UNIVERSITÄT OSNABRÜCK
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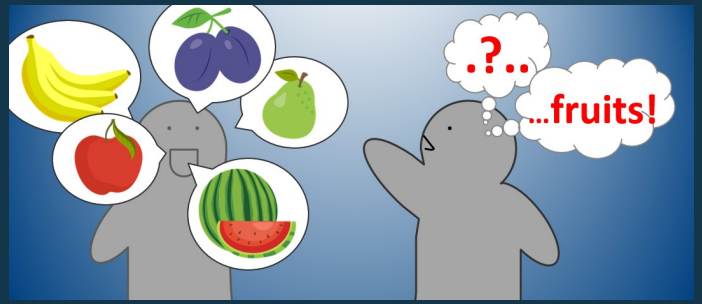
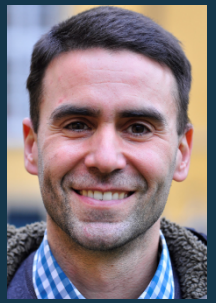
COMPUTATIONAL COGNITION Research Training Group

Kobrock, K., Ohmer, X., Bruni, E., and Gotzner, N. (2024)



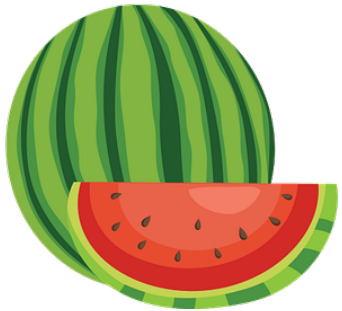





Context Shapes Emergent Communication about Concepts at Different Levels of Abstraction

Levels of abstraction

A



“Carolina Cross”

“watermelon”

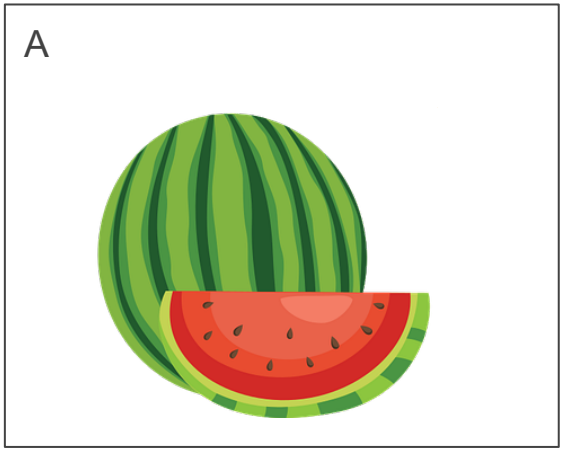
“melon”

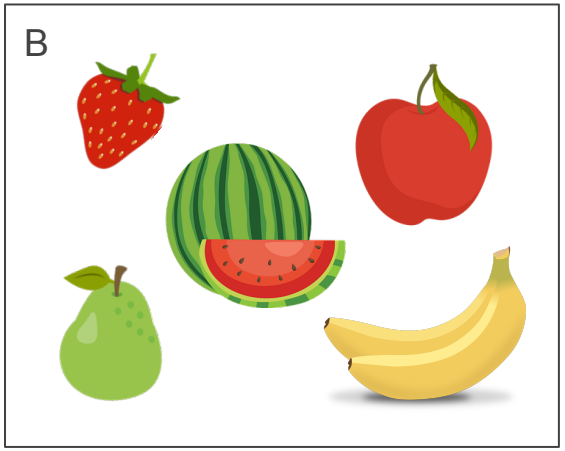
“fruit”

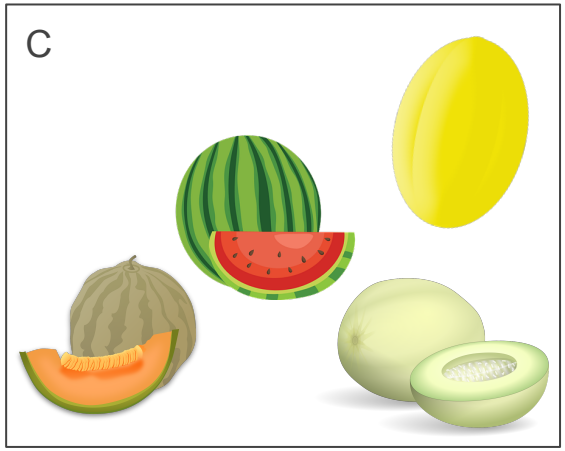
specific

generic

Levels of abstraction shaped by context







“Carolina Cross”

“watermelon”

“melon”

“fruit”

specific

generic

“melon”

“watermelon”

coarse context *fine*

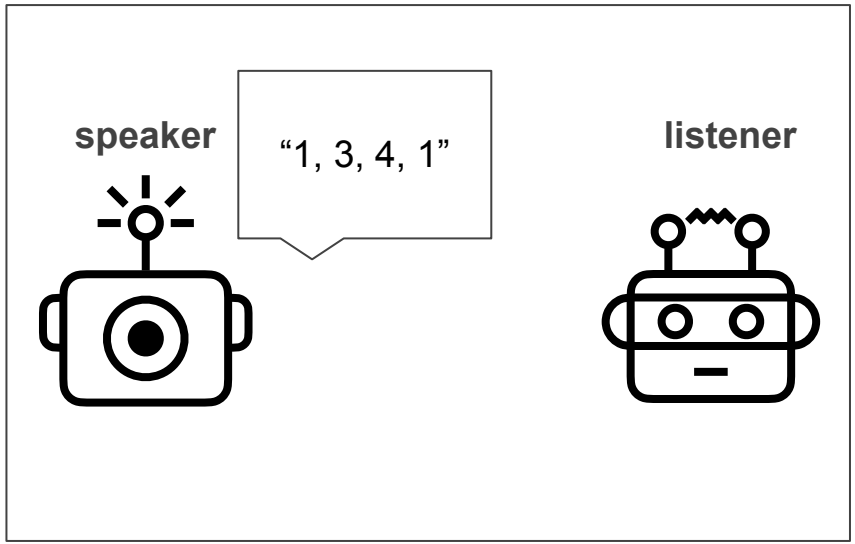
Goals

1) Study the role of the **concept's level of abstraction** and of the **context** in the referential communication of concepts.
2) Investigate **communicative strategies**, and specifically whether the communicative context is reflected in the emerging language.

Methodology

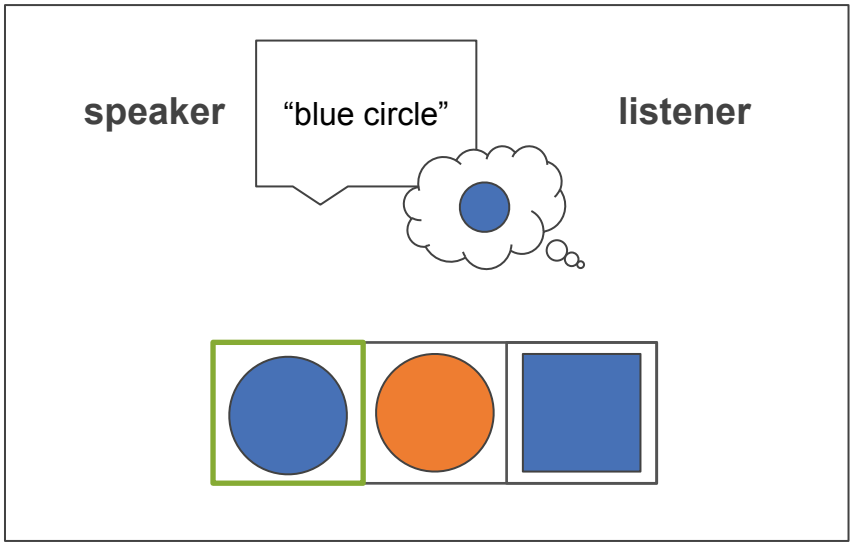
Paradigm and set-up

Emergent communication



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

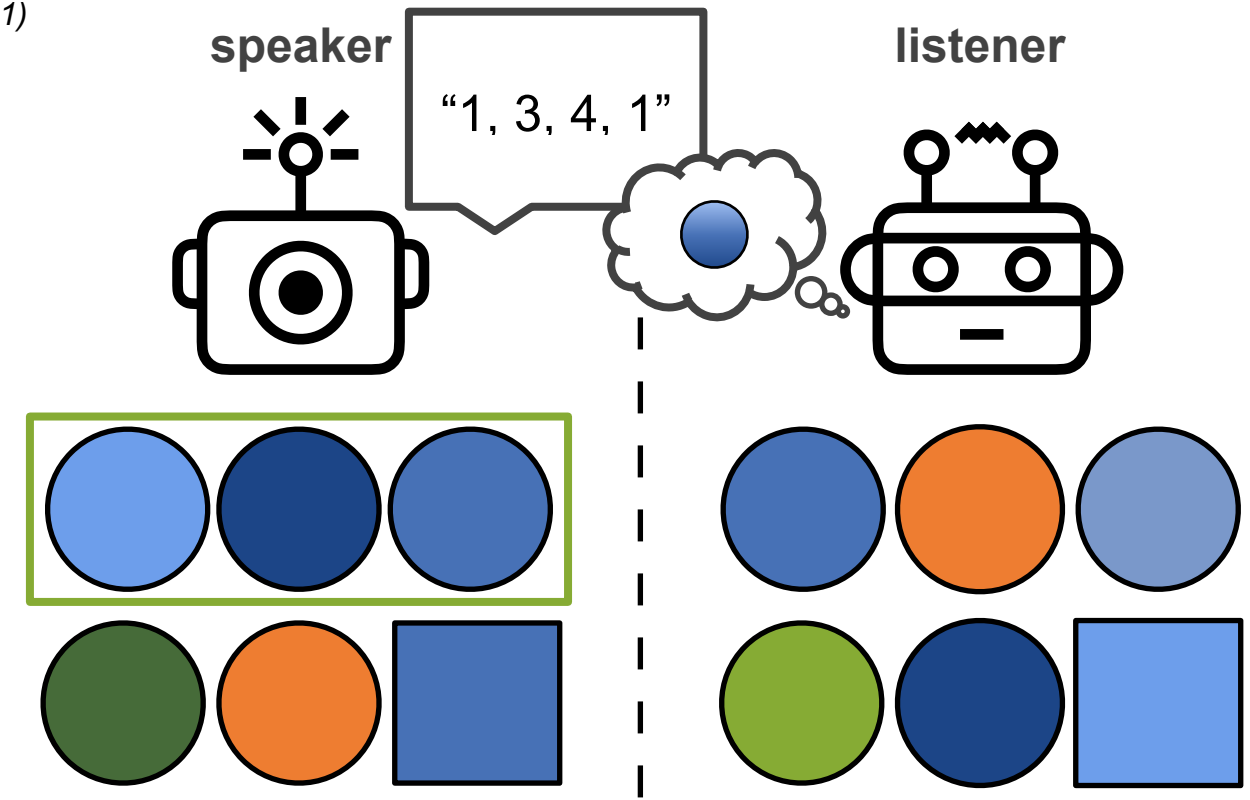
Reference game



e.g., Franke & Degen (2016), Hawkins et al. (2018)

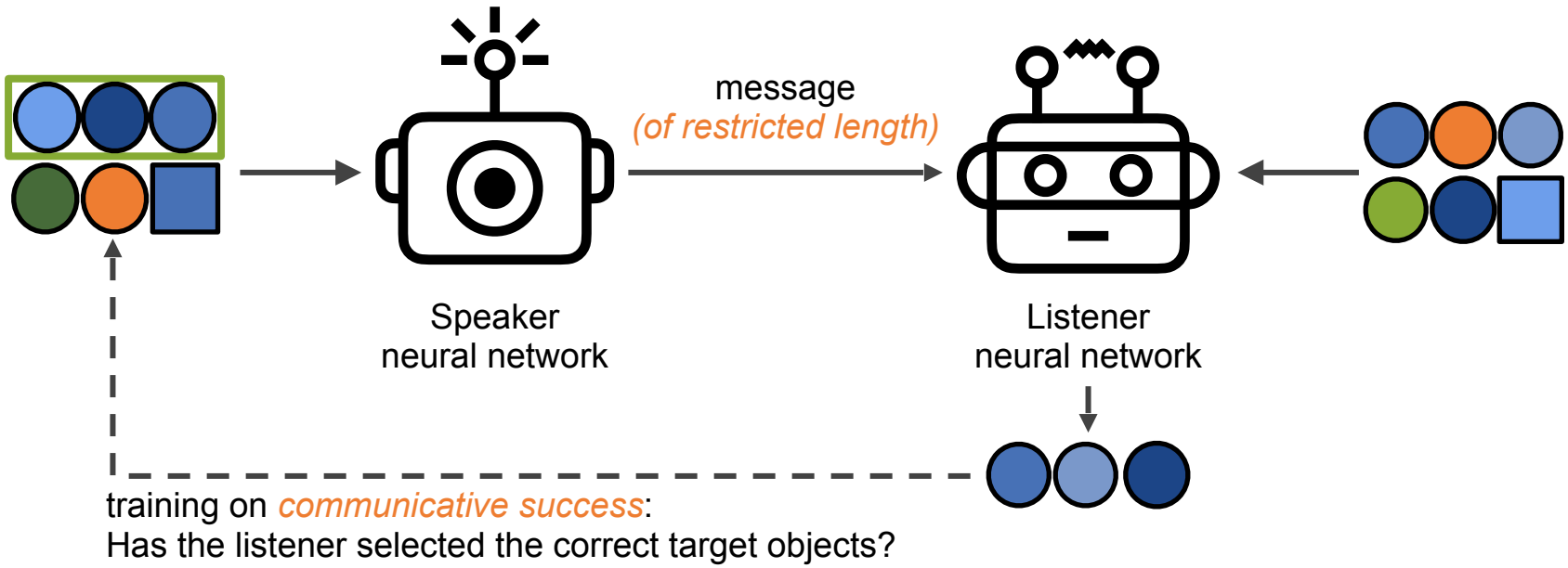
Modeling framework: Concept-level reference game

Mu & Goodman (2021)



Efficiency in a communication system

e.g. Gibson et al. (2019)



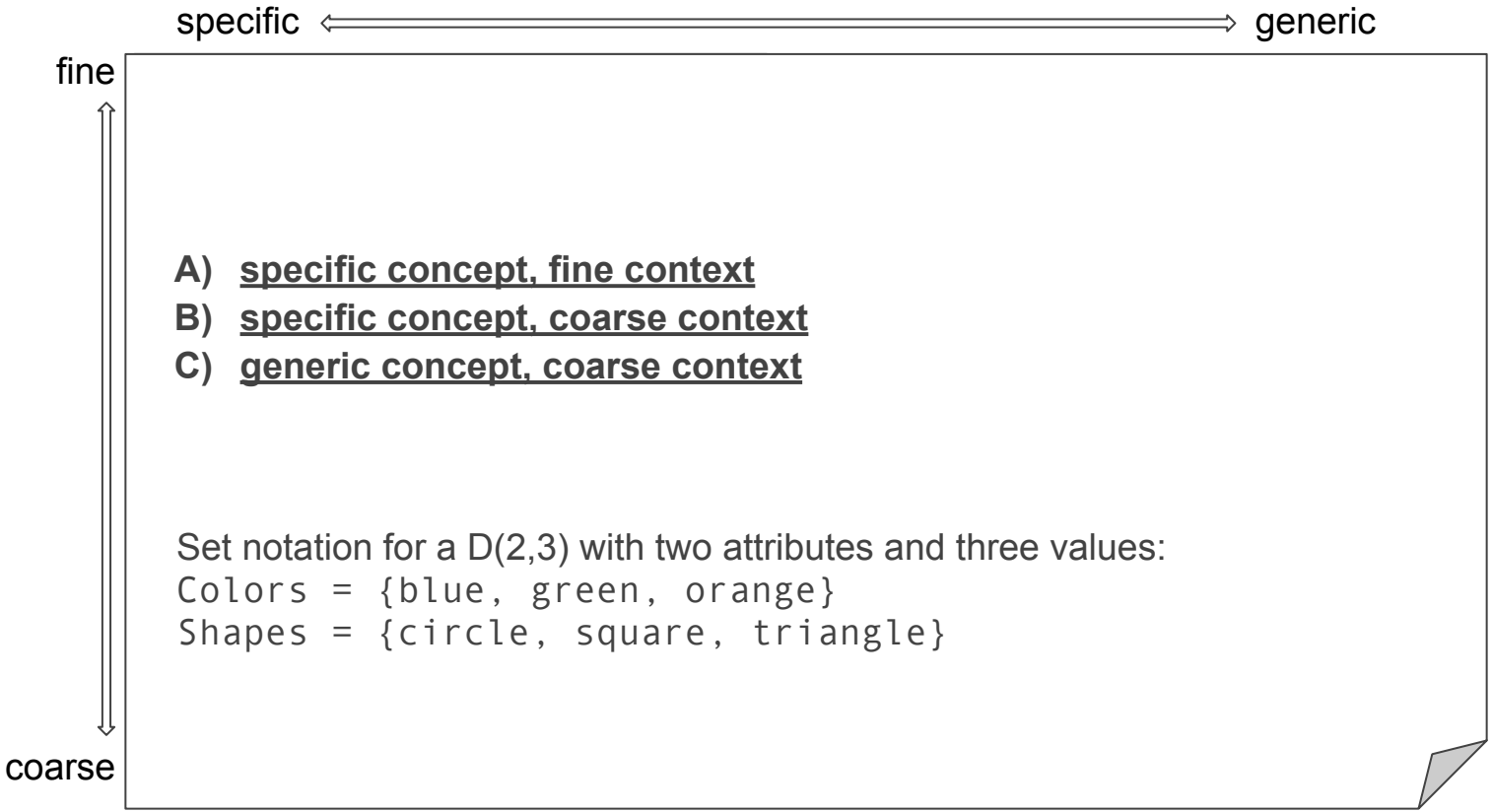
Goals

1) Study the role of the **concept's level of abstraction** and of the **context** in the referential communication of concepts.
2) Investigate **communicative strategies**, and specifically whether the communicative context is reflected in the emerging language.

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.

Dataset manipulates concept level and context



A) **specific concept, fine context**
B) **specific concept, coarse context**
C) **generic concept, coarse context**

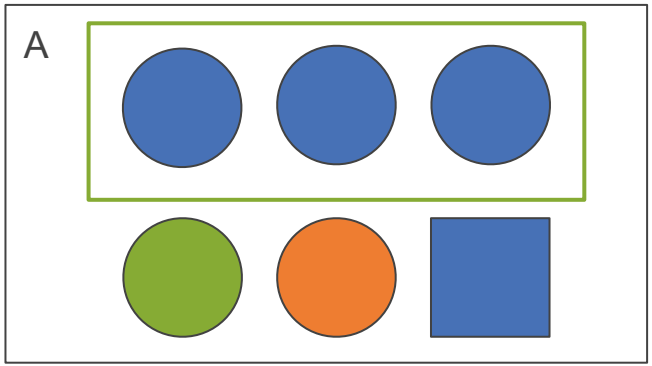
Set notation for a D(2,3) with two attributes and three values:

```
Colors = {blue, green, orange}
Shapes = {circle, square, triangle}
```

Dataset manipulates concept level and context

specific ⟺ generic

fine ⟷ coarse

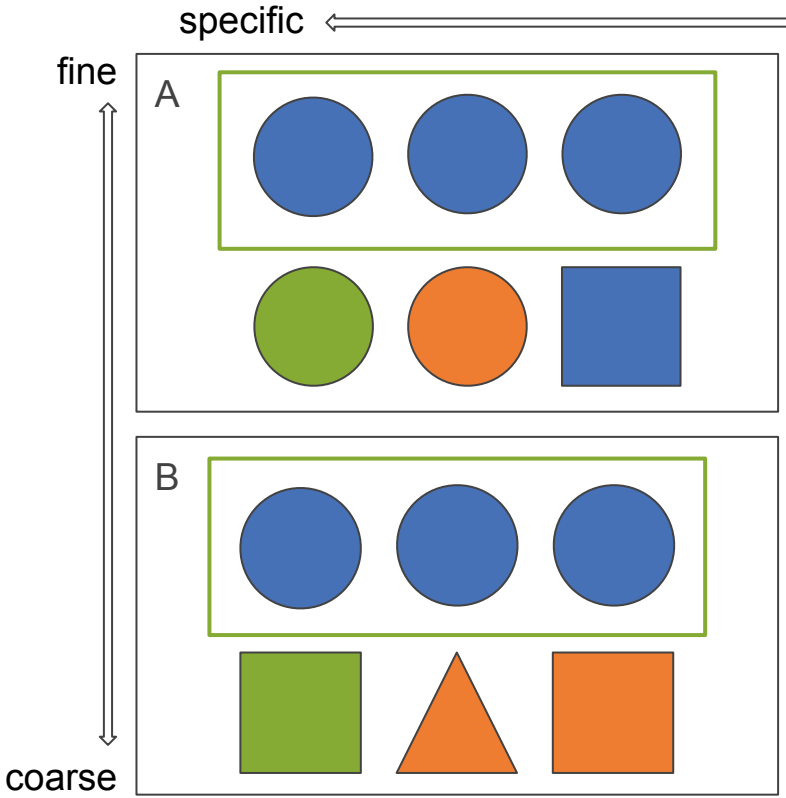


A) specific concept, fine context:

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)}`

Dataset manipulates concept level and context



B) specific concept, coarse context:

target concept: “blue circle”

`{(blue, circle)}`

distractor concept: “all that is not blue or a circle”

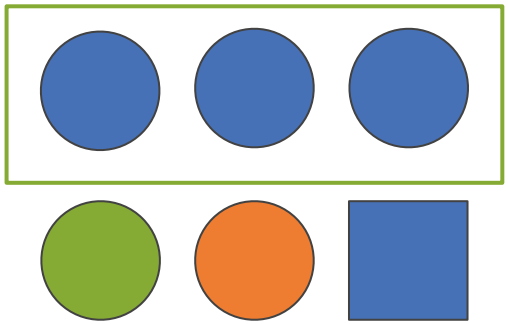
`{(green, square), (orange, square), (green, triangle), (orange, triangle)}`

Dataset manipulates concept level and context

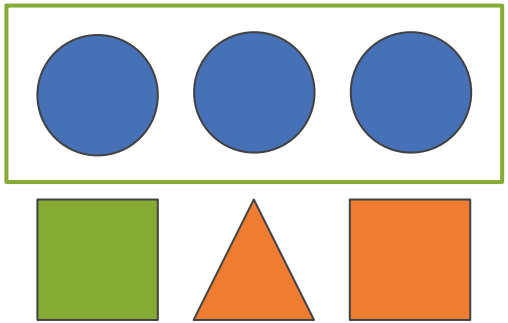
specific ⟺ generic

fine ↕ coarse

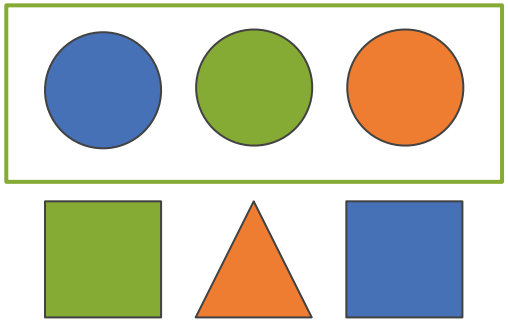
A



B



C



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)}

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.

Goals

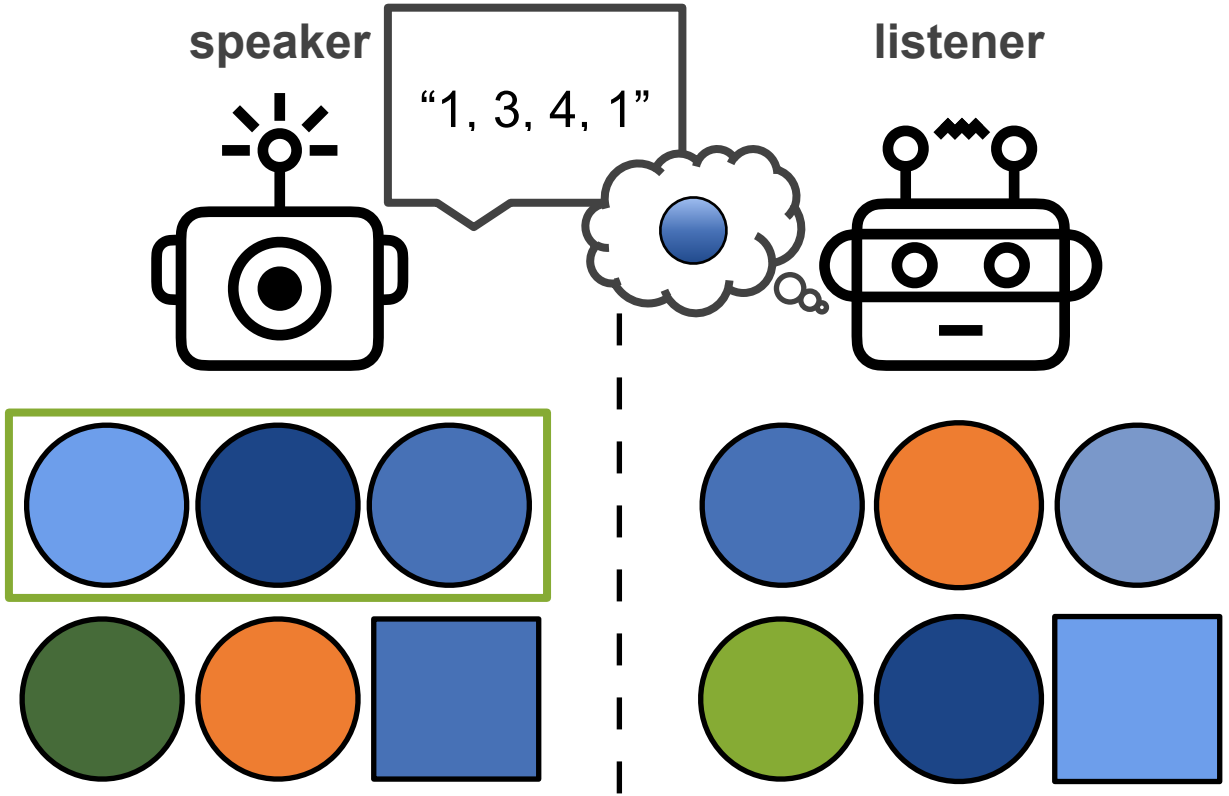
1) Study the role of the **concept's level of abstraction** and of the **context** in the referential communication of concepts.
2) Investigate **communicative strategies**, and specifically whether the communicative context is reflected in the emerging language.

Game scenarios

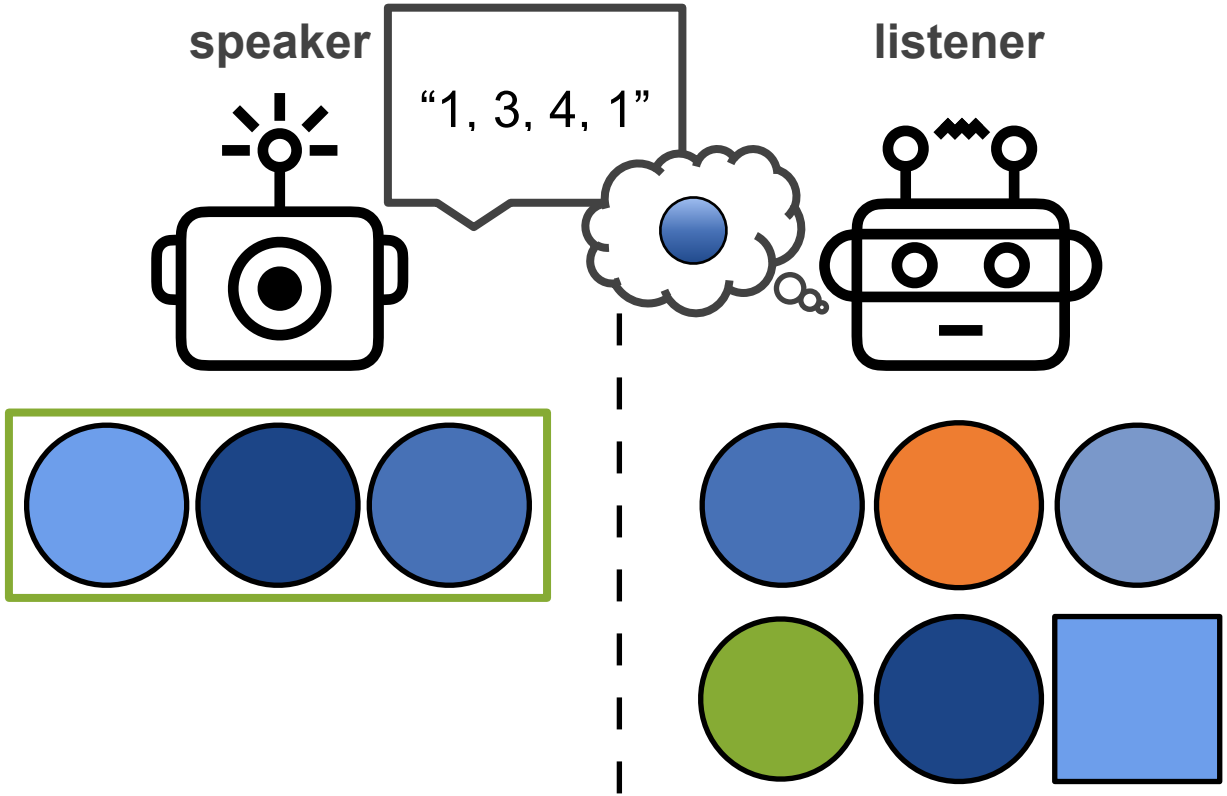
Baseline: Context-unaware literal agents (L): Speakers have access only to the target objects (i.e. *concept*), not to the distractor objects (i.e. *context*).

• **Scenario 1: Context-aware literal agents (L-aware):** Speakers have access to both targets (*concept*) and distractors (*context*) (context-based pragmatics; see Sedivy, 2003).

Context-aware



Context-unaware



Hypotheses

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

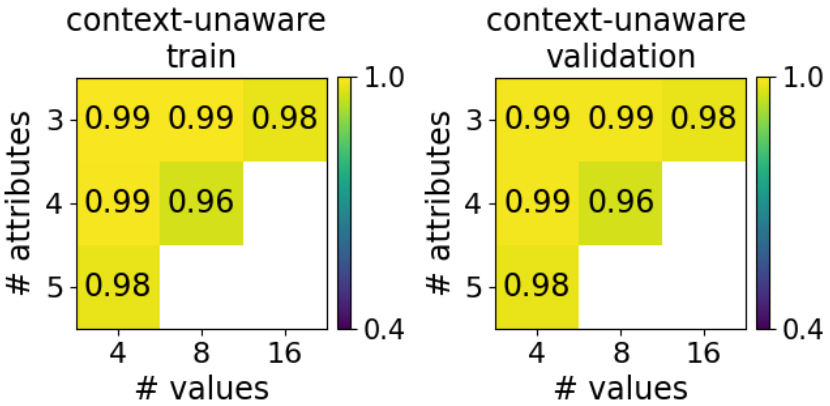
• **H1: Context-aware literal agents (L-aware)** can communicate fewer than all attributes and let uncertainty be resolved by context (context-based pragmatics).

Results

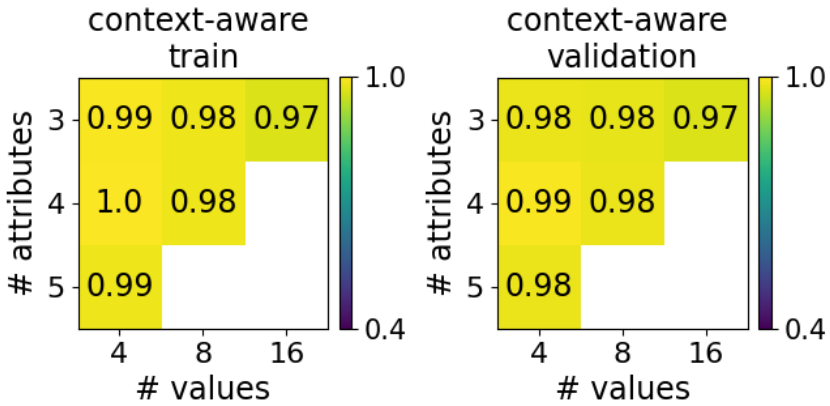
Do the agents learn to successfully communicate?

Final accuracies of trained model

Context-unaware



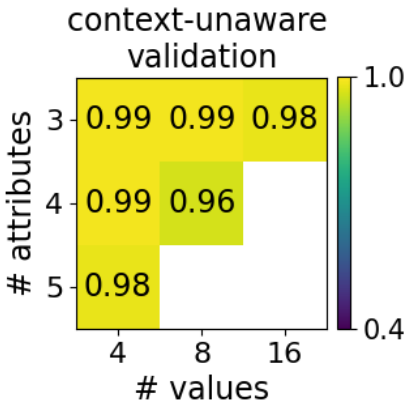
Context-aware

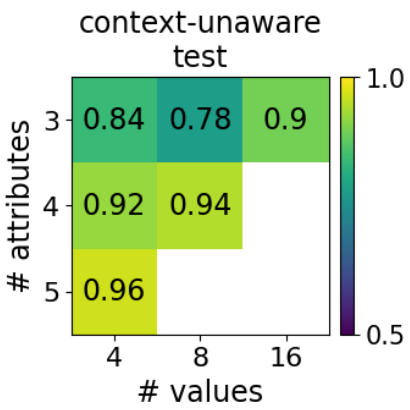


→ trained five runs on six datasets: D(3,4), D(3,8), D(3,16), D(4,4), D(4,8), D(5,4)

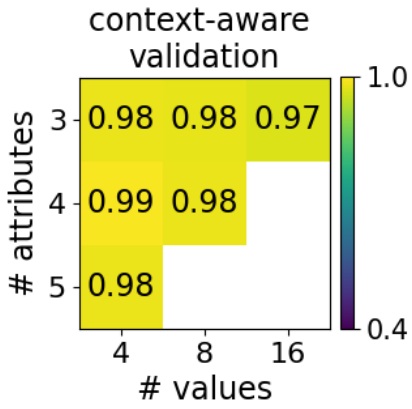
Test accuracies on unseen concepts

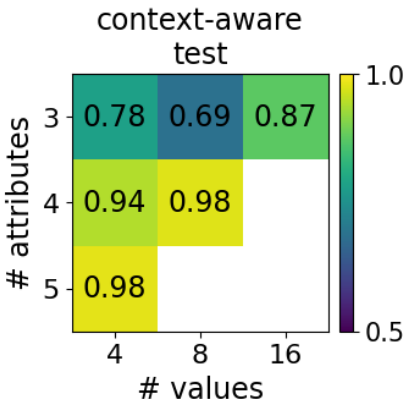
Context-unaware





Context-aware





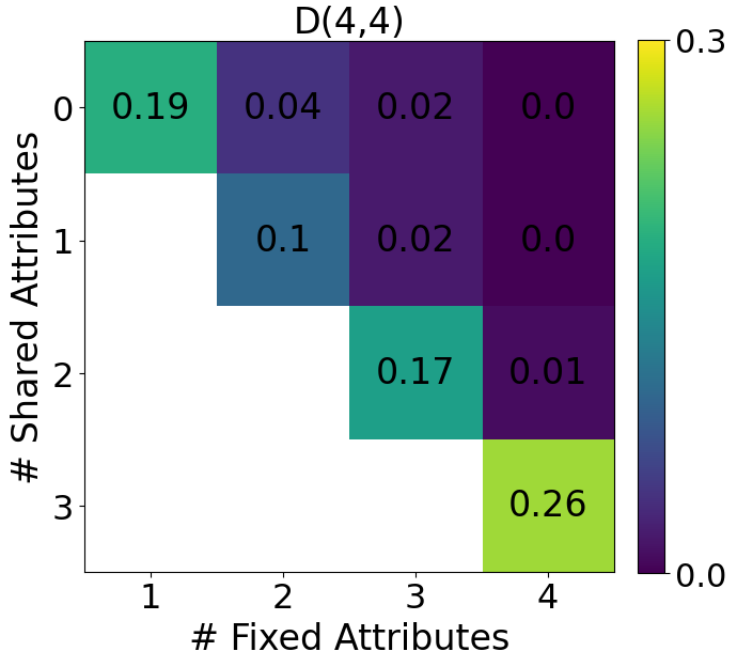
→ trained five runs on six datasets: D(3,4), D(3,8), D(3,16), D(4,4), D(4,8), D(5,4)

Do agents learn to efficiently communicate?

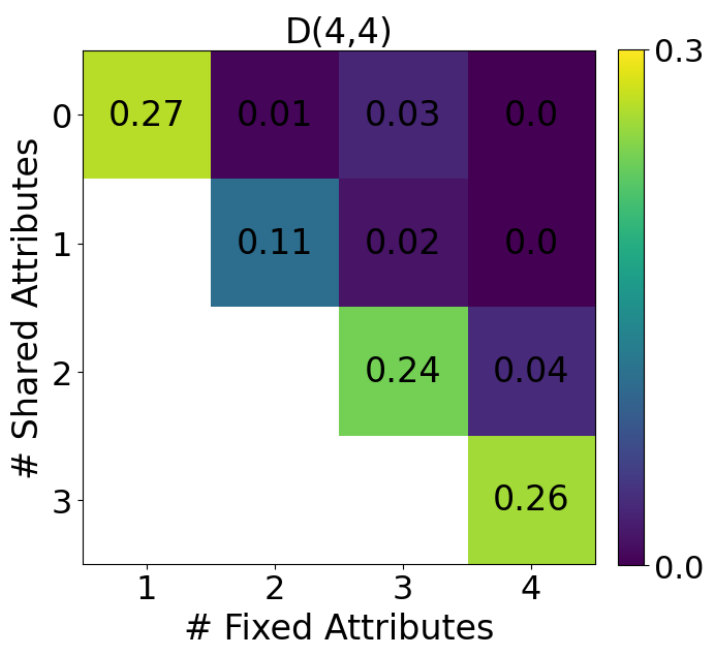
Errors

Game rounds with at least one incorrectly classified object normalized by number of occurrences in dataset.

Context-unaware



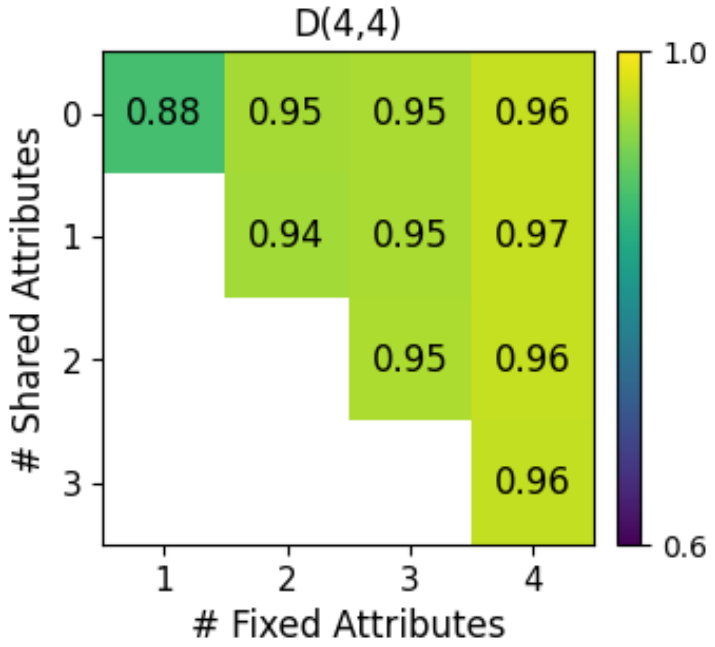
Context-aware



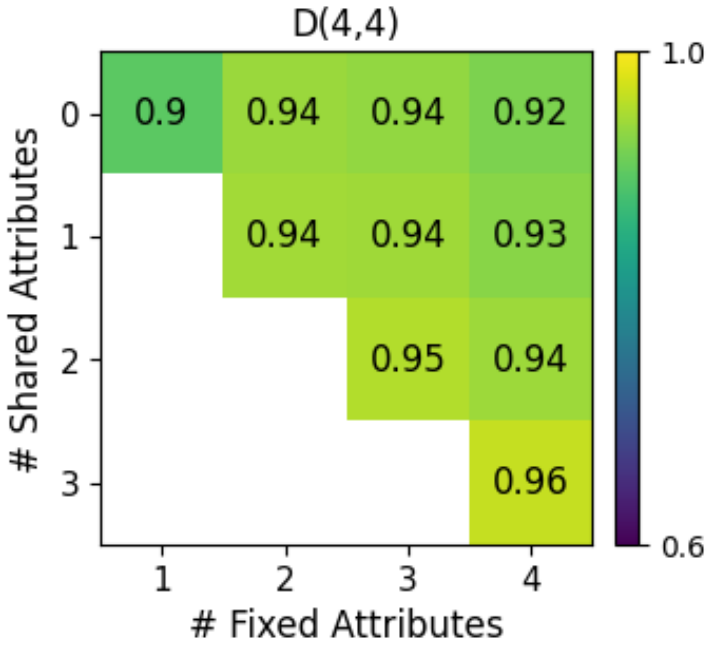
Informativity: Normalized mutual information (NMI)

One-to-one correspondence between messages and concepts.

Context-unaware



Context-aware



Do agents learn to take the context into account when deciding on the referring expression's appropriate level of abstraction?

Qualitative analysis of the messages

Context-unaware

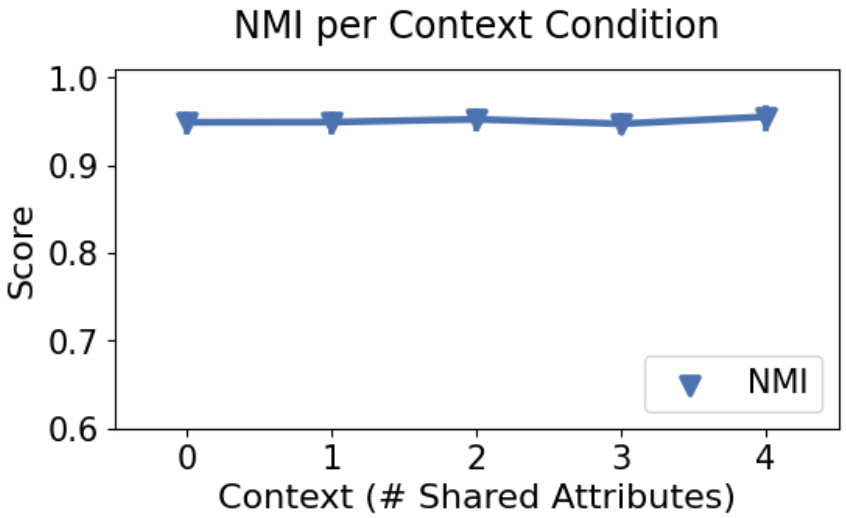
object	fixed indices	context condition	message
[0, 2, 1]	[1, 1, 1]	0	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	0	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	0	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	1	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	1	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	1	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	2	[2, 2, 2]
[0, 2, 1]	[1, 1, 1]	2	[2, 2, 2]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

Context-aware

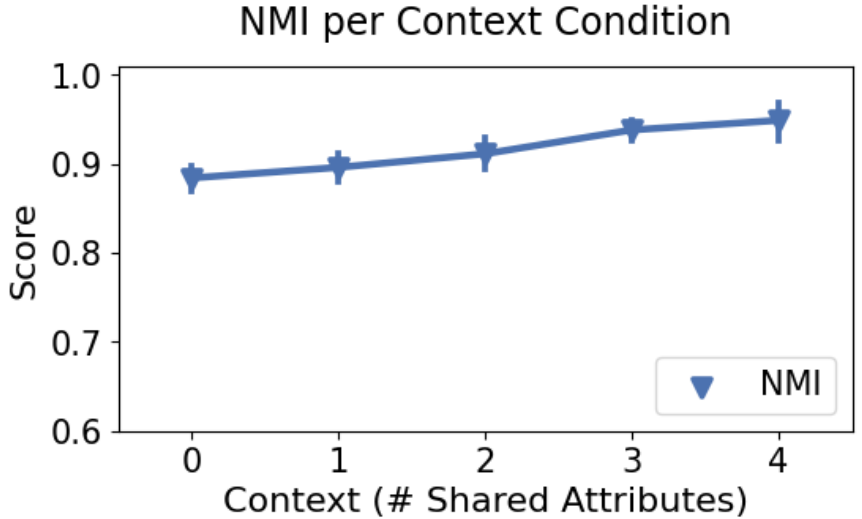
object	fixed indices	context condition	message
[2, 3, 1]	[1, 1, 1]	0	[6, 13, 10]
[2, 3, 1]	[1, 1, 1]	0	[6, 13, 10]
[2, 3, 1]	[1, 1, 1]	0	[6, 13, 10]
[2, 3, 1]	[1, 1, 1]	1	[13, 6, 3]
[2, 3, 1]	[1, 1, 1]	1	[6, 13, 10]
[2, 3, 1]	[1, 1, 1]	1	[6, 13, 10]
[2, 3, 1]	[1, 1, 1]	2	[13, 10, 13]
[2, 3, 1]	[1, 1,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

Informativity: Entropy scores per context condition

Context-unaware: overinformative



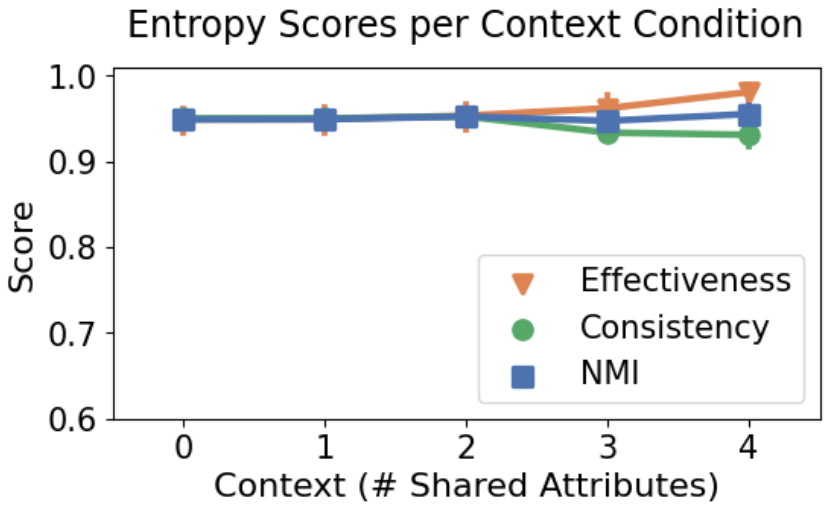
Context-aware: adaptation to context



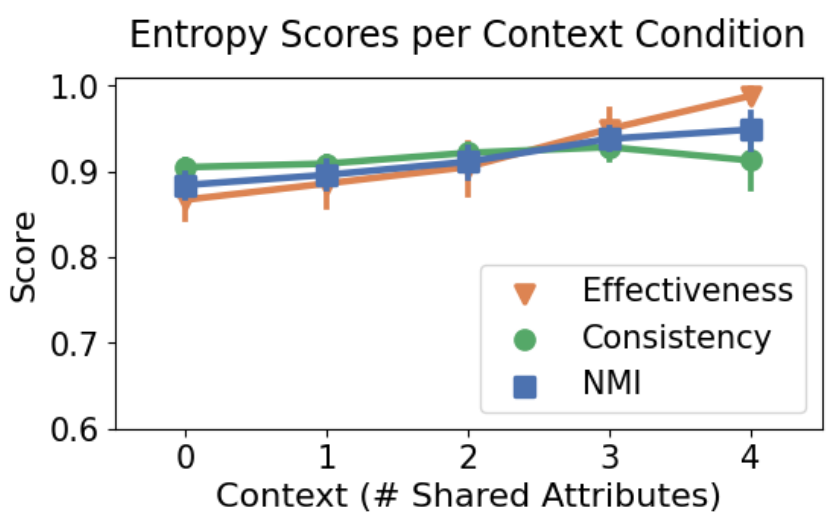
→ Context-aware: The ***finer*** the context, the **more** one-to-one mappings and the ***coarser*** the context, the **fewer** one-to-one mappings (similar to Hawkins et al., 2018).

Informativity: Entropy scores per context condition

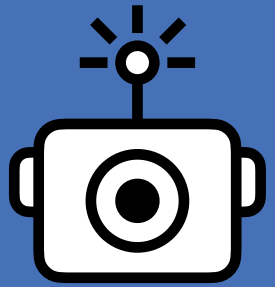
Context-unaware: overinformative



Context-aware: adaptation to context

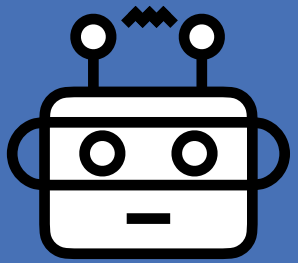


→ Context-aware: The ***finer*** the context, the **more** effective use of messages that uniquely identify the target concept (i.e. non-polysemous expressions) and the ***coarser*** the context, the **more** consistent use of the same messages to refer to the same concepts (i.e. no synonyms).



Thank you!

Any questions?



Short summary

Agents learn to successfully communicate in a concept-level reference game.

Only context-aware agents learn to communicate efficiently by adapting their messages to the context conditions.

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

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List of references

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