but also creating mutated variants of best-performing agents to replace the worst-performing ones (Dagan, Hupkes, & Bruni, 2020).

**Role alteration,** or an agent’s ability to switch between the roles of the sender and the receiver using the same memory and knowledge, is natural in human language interactions, while most research on emergent communication simulation does not address this aspect (Galke, Ram, & Raviv, 2022). The symmetricity of agents comes with role alteration since otherwise the agents must be specialized into two independent sets of speakers and listeners. A common way of implementing symmetricity among agents is to introduce the weights in the output layer of the model to the input embedding layer (Mikolov et al., 2013; Raffel et al., 2020). One study mentioned before implemented the alteration of roles but in a scenario of an atypical referential game, where agents each hold a part of an image and communicate to reconstruct the entire picture (Graesser, Cho, & Kiela, 2019).

**Properties of Language and Metrics of Emergent Communication Protocol**

The most common metric for emergent communication games is the task success rate and the time of convergence. Researchers also tend to interpret the language generated by agents, thus evaluating the interpretability. Other considerations are taken in the emergent communication games, as follows.

**Compositionality and Generalization.** Both the agents’ ability to generalize the language to communicate unseen objects and the compositionality of the emergent language, measured by the agent’s zero-shot performance and topo-similarity, respectively, are important aspects in examining emergent communication games (Brighton et al., 2005). The relationship between compositionality and generalization is relatively subtle (Chaabouni et al., 2020), as the study suggests that generalization is more easily achieved, (or, naturally emerges if multi-agent communication games have input variations), while compositionality does not necessarily come with generalization. For neural networks, since generalization can be done without compositionality, there is no explicit correlation between these two properties (Kharitonov & Baroni, 2020). Therefore, compositionality is only one of the methods to achieve generalization, and the compositional structure itself is much harder to acquire than generalization. The pursuit of compositional structure is not only harder but also more valuable compared to generalization, since compositionality can promote the learnability of the language (as confirmed with neural agents by Guo et al., 2019) and language transmission to the next generation (e.g., Kirby et al., 2015; Cornish et al., 2017).

**The complexity of emergent language** is taken into account in language simulation games (e.g., Luna et al., 2020), with measurements and evaluations including average message length, active symbols, number of distinctive messages, perplexity per symbol (Havrylov and Titov, 2017), and language entropy (the unpredictability of the language). The complexity of the language is an auxiliary measure that, when combined with compositionality, can give a more comprehensive assessment of the performance of the language.

# Methodology

# Objectives and Hypotheses

This study delves into the effect of role alteration on the emergent language protocol in the multi-agent communication game (referential game in this case). Role alteration, or agent symmetry used interchangeably in this paper, refers to the agent’s ability to switch between the roles of the sender and the receiver. Despite its significant influence on agents’ structure and behavior, role alteration receives a scant amount of attention and is rarely taken into account when it comes to emergent language simulation (Galke et al., 2022). This study aims to fill in the gaps in research on this variable. Furthermore, the agent implementation method is also explorational. To create bifunctional agents necessary for implementing role alteration, this paper adopts an innovative approach to integrating the functions of senders and receivers: using a single shared DualRole LSTM for the sender and the receiver roles of an agent. Thus, agents can switch the roles of sender and receiver when needed.

Besides exploring the effect of agent symmetry on language generalizability (which corresponds to the primary hypothesis to be introduced later), it is also crucial to take agent population design into consideration, which may have the potential of altering or even reversing our conclusion about the correlation between role alteration and language generalizability. In other words, individual agents’ designs, such as role alteration, may demonstrate their effectiveness under some population dynamics but not others, as different population designs create disturbances to the emergent language in different ways. Having results conducted under different population designs is vital for determining the robustness of the conclusion about the effectiveness of role alteration. Here draws the secondary hypothesis to be discussed later.

The central questions to be answered are summarized here: does role alteration, implemented through a shared LSTM framework, enhance the adaptability and generalizability of emergent communication? Further, does the positive relationship between role alteration and language generalizability persist across different agent population dynamics, particularly in the merging-tribe settings where agents initially communicate within their specific groups and subsequently engage in cross-group conversations?

The primary hypothesis is that: role alteration enhances communication adaptability, measured by language generalizability. Specifically, due to the symmetric agents’ resemblance to natural human beings, it is assumed that agent symmetry, or role alteration, would have a positive impact on the generalizability of the emergent communication system.

The secondary hypothesis, extending the primary one, states that such alteration contributes differently under different population settings. This paper proposes two different agent population designs, one being static and the other being dynamic, aiming to provide empirical conclusions and insights to compare the adaptability of symmetric agents and specialized agents to the proposed population designs.

Generally, it is expected the experiments to demonstrate that symmetric agents outperform specialized ones in generalizing the emergent communication under both the dynamic and the static population design, which would testify to the hypotheses we proposed.

**General Experiment Setup**

**Referential Game Design.** The game includes multiple turns. In each turn, an image represented by a z-dimensional feature vector sampled from a 2D geometric shapes dataset is presented to the sender. The sender, after processing the target images, sends a message of maximum length L (probably containing the description of the target image) to the receiver. The receiver, based on this message, has to guess the target image presented to the sender from lined-up confounders. The communication loss function (simultaneously applied to both the sender and the receiver), or the inverse of both the sender’s and the receiver’s shared utility, is defined as follows:

where *Lc* denotes the loss function; *q*(*t*) is the similarity between the receiver’s guess and the target image; *q*(*dk*​) is how similar it is between the receiver’s guess and the kth distractor image. Specifically, the similarity,  , is defined by the dot product between the receiver’s guess vector, and the feature representation vector of an image, . After the loss function is computed in each turn, the sender and the receiver adjust their strategies accordingly.

**The dataset** contains 224\*224-pixel images of 2D geometric figures with different shapes, colors, positions, rotation angles, and sizes labeled with their colors and shapes. They are used as the input of the visual module.

**The Visual Module** is designed to extract features from an image and is pre-trained separately. It processes the 224\*224-pixel images from the dataset with 6 layers. The first 5 layers each combine a convolutional layer, a batch normalization, and a ReLu activation. Each layer has 20 filters, a kernel size of 3, and a stride of 2. The sixth layer is a fully connected layer with a ReLu activation, producing a 2048-dimensional feature vector.

**The Sender’s Architecture.** The feature of an image extracted by a visual module, after a linear transformation, is used as the initial hidden state of the first layer, and the starting token, <S>, is the initial input token. After that, a token is sampled from the output distribution using the Gumbel-Softmax technique (temperature=1.2, learning rate=0.0001). The following four layers each inherit the cell state and the hidden state of the previous one and take the output sequence of the previous layer as the input sequence. Also, the sampled token from the output distribution of the previous layer is passed into the layer as the input token. The tokens generated are stacked and thus form a sequence of tokens, or the output message.

**The Receiver’s Architecture.** The receiver role uses a similarly structured 5-layer LSTM network as the sender role of the same agent so that in the role alteration design receivers can share the LSTM with the corresponding senders: the input dimensions of each receiver LSTM layer are kept the same as the sender’s counterpart to ensure the compatibility when needed in role alteration design. The receiver’s input is the message generated by the sender. As in the sender’s architecture, the layers also each inherit the cell state and the hidden state of the previous one and take the output sequence of the previous layer as the input sequence. The difference is that the receiver’s LSTM layers’ input token is the corresponding token in the received message since the LSTM network is now used for decoding the message, not generating it. A dense layer processes the final hidden layer of the LSTM and produces a guessing vector, which also has 2048 dimensions and serves as the output of the receiver.

**Experimental Conditions**

**An Overview.** Two experiments are conducted to compare role-alteration design and specialized-agent design under static and dynamic agent populations. Each experiment contains two simulations, one with symmetric agents and the other with specialized agents. In the symmetric agent design, self-talk is allowed: there is a probability that the sender and the receiver function of the same agent are drawn to play the referential game. The static agent population refers to a group of agents without any replacement in the constituent agents, while the dynamic one, here, refers specifically to the two-stage merging-group condition: agents are first drawn from two separate sets and later these two groups merge to form one larger group. In other words, in the role-altercating merging-group simulation, agents are only allowed to talk with agents from the same group (including itself) in stage one, and they have the opportunity to talk with any agents in stage two. For the non-alteration case, the senders are allowed to communicate with the receivers in the same group in the first stage and any receivers in the second stage (namely, the cross-talk stage).

**Role Alteration Implementation.** The only difference between the symmetric-agent design (role alteration) and the specialized-agent design is that, in role alteration design, a single agent’s sender and receiver roles share a 5-layer LSTM network. In role alteration, the instances of a class named “communication pair” have a sender object and a receiver object as their attributions. A “communication pair” represents an agent individual who is capable of both sending and receiving messages. The shared LSTM network is defined in the communication pair object and is passed to its sender and receiver attributions when creating them so that the network can be shared between the two roles. Except for the LSTM network, all other dense layers in the model are specific to each sender and receiver object (not shared). The input embedding layer that embeds all inputs before being fed into the LSTM layers, is a static attribution shared among all objects created in the game.

**Experiment 1: The static population design.** Designed to address the effectiveness of role alteration under a static population setting, Experiment 1 compares the performance of symmetric agents (role alteration) and specialized agents (non-alteration) in generalizing emergent language under a static population design, where the set of agents an individual is allowed to interact with does not change as the simulation proceeds. In all simulations run in this experiment, the learning rate, the data set, the visual module, the dropout rate, the number of epochs, the batch size, the number of training steps per epoch, and all other hyperparameters are controlled to be the same. Six simulations are conducted: a role-alteration simulation and a non-alteration simulation are executed under three different sizes of agent populations. The three levels of population size are meant to test the robustness of the test result. After the agents are trained, their weights are frozen. Then, they communicate about unseen types of geometric figures (unseen color-shape combination), with the loss recorded as “zero-shot loss.” Zero-shot loss is the measurement of the agents’ ability to generalization, or, the emergent language’s generalizability. The lower the loss, the stronger the agents are in generalizing the emergent language. The metric, of course, also includes the validation loss to represent model convergence by the end of the training. We take the average validation loss of the last two epochs (where the loss plateaus) into account.

**Experiment 2: The dynamic population design.** Experiment 2’s main objective is to examine the effectiveness of role alteration under the disturbances created by a dynamic population design. Experiment 2, as in Experiment 1, also compares the symmetric and specialized agents’ ability of generalization, but under a dynamic population design, where agents are initially allowed to communicate with only a limited set of agents and later allowed to interact with all possible agents. As in Experiment 1, the variables are controlled similarly. Four simulations are executed, with a role-alteration simulation and a non-alteration one conducted under two different agent population dynamics. In the first agent population design, agents are firstly split into two groups of 2 and 2, later merged to make a 4-agent group. In the second design, the two separated groups at first are of the sizes 2 and 3. The metric of zero-shot loss is also taken the same as in Experiment 1.

**Experiment Results**

**Results of Experiment 1**

| Agent Pop. Size | Role-Alteration Avg Val. loss | Role-Alteration  Zero-shot loss | Non-Alteration Avg Val. loss | Non-Alteration Zero-shot loss |
| --- | --- | --- | --- | --- |
| N=2 | 0.349 | 0.192 | 0.315 | 0.214 |
| N=3 | 0.236 | 0.336 | 0.195 | 0.288 |
| N=4 | 0.263 | 0.244 | 0.204 | 0.254 |

Overall, the distinction between the symmetric-agent design and the specialized-agent design is insignificant, despite that the specialized agents consistently perform better than the symmetric agents in model convergence (having lower validation loss).

**Results of Experiment 2**

| Agent Pop. Size | Role-Alteration Avg Val. loss | Role-Alteration  Zero-shot loss | Non-Alteration Avg Val. loss | Non-Alteration Zero-shot loss |
| --- | --- | --- | --- | --- |
| N=2+2 | 0.249 | 0.366 | 0.272 | 0.625 |
| N=2+3 | 0.235 | 0.316 | 0.352 | 0.395 |

In the merging-group setting, symmetric agents start to play better than the specialized ones in both convergence (having lower validation loss) and emergent language’s generalizability (having lower zero-shot loss).

# Discussion

For a high-level overview of the experiment result, role alteration does not make a difference under the static population setting, but significantly increases the generalizability of the emergent language under the dynamic population setting, where communications are first confined in two separate groups and later unlimited by group boundaries. In other words, the disturbances created by the merger of two separate communication groups and the collision between the two established emergent languages “ruin” the specialized agents much more badly than the symmetric ones.

Contrary to our expectation, the role alteration design exhibits a less favorable model convergence under the static population, compared to the non-alteration design. However, there is no sufficient evidence to attribute the inferiority in convergence to the agent symmetry or conclude that specialized agents create a more efficient language with the same amount of training. A plausible explanation lies in the way role alteration is implemented, regarding the dual-responsibility of the LSTM model. In the role alteration simulation, every single LSTM is trained to be bifunctional, or, to both generate and interpret messages, which may be more challenging than training two specialized LSTMs each focusing on one specific task. As mentioned in prior literature, there are other ways to implement role alteration, such as introducing the output layer weights to the input embedding and sharing attention module, and these methods may exhibit different results in model convergence, waiting to be discovered by future research.

Comparing results from Experiment 1 and Experiment 2 helps address our initial hypotheses. Agent symmetry has a greater impact on emergent language generalizability in merging-group settings than in static-group settings. This is evident from the significant gap in zero-shot loss between role-alteration and non-alteration simulations. Therefore, our secondary hypothesis is confirmed, while our primary hypothesis merely receives partial support.

The worse performance in the unseen-object communication task for specialized agents in merging-group settings can potentially be explained as follows: while specialized agents are more likely to acquire both languages, symmetric agents under merging-group designs are likelier to converge on a language protocol that blends elements from the two original languages established in separate groups. If this postulation persists, specialized agents would find it hard to determine the appropriate language protocol when communicating about unseen objects, showing a weaker ability for generalization. Drawing parallels from real life, a bilingual person (capable of both speaking and listening) could create messages blending words from two known languages. It is difficult to imagine how such a synthesis of languages can occur naturally with specialized senders or receivers. Given that real-world linguistic communities are dynamic, with constant contacts, interactions, and evolution of languages and speakers, there is still a long way to go when it comes to studying the influence of role alteration on emergent language. Future studies could experiment with varying agent population dynamics, incorporating generation turnovers, limited inter-community interactions, or replacing underperforming agents with the variants of the best-performing ones, as mentioned in the literature survey.

**Conclusion**

In the discussed experiment, the dynamic agent populations, specifically the merging-group setting, have been found to significantly influence the impact of individual agents' architecture on the emergent language. Specifically, agent symmetry, also referred to as role alteration, can either enhance (as seen in experiment 2) or reduce (as observed in experiment 1) the generalizability of the emergent communication, depending on the group population design. This conclusion may be extended to other agent architectures (such as memory limit, internal pressure, etc.) and other agent population designs (such as periodical agent replacement), as we regard the survey done earlier in this paper on related works on emergent communication simulation. In other words, we may have to revisit and re-examine the effect of the agent’s memory limit, internal pressure, etc. on the compositionality, generalizability, and complexity of the emergent language protocol under different agent population evolution dynamics, such as the agent’s reproduction and death, the confluence of three or more languages, etc. Future works can also be done to investigate the combined effect of individual agent design and the overall population dynamics on emergent communication in contexts other than the referential settings, such as negotiation, navigation, and coordination games.

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**References**

Brighton, H., Smith, K., & Kirby, S. (2005). Language as an evolutionary system. Physics of Life Reviews, 2(3), 177-226.

Cao, K., Lazaridou, A., Lanctot, M., Leibo, J. Z., Tuyls, K., & Clark, S. (2018). Emergent communication through negotiation. *arXiv preprint arXiv:1804.03980*.

Chaabouni, R., Kharitonov, E., Bouchacourt, D., Dupoux, E., & Baroni, M. (2020). Compositionality and generalization in emergent languages. *arXiv preprint arXiv:2004.09124*.

Cogswell, M., Lu, J., Lee, S., Parikh, D., & Batra, D. (2019). Emergence of compositional language with deep generational transmission. *arXiv preprint arXiv:1904.09067*.

Cornish, H., Dale, R., Kirby, S., & Christiansen, M. H. (2017). Sequence memory constraints give rise to language-like structure through iterated learning. *PloS one*, *12*(1), e0168532.

Dagan, G., Hupkes, D., & Bruni, E. (2020). Co-evolution of language and agents in referential games. *arXiv preprint arXiv:2001.03361*.

Evtimova, K., Drozdov, A., Kiela, D., & Cho, K. (2017). Emergent communication in a multi-modal, multi-step referential game. *arXiv preprint arXiv:1705.10369*.

Galke, L., Ram, Y., & Raviv, L. (2022). Emergent communication for understanding human language evolution: What's missing?. *arXiv preprint arXiv:2204.10590*.

Goldman, C. V., Allen, M., & Zilberstein, S. (2007). Learning to communicate in a decentralized environment. *Autonomous agents and multi-agent systems*, *15*, 47-90.

Graesser, L., Cho, K., & Kiela, D. (2019). Emergent linguistic phenomena in multi-agent communication games. *arXiv preprint arXiv:1901.08706*.

Grice, H. P. (1975). Logic and conversation. In *Speech acts* (pp. 41-58). Brill.

Guo, S., Ren, Y., Havrylov, S., Frank, S., Titov, I., & Smith, K. (2019). The emergence of compositional languages for numeric concepts through iterated learning in neural agents. *arXiv preprint arXiv:1910.05291*.

Haiman, J. (1983). Iconic and economic motivation. *Language*, 781-819.

Havrylov, S., & Titov, I. (2017). Emergence of language with multi-agent games: Learning to communicate with sequences of symbols. *Advances in neural information processing systems*, *30*.

Hughes, E., Leibo, J. Z., Phillips, M., Tuyls, K., Dueñez-Guzman, E., García Castañeda, A., ... & Graepel, T. (2018). Inequity aversion improves cooperation in intertemporal social dilemmas. *Advances in neural information processing systems*, *31*.

Jaques, N., Lazaridou, A., Hughes, E., Gulcehre, C., Ortega, P., Strouse, D. J., ... & De Freitas, N. (2019, May). Social influence as intrinsic motivation for multi-agent deep reinforcement learning. In *International conference on machine learning* (pp. 3040-3049). PMLR.

Kajić, I., Aygün, E., & Precup, D. (2020). Learning to cooperate: Emergent communication in multi-agent navigation. *arXiv preprint arXiv:2004.01097*.

Kharitonov, E., & Baroni, M. (2020). Emergent language generalization and acquisition speed are not tied to compositionality. *arXiv preprint arXiv:2004.03420*.

Kirby, S., Tamariz, M., Cornish, H., & Smith, K. (2015). Compression and communication in the cultural evolution of linguistic structure. *Cognition*, *141*, 87-102.

Kirby, S., Griffiths, T., & Smith, K. (2014). Iterated learning and the evolution of language. *Current opinion in neurobiology*, *28*, 108-114.

Lazaridou, A., Peysakhovich, A., & Baroni, M. (2016). Multi-agent cooperation and the emergence of (natural) language. *arXiv preprint arXiv:1612.07182*.

Leibo, J. Z., Zambaldi, V., Lanctot, M., Marecki, J., & Graepel, T. (2017). Multi-agent reinforcement learning in sequential social dilemmas. *arXiv preprint arXiv:1702.03037*.

Lewis David, K. (1969). Convention: a philosophical study. *Cambridge MA: Harvard*.

Levinson, S. C. (2000). *Presumptive meanings: The theory of generalized conversational implicature*. MIT press.

Lowe, R., Wu, Y. I., Tamar, A., Harb, J., Pieter Abbeel, O., & Mordatch, I. (2017). Multi-agent actor-critic for mixed cooperative-competitive environments. *Advances in neural information processing systems*, *30*.

Luna, D. R., Ponti, E. M., Hupkes, D., & Bruni, E. (2020). Internal and external pressures on language emergence: least effort, object constancy and frequency. *arXiv preprint arXiv:2004.03868*.

Mordatch, I., & Abbeel, P. (2018, April). Emergence of grounded compositional language in multi-agent populations. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 32, No. 1).

Nowak, M. A., & Krakauer, D. C. (1999). The evolution of language. *Proceedings of the National Academy of Sciences*, *96*(14), 8028-8033.

Resnick, C., Gupta, A., Foerster, J., Dai, A. M., & Cho, K. (2019). Capacity, bandwidth, and compositionality in emergent language learning. *arXiv preprint arXiv:1910.11424*.

Ruland, M., Andirkó, A., Romanowska, I., & Boeckx, C. (2023). Modelling of factors underlying the evolution of human language. *Adaptive Behavior*, 10597123221147336.

Sukhbaatar, S., & Fergus, R. (2016). Learning multiagent communication with backpropagation. *Advances in neural information processing systems*, *29*.

Yu, H., Lu, H., Yuan, C., & Wang, X. (2022). Manipulating Multi-agent Navigation Task via Emergent Communications.