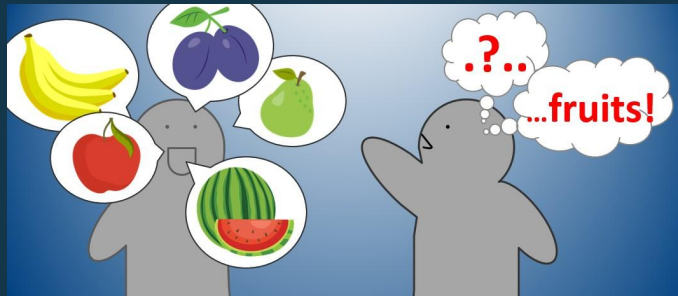
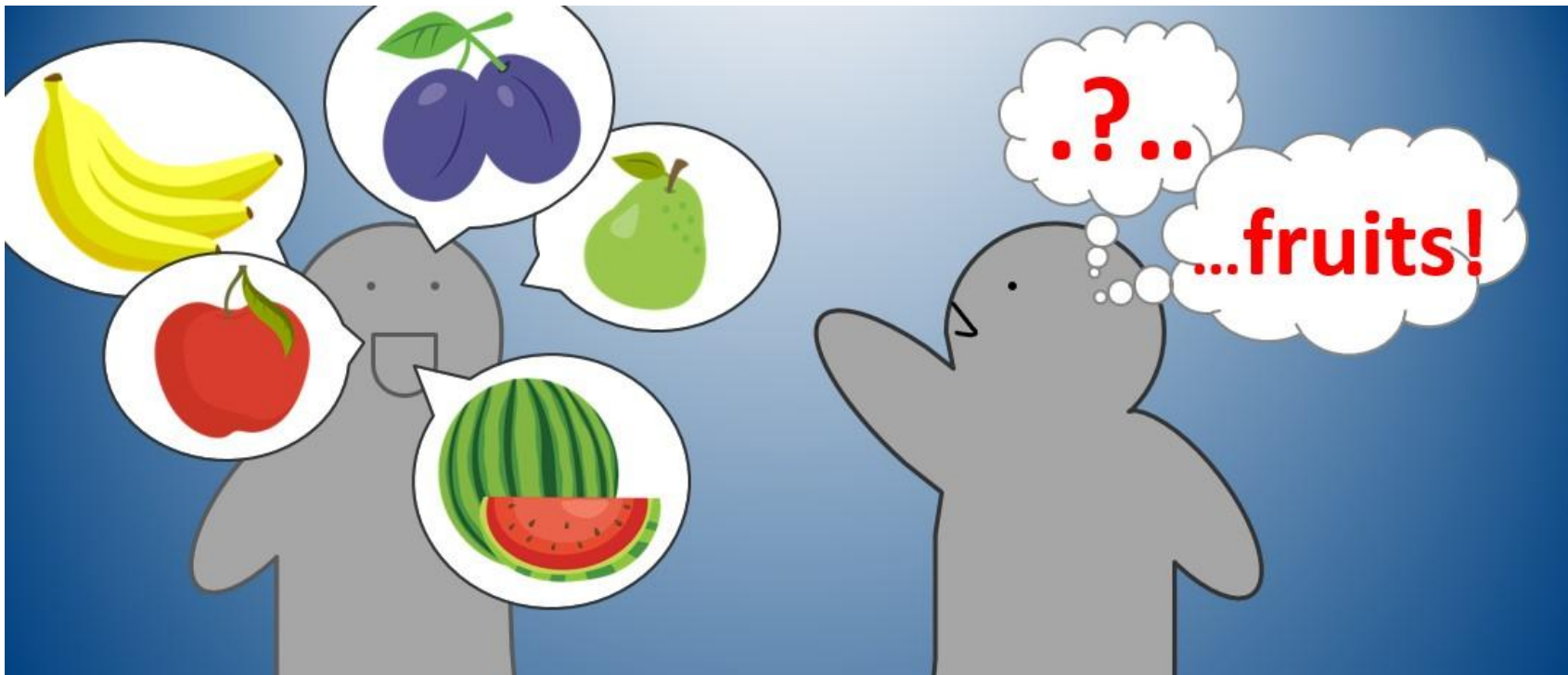


*Kobrock, K., Ohmer, X., Bruni, E., and Gotzner, N. (2023)*

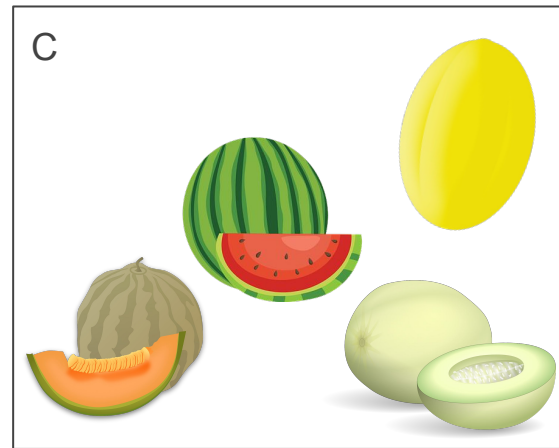
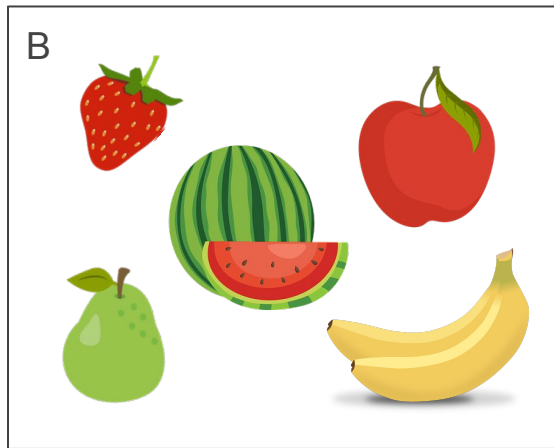
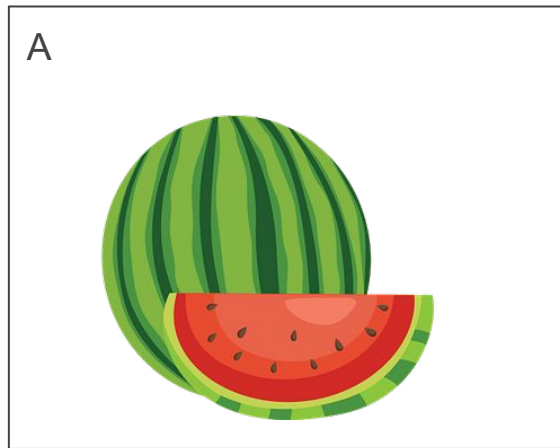


# Pragmatics in referential communication

**An investigation of concept communication and the role of pragmatics with an emergent communication game**



# Levels of abstraction shaped by context



“watermelon”

“melon”

“fruit”

“food”

*specific*

*generic*

“melon”

“watermelon”

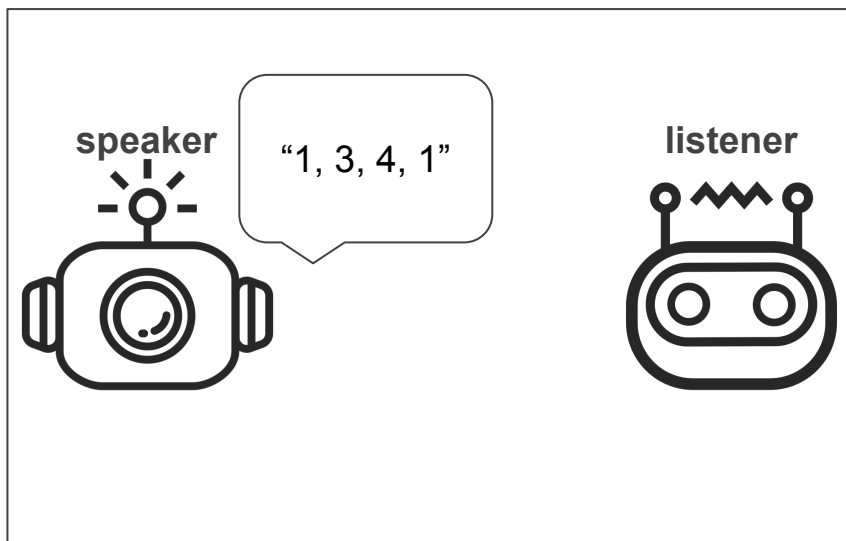
*coarse*

context

*fine*

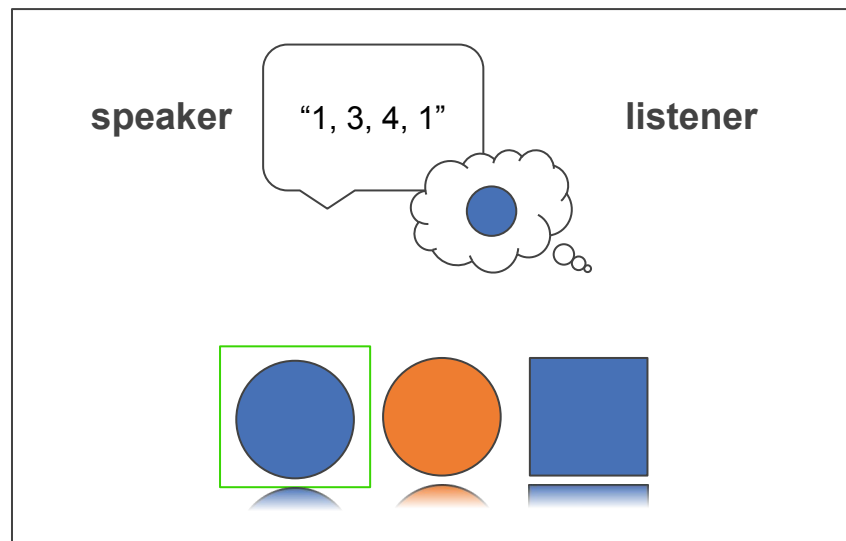
# Paradigm and set-up

## 1) Emergent communication



*e.g., Lazaridou et al. (2017), Ohmer et al. (2022)*

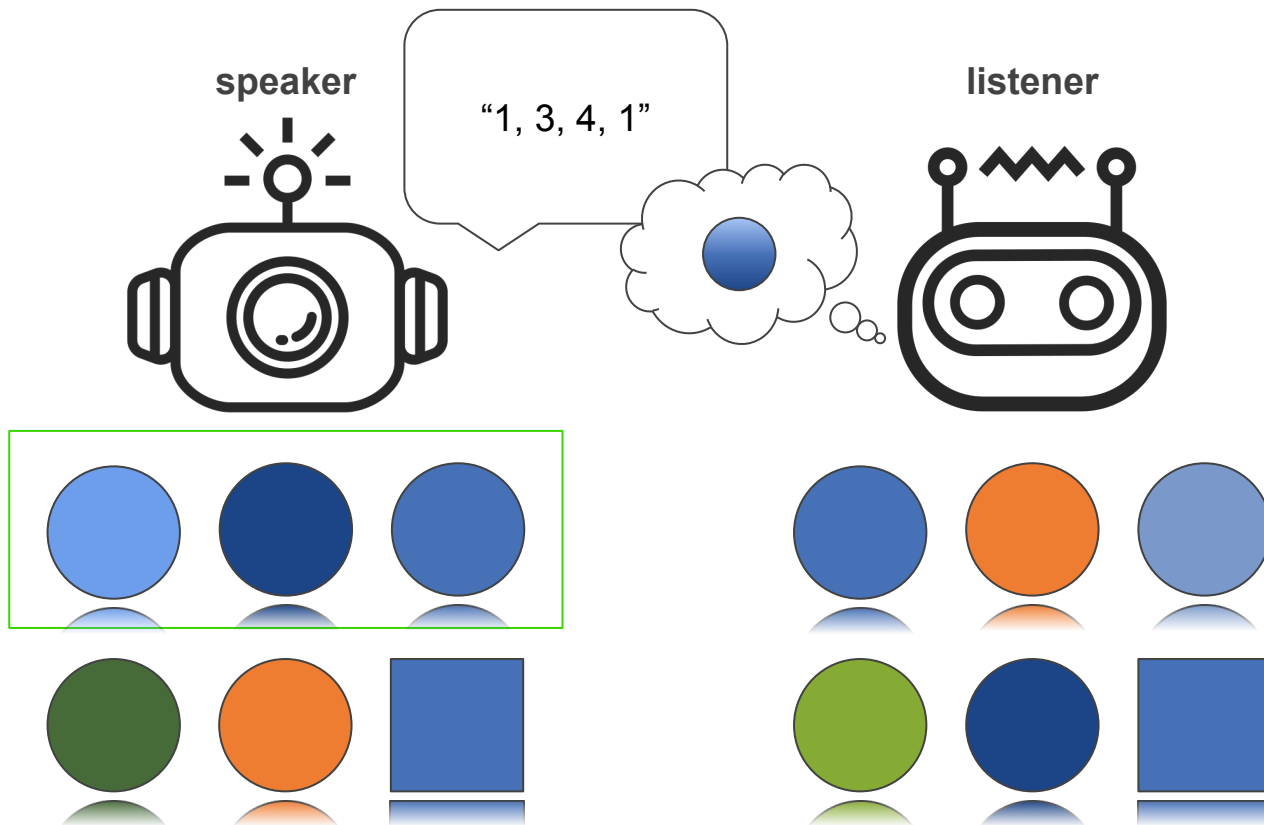
## 2) Reference game



*e.g., Franke & Degen (2016)*

# Concept-level reference game

*Mu & Goodman (2021)*



Symbolic dataset: Objects consist of  $n$  attributes which each can take  $k$  values.

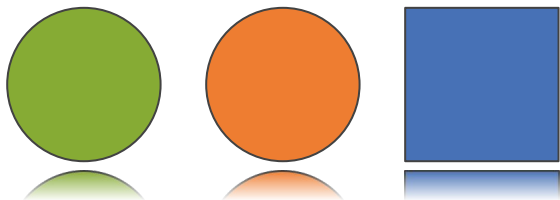
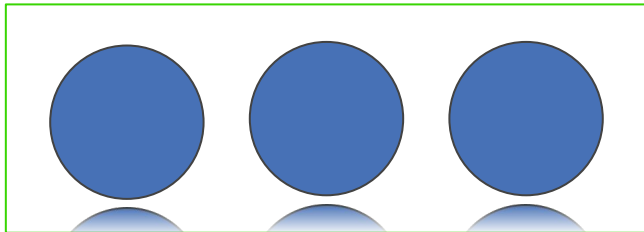
# Dataset manipulates concept level and context

- The more attributes are **fixed**, the more ***specific*** the concept.
- The more fixed attributes are **shared** between targets and distractors, the ***finer*** the context.

# Concept x context conditions

— — —

A) specific concept, fine context:



Set notation:

Colors = {blue, green, orange}

Shapes = {circle, square, triangle}

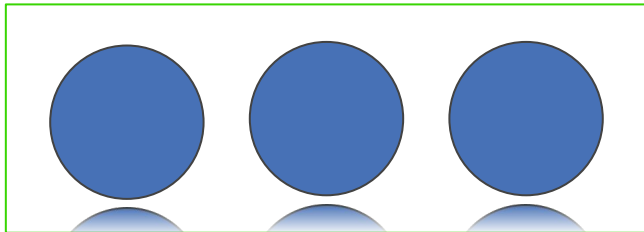
**target concept:** “blue circle”  
{(blue, circle)}

**distractor concept:** “blue shapes which are no circles and circles which are not blue”  
{(blue, square), (blue, triangle), (orange, circle), (green, circle)}

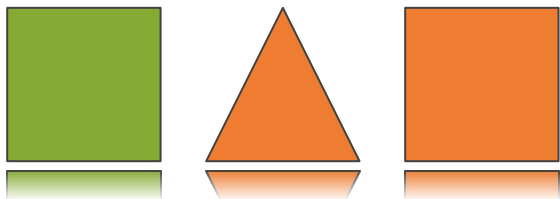
# Concept x context conditions

— — —

B) specific concept, coarse context:



**target concept:** “blue circle”  
{(blue, circle)}



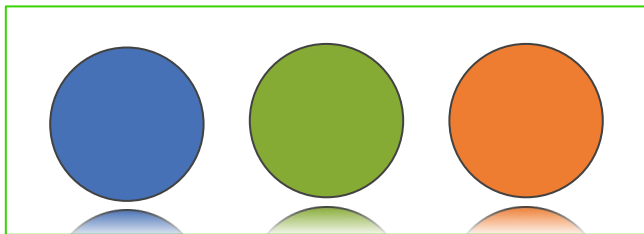
**distractor concept:** “all that is not blue or a circle”  
{(green, square), (orange, square),  
(green, triangle), (orange, triangle)}



# Concept x context conditions

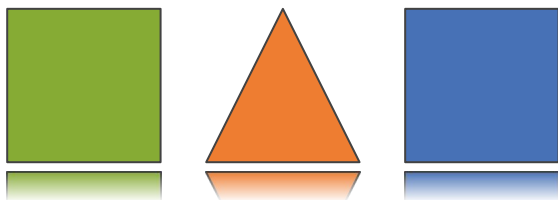
— — —

C) generic concept, coarse context:



**target concept:** “circle”

{(blue, circle), (green, circle),  
(orange, circle)}



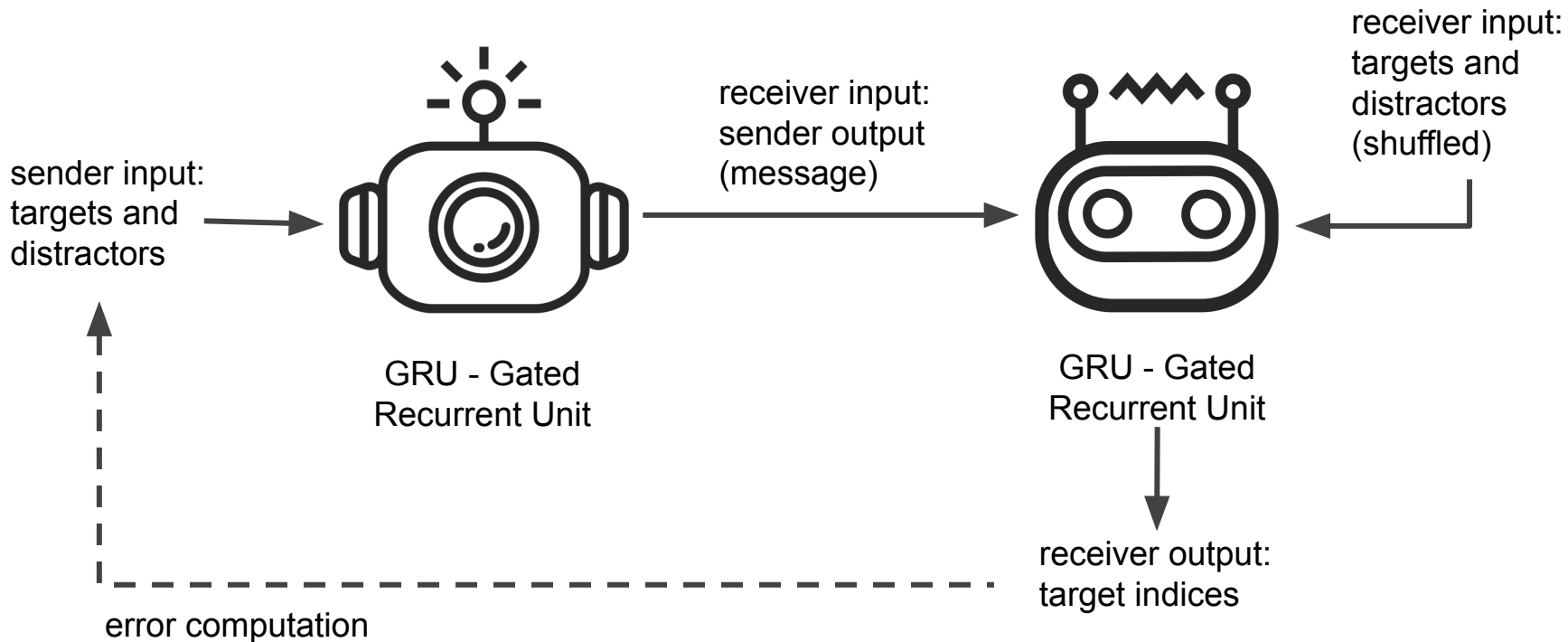
**distractor concept:** “all that is not a circle”

{(blue, square), (green, square), (orange,  
square), (blue, triangle), (green, triangle),  
(orange, triangle)}

# Training

# Speakers and listeners

using EGG implementation (Kharitonov et al., 2019)



Which communicative strategies do speakers follow when referring to concepts at different levels of abstraction?



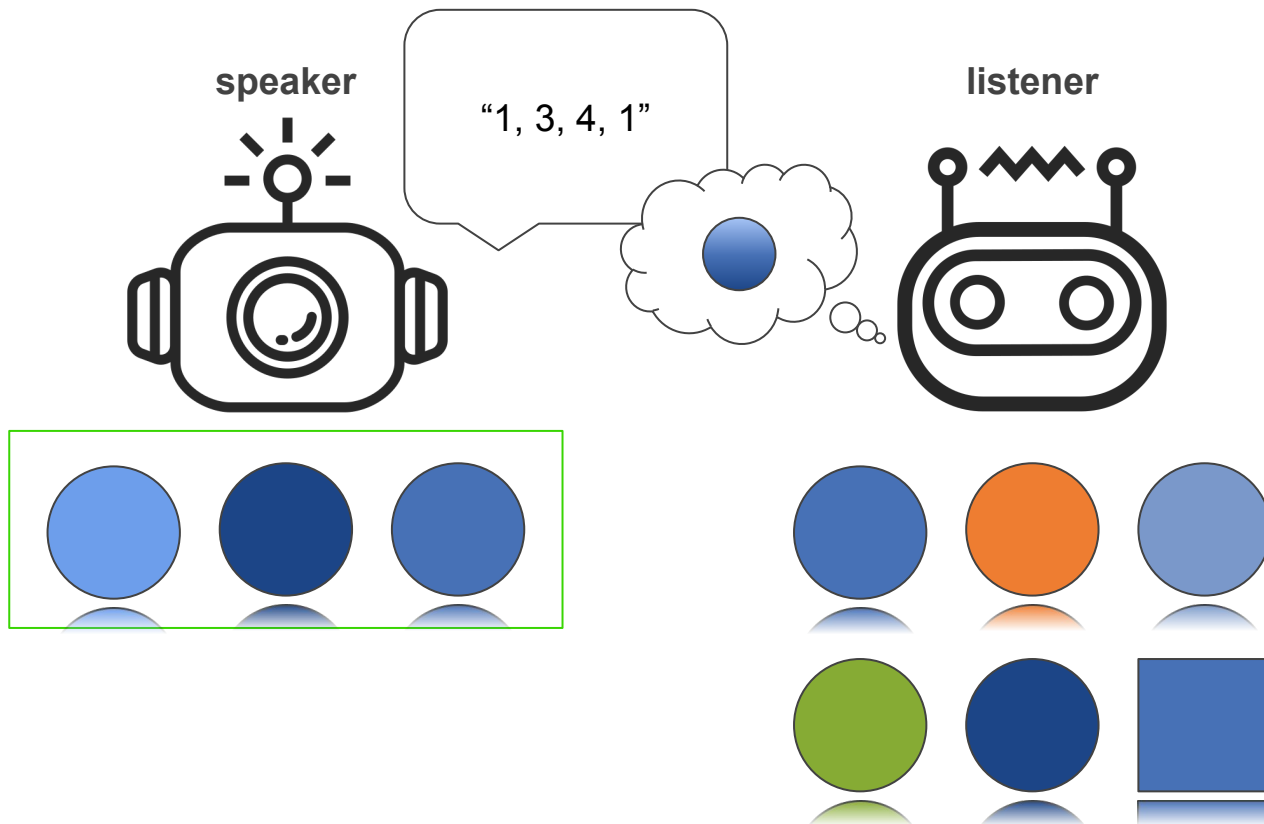
# Hypotheses

— — —

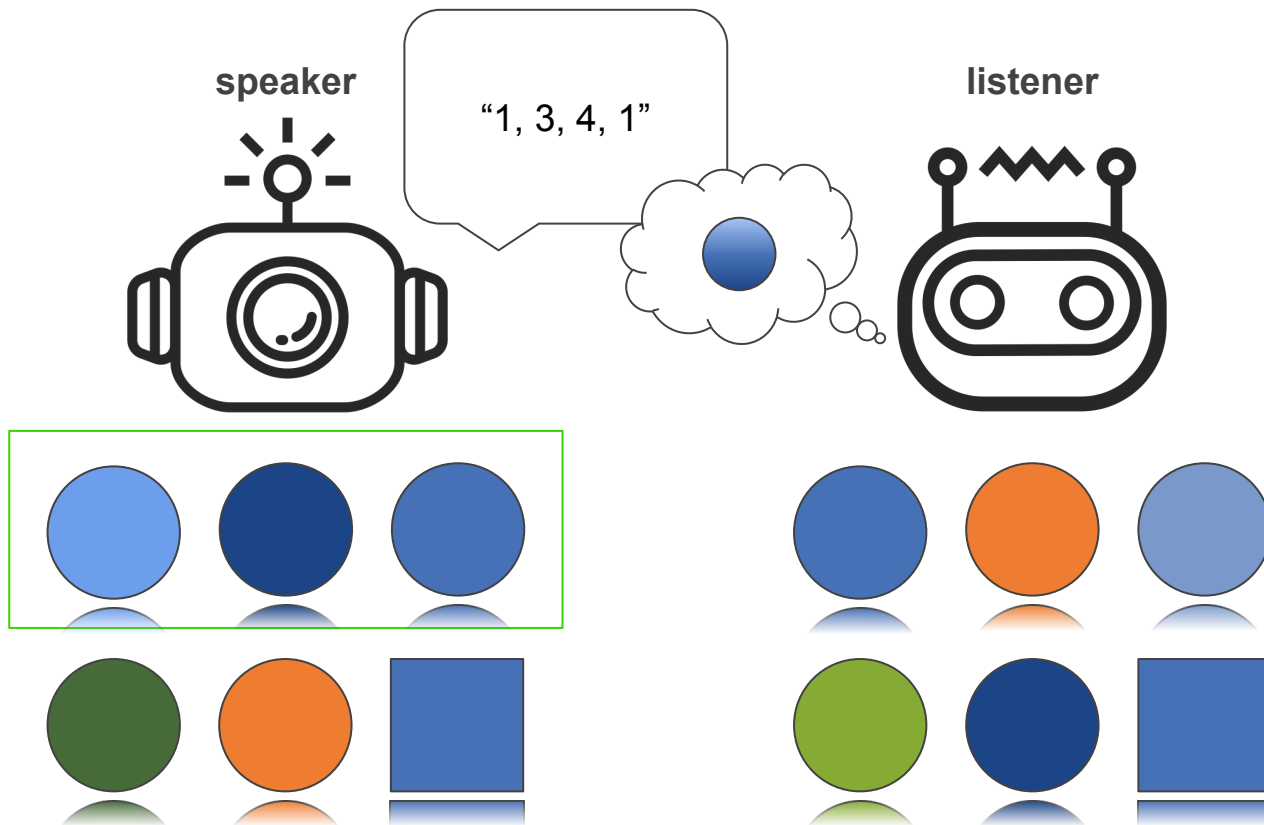
**Baseline: Context-unaware literal agents (L)** have to communicate all relevant attributes to be successful, thus may be overinformative (non-pragmatic baseline).

- **H1: Context-aware literal agents (L-aware)** can communicate fewer than all attributes and let uncertainty be resolved by context (context-based pragmatics).
- **H2: L-aware + utterance cost** will further reduce overinformation because communicating fewer attributes becomes beneficial (context-based pragmatics + implicit abstraction).
- **H3: L + RSA** will increase the agents' performance through additional recursive reasoning of the speaker (reasoning about intentions).

# Context-unaware



# Context-aware



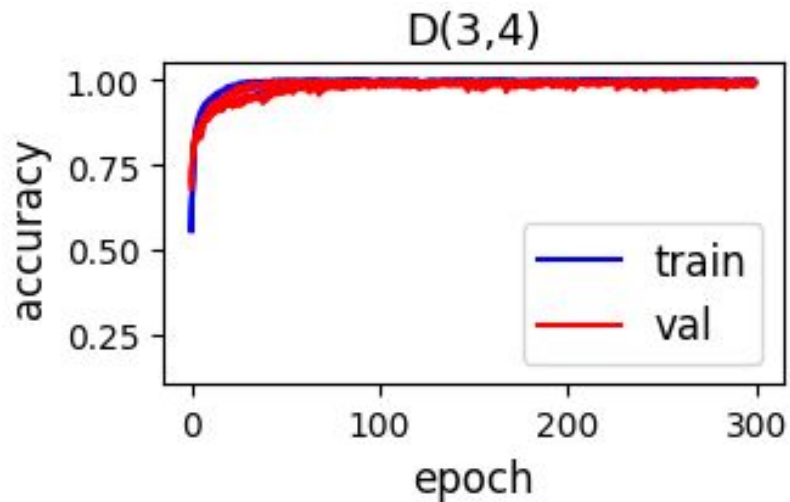
**Do the agents learn to  
successfully communicate?**



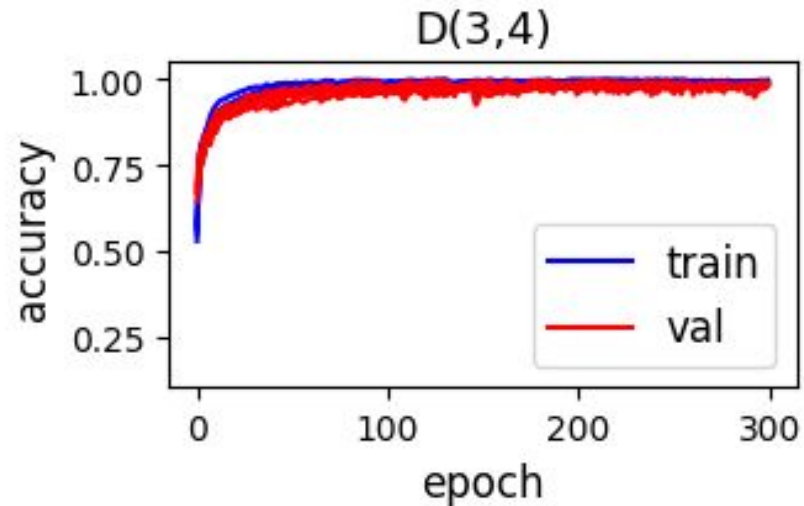
# Accuracies over time

— — —

Context-unaware

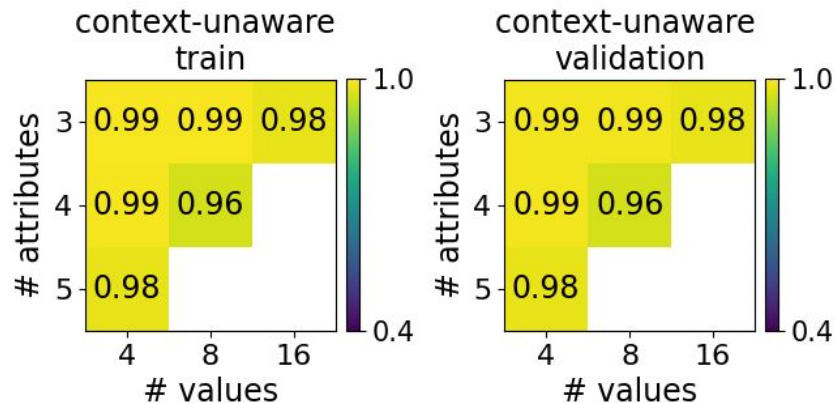


Context-aware

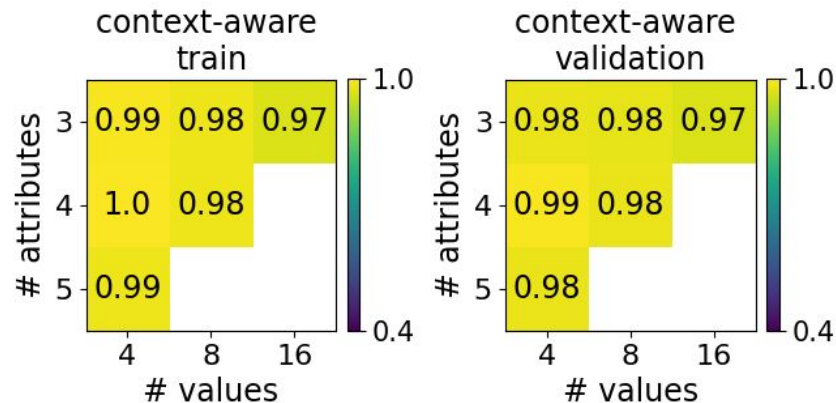


# Final accuracies

## Context-unaware



## Context-aware



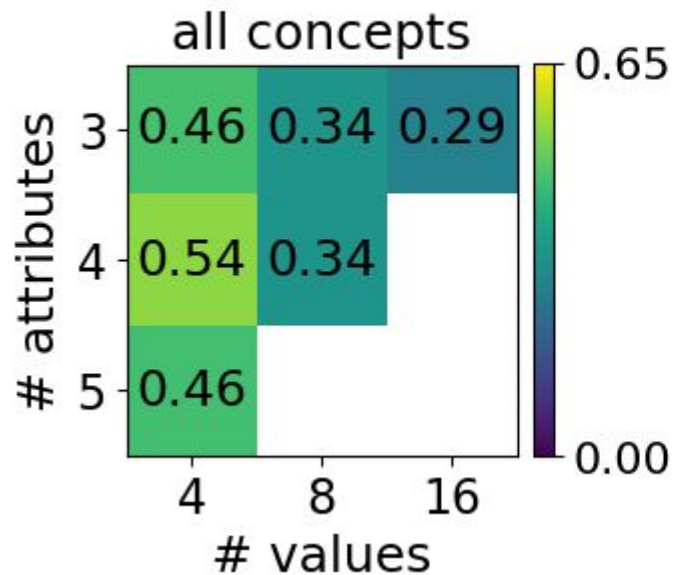
→ trained five runs on six datasets: D(3,4), D(3,8), D(3,16), D(4,4), D(4,8), D(5,4)

Do agents learn to **efficiently** communicate?

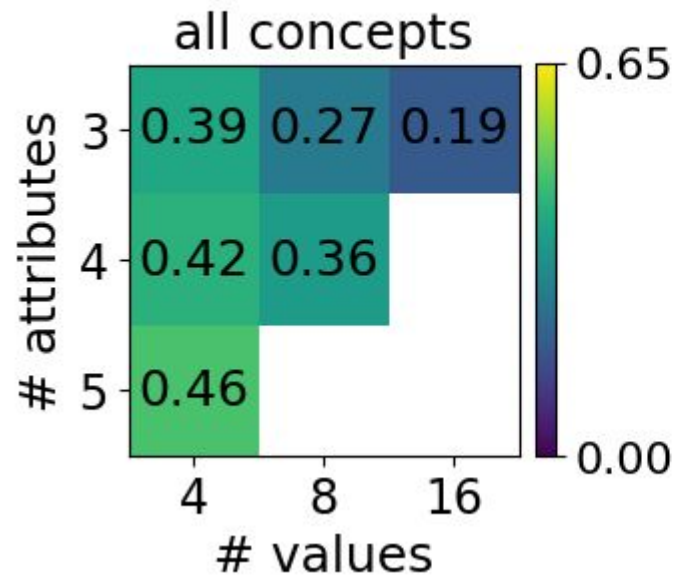
# Compositionality: Topographic similarity

Brighton & Kirby (2006)

Context-unaware

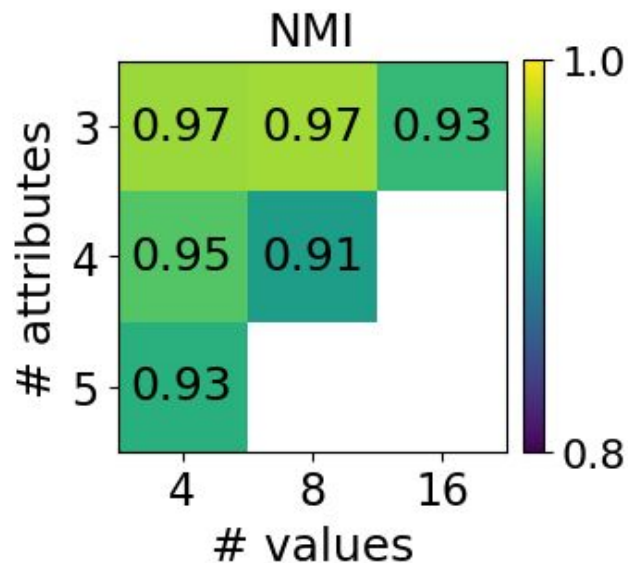


Context-aware

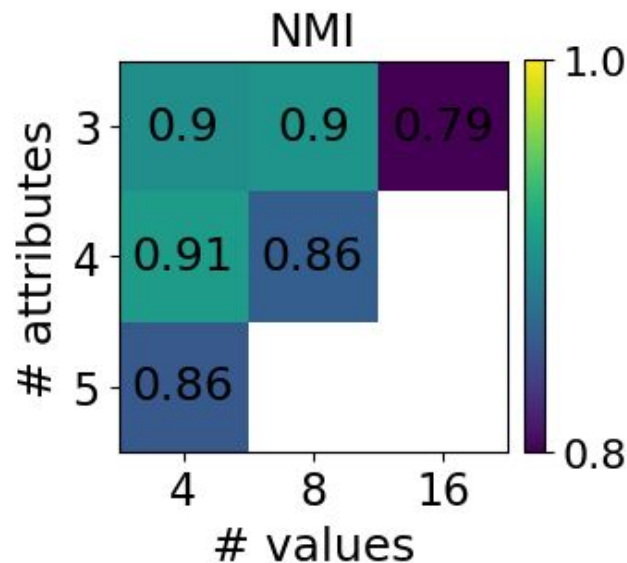


# Informativity: Normalized mutual information (NMI)

Context-unaware



Context-aware



**Do agents learn to reason about the context when deciding on the referring expression's appropriate level of abstraction?**

# Qualitative analysis of the messages - context-unaware

object	fixed indices	context condition	message
[0, 2, 1]	[1, 1, 1]	0	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	0	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	0	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	1	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	1	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	1	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	2	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	2	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	2	[2, 2, 2]

object	fixed indices	context condition	message
[3, 1, 2]	[1, 1, 1]	0	[13, 13, 13]
[3, 1, 2]	[1, 1, 1]	0	[13, 13, 13]
[3, 1, 2]	[1, 1, 1]	0	[13, 13, 13]
[3, 1, 2]	[1, 1, 1]	1	[13, 13, 13]
[3, 1, 2]	[1, 1, 1]	1	[13, 13, 13]
[3, 1, 2]	[1, 1, 1]	1	[13, 13, 13]
[3, 1, 2]	[1, 1, 1]	2	[13, 13, 13]
[3, 1, 2]	[1, 1, 1]	2	[13, 13, 13]
[3, 1, 2]	[1, 1, 1]	2	[13, 13, 13]

# Qualitative analysis of the messages - context-aware

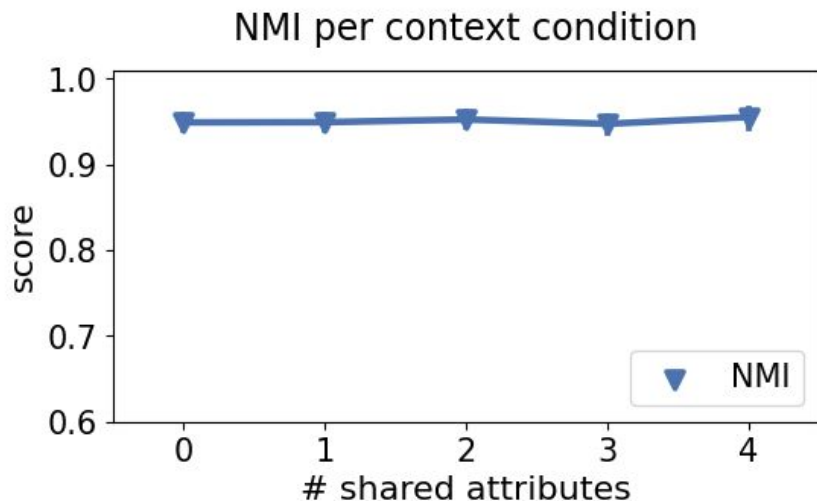
object	fixed indices	context condition	message
[0, 3, 2]	[1, 1, 1]	0	[11, 1, 9]
[0, 3, 2]	[1, 1, 1]	0	[11, 1, 14]
[0, 3, 2]	[1, 1, 1]	0	[11, 1, 1]
[0, 3, 2]	[1, 1, 1]	1	[1, 1, 1]
[0, 3, 2]	[1, 1, 1]	1	[11, 1, 1]
[0, 3, 2]	[1, 1, 1]	1	[1, 1, 9]
[0, 3, 2]	[1, 1, 1]	2	[1, 1, 1]
[0, 3, 2]	[1, 1, 1]	2	[1, 1, 1]
[0, 3, 2]	[1, 1, 1]	2	[1, 1, 1]

object	fixed indices	context condition	message
[2, 3, 1]	[1, 1, 1]	0	[6, 13, 10]
[2, 3, 1]	[1, 1, 1]	0	[6, 13, 10]
[2, 3, 1]	[1, 1, 1]	0	[6, 13, 10]
[2, 3, 1]	[1, 1, 1]	1	[13, 6, 3]
[2, 3, 1]	[1, 1, 1]	1	[6, 13, 10]
[2, 3, 1]	[1, 1, 1]	1	[6, 13, 10]
[2, 3, 1]	[1, 1, 1]	2	[13, 10, 13]
[2, 3, 1]	[1, 1, 1]	2	[13, 10, 13]
[2, 3, 1]	[1, 1, 1]	2	[13, 10, 13]

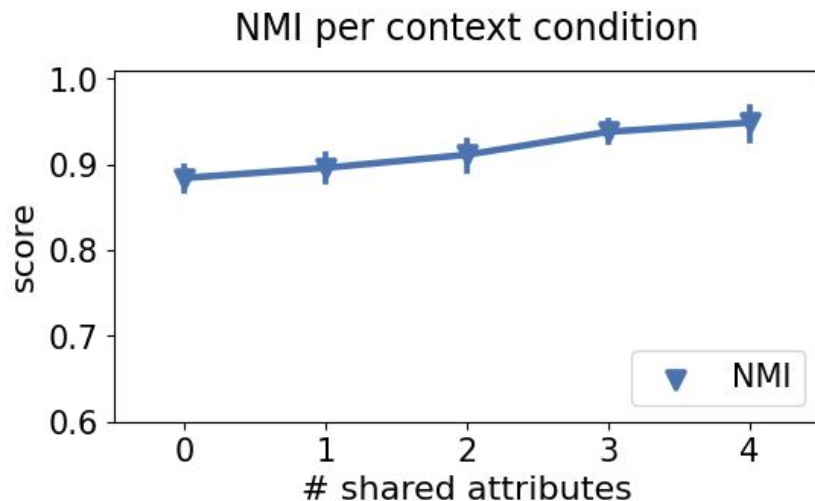


# Informativity: NMI per context condition

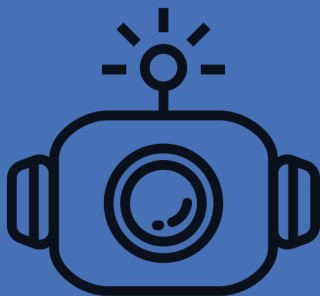
## Context-unaware



## Context-aware

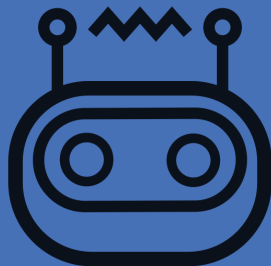


→ Context-aware: The **finer** the context, the **more** one-to-one mappings and the **coarser** the context, the **fewer** one-to-one mappings (similar to Hawkins et al., 2018).



# Thank you!

Any questions?



## Short summary

Agents learn to successfully (and somewhat efficiently) communicate in a concept-level reference game.

The mere presence of context drives its use in communication (without further incentives).

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# List of references

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- Brighton, H., & Kirby, S. (2006). Understanding linguistic evolution by visualizing the emergence of topographic mappings. *Artificial Life*, 12(2):229-242.
- Franke, M., & Degen, J. (2016). Reasoning in Reference Games: Individual- vs. Population-Level Probabilistic Modeling. *PLOS ONE*, 11(5), e0154854. <https://doi.org/10.1371/journal.pone.0154854>
- Hawkins, R. X. D., Franke, M., Smith, K., & Goodman, N. D. (2018). Emerging abstractions: Lexical conventions are shaped by communicative context. *Proceedings of the 40th annual conference of the cognitive science society (CogSci)*, 463–468. <http://cocolab.stanford.edu/papers/HawkinsEtAl2018-Cogsci.pdf>
- Kharitonov, E., Chaabouni, R., Bouchacourt, D., & Baroni, M. (2019). EGG: a toolkit for research on Emergence of lanGuage in Games. *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP): System Demonstrations*, pages 55–60, Hong Kong, China. Association for Computational Linguistics. <https://aclanthology.org/D19-3010>
- Lazaridou, A., Peysakhovich, A., & Baroni, M. (2017). Multi-agent cooperation and the emergence of (natural) language. *International Conference on Learning Representations*. <https://openreview.net/forum?id=Hk8N3ScIq>
- Mu, J., & Goodman, N. (2021). Emergent Communication of Generalizations. *Advances in Neural Information Processing Systems*, 34, 17994–18007. [https://proceedings.neurips.cc/paper\\_files/paper/2021/file/9597353e41e6957b5e7aa79214fcb256-Paper.pdf](https://proceedings.neurips.cc/paper_files/paper/2021/file/9597353e41e6957b5e7aa79214fcb256-Paper.pdf)
- Ohmer, X., Duda, M., & Bruni, E. (2022). Emergence of Hierarchical Reference Systems in Multi-agent Communication. *Proceedings of the 29th International Conference on Computational Linguistics*, 5689–5706. <https://aclanthology.org/2022.coling-1.501>