Emergence of communication and inductive biases towards compositionality

CaféTAL

May 23, 2022

In collaboration with Timothée Bernard

Outline

Intro

Exp. 1: Doing the math

Exp. 2: Signaling games & pretraining

Exp. 3: Signaling game & GANs (Teaser)

Conclusions

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Emergence of Communication

- How did language evolve?

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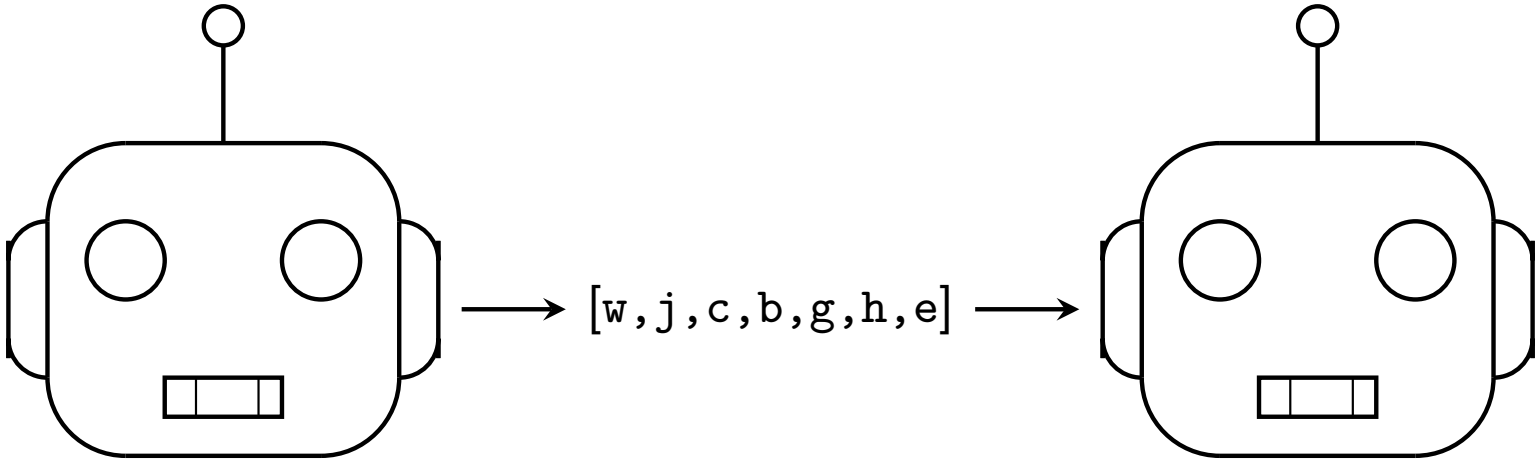

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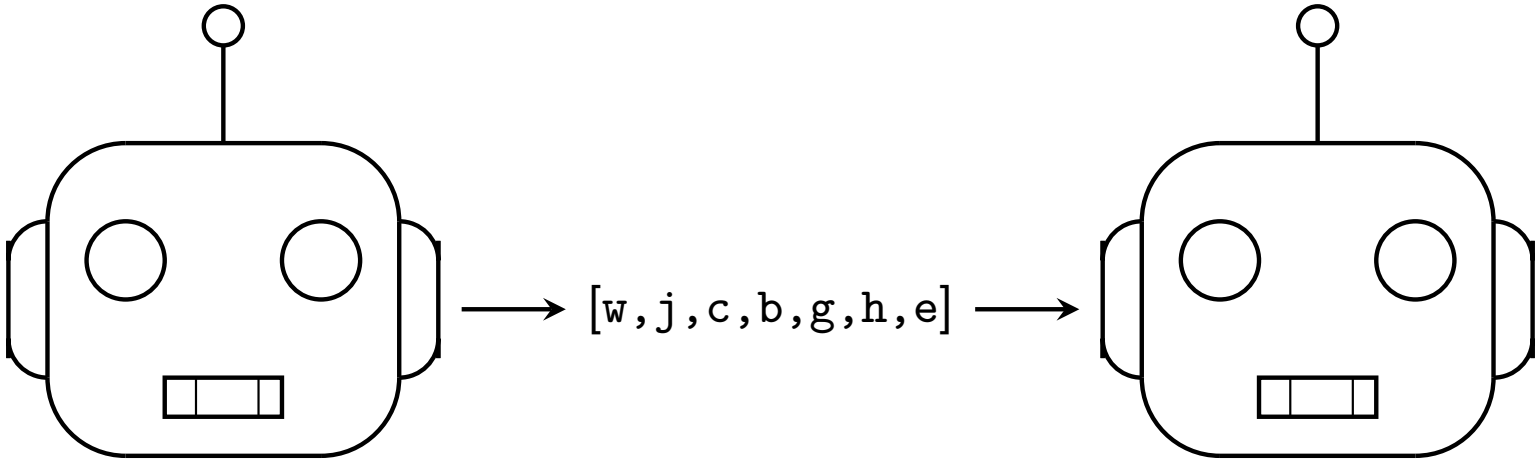

- Can we get specific characteristics, like compositionality?

Measuring compositionality

- One way to measure compositionality is topographic similarity (Brighton et al., 2006)

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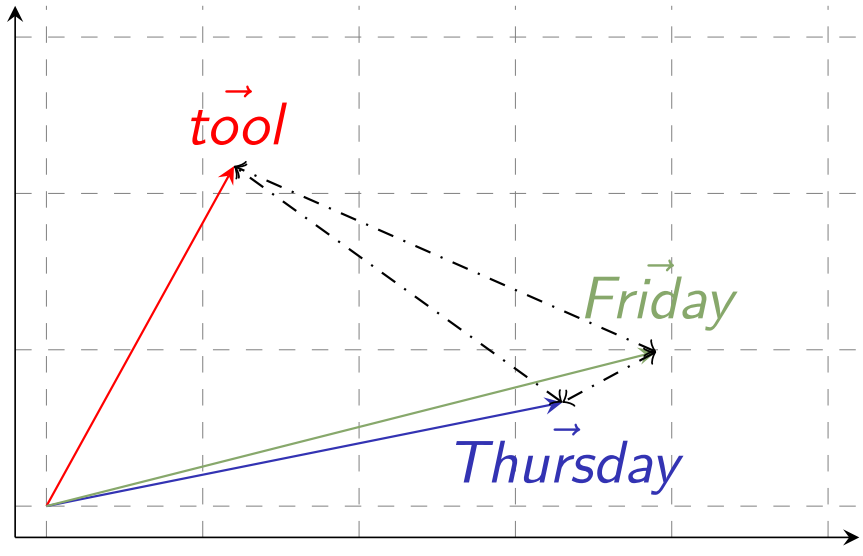

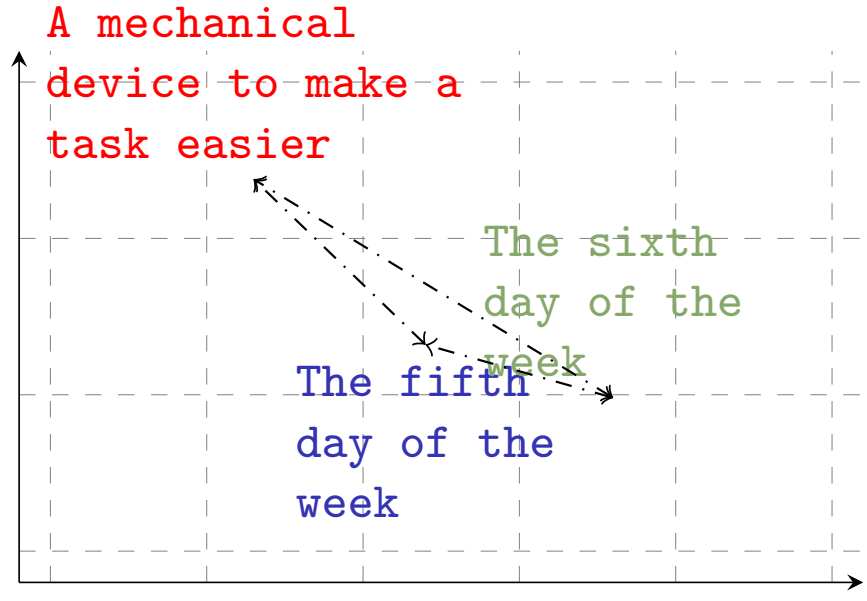

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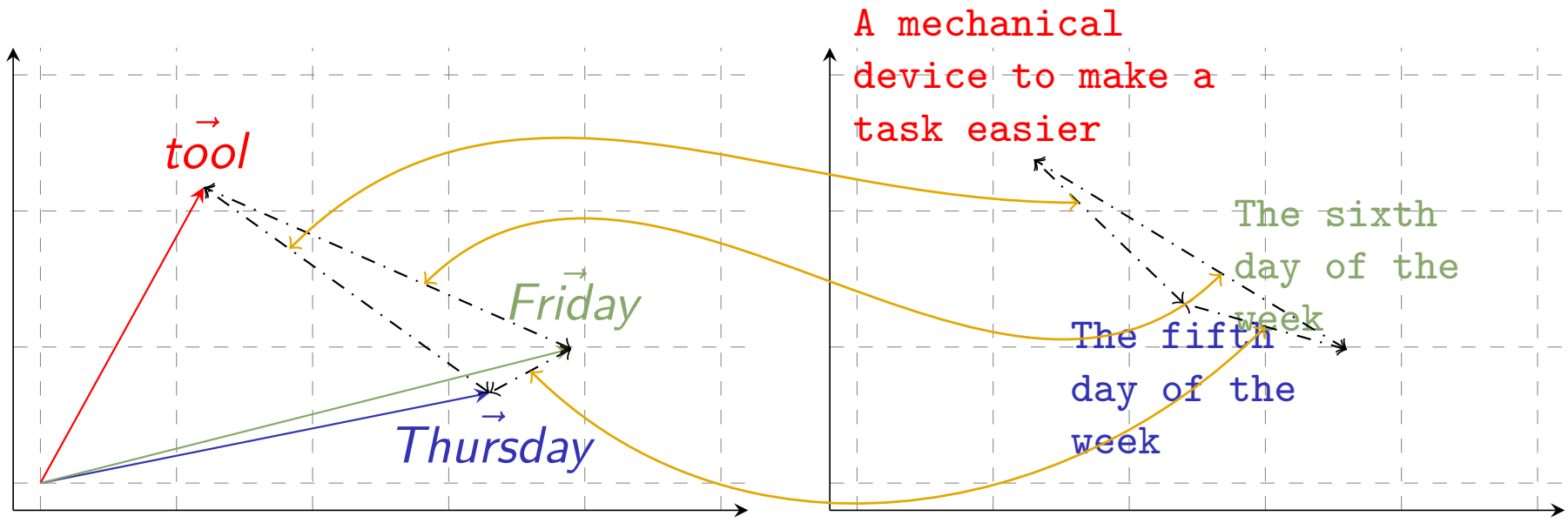

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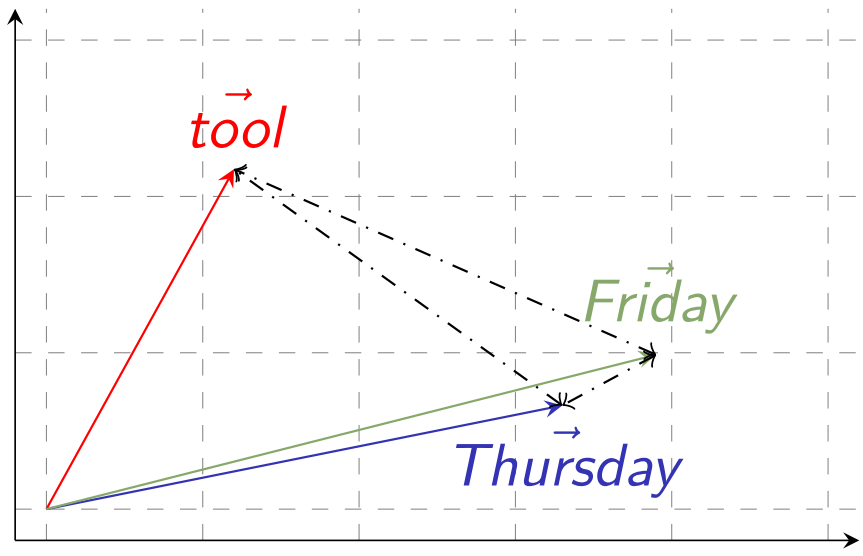

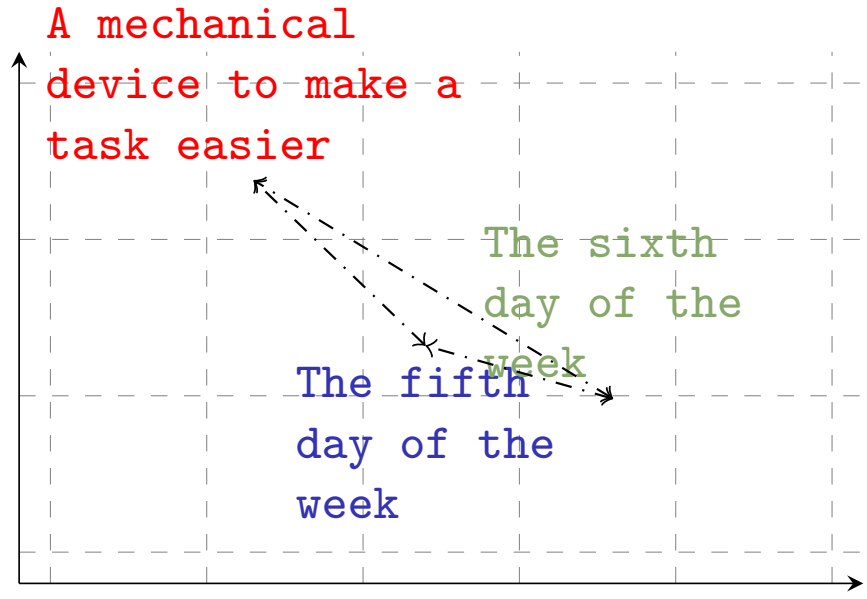

- Still an open question

What we'll see today:

1. some language games designed for the emergence of compositionality
2. some tweaks and tricks to get the model to produce more reliable outputs

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- What's a good task for testing compositionality?

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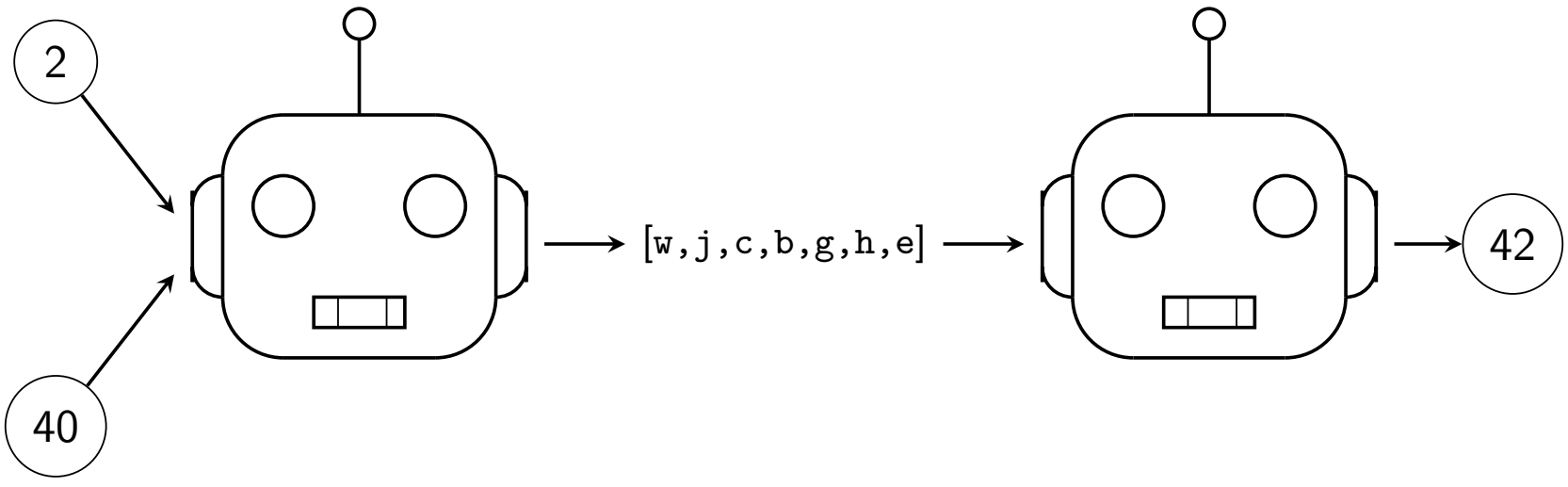

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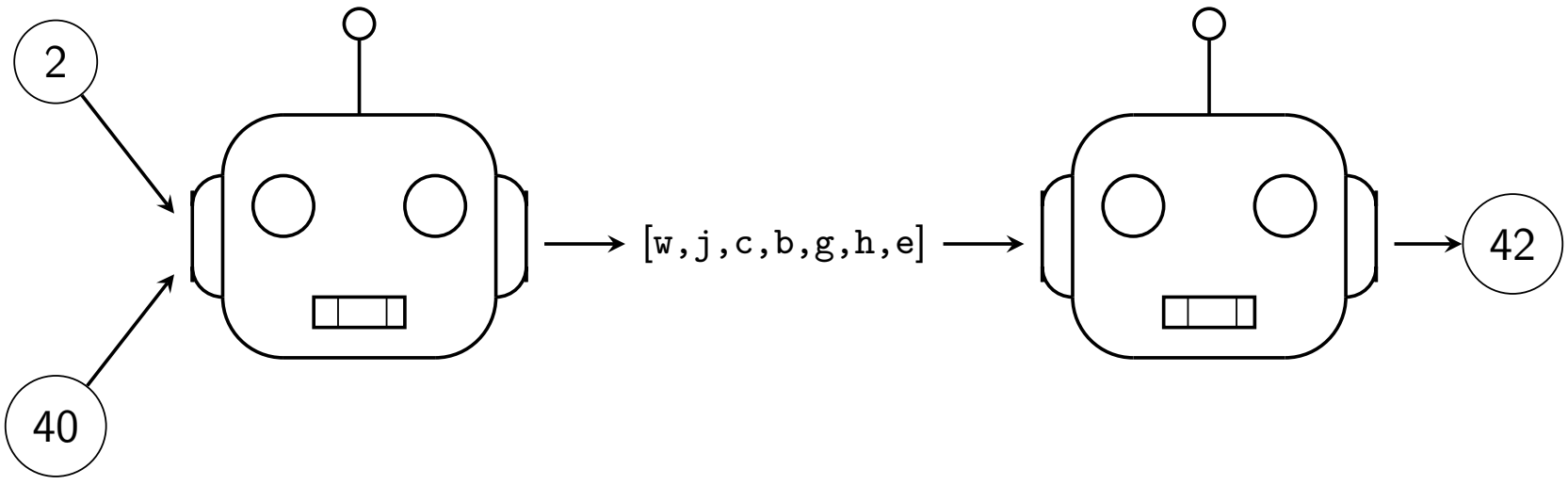

- We can use the known additive structure to see what's encoded: pairs of integers, sum of integers, other?

Classification vs. Regression

How should we train such a setup?

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Computational details:

- LSTM-based agents
- inptus ar represented using a concatenation of learned embeddings: $e(40) \oplus e(2)$
- Exploring hyperparameters with Bayesian Optimization.

Classification-based results

	Train	**Dev**	**Test**
XENT	2.718	2.751	2.723
Acc.	0.191	0.195	0.163
$\rho_{\vec{e}}$	0.204	0.210	0.192
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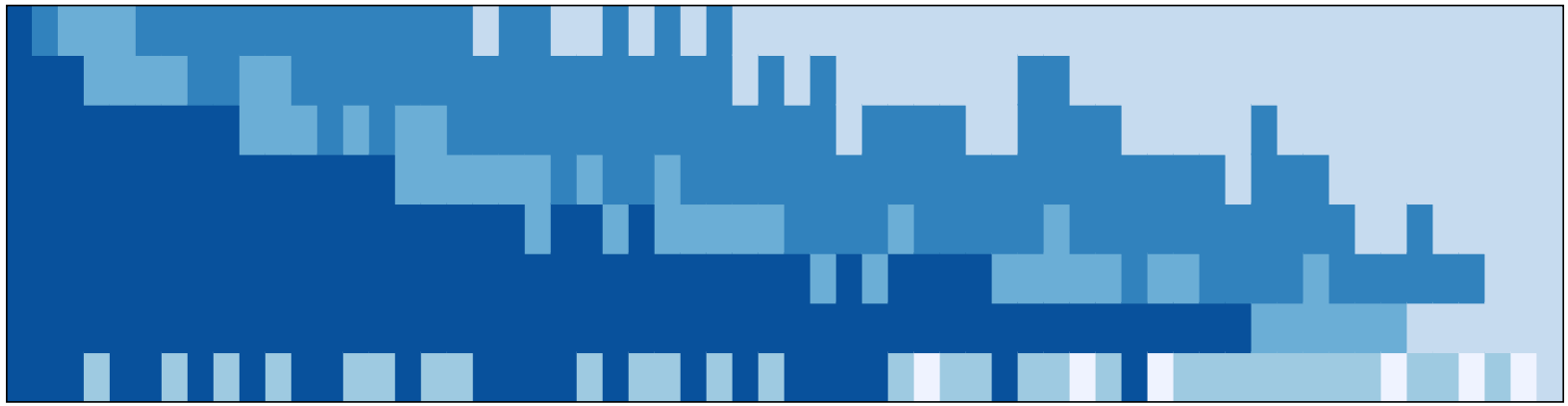

messages produced

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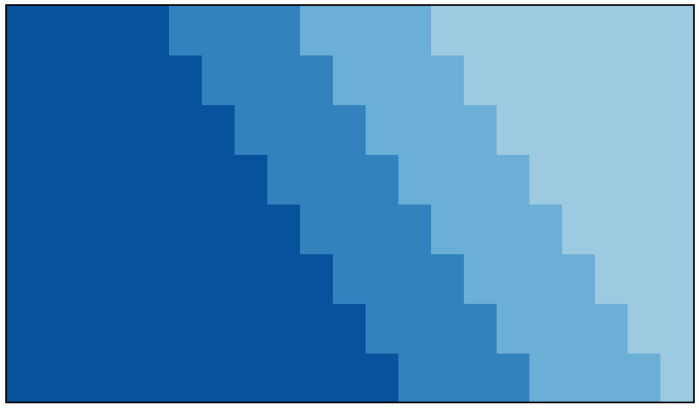
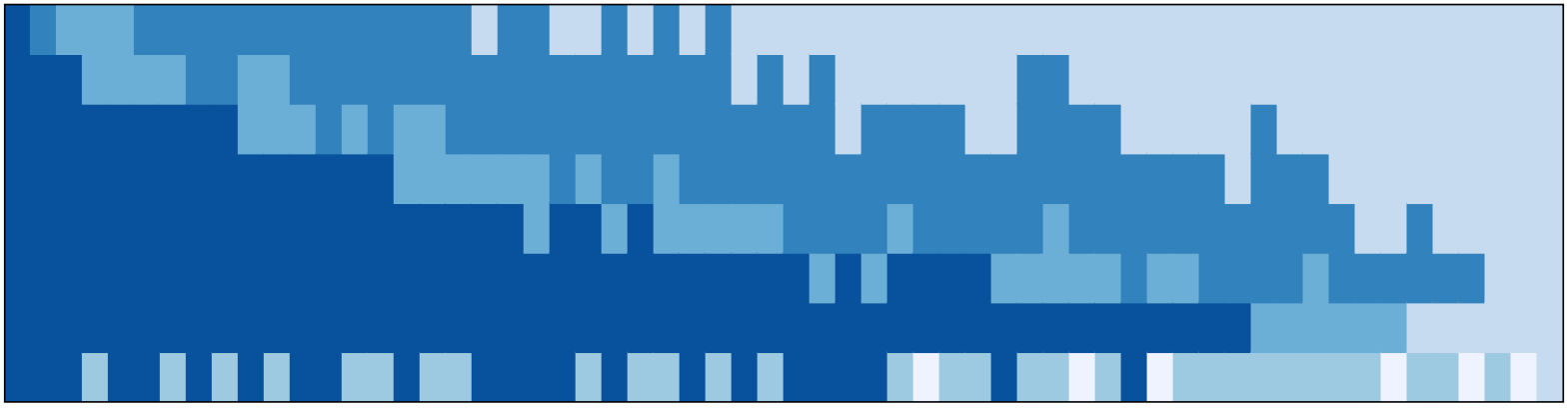


FILO structure



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Regression-based results

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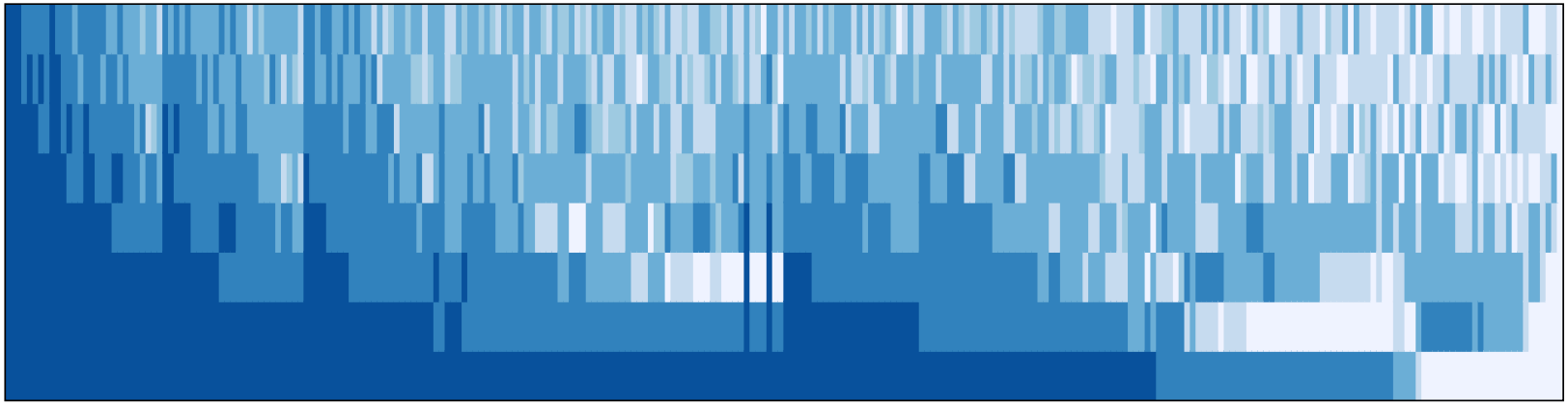

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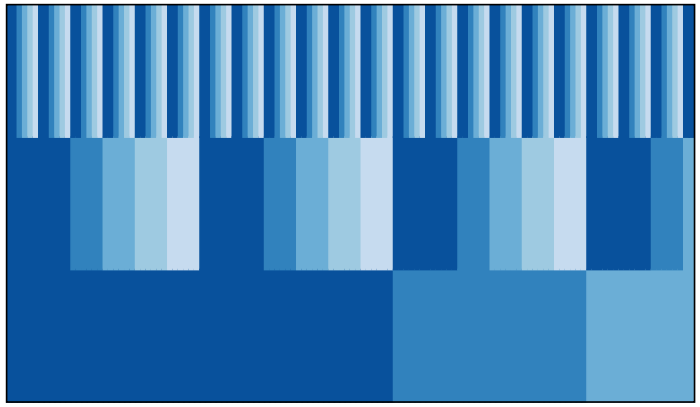
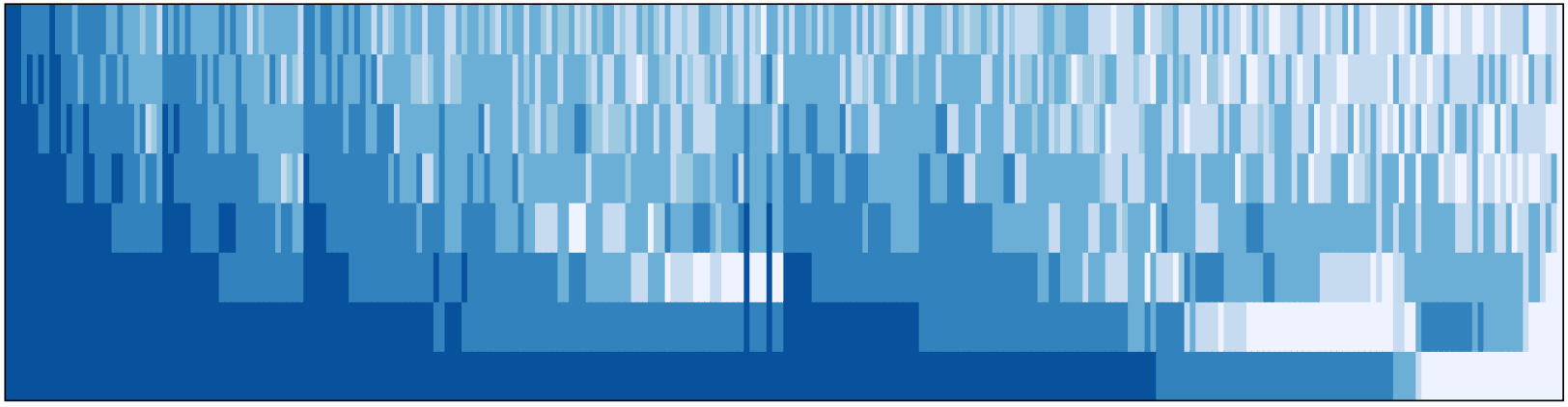


$a + b$, expressed in base 6



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- This task is fairly limited

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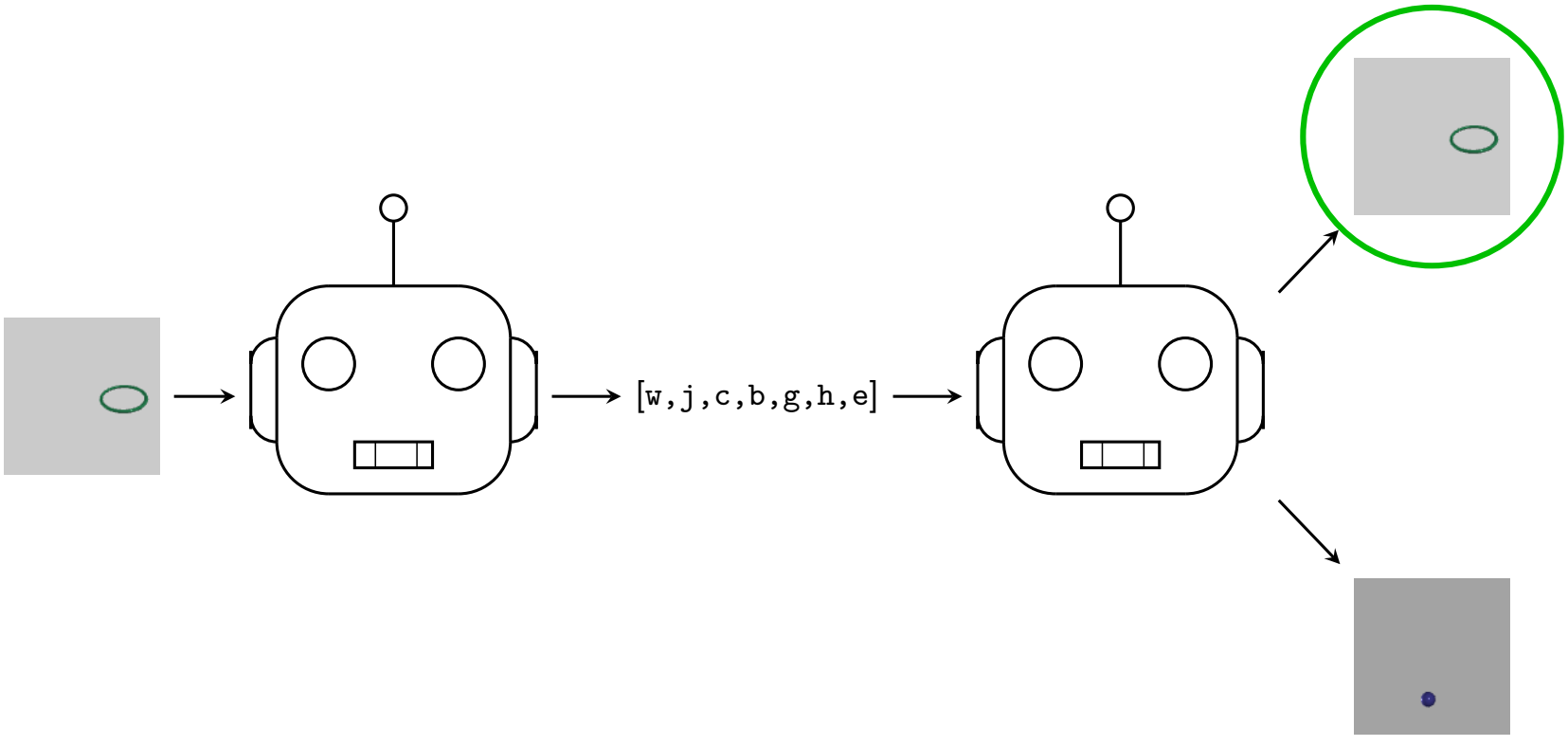
Signaling Game

- Have the receiver select the image shown to the sender



Synthetic Dataset

Images each containing one object, based on five *features*: **color**, **shape**, **size**, **vertical position** and **horizontal position**

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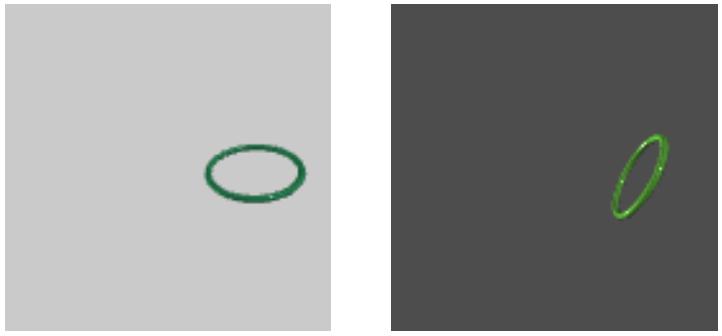
Some examples:

Images of different categories



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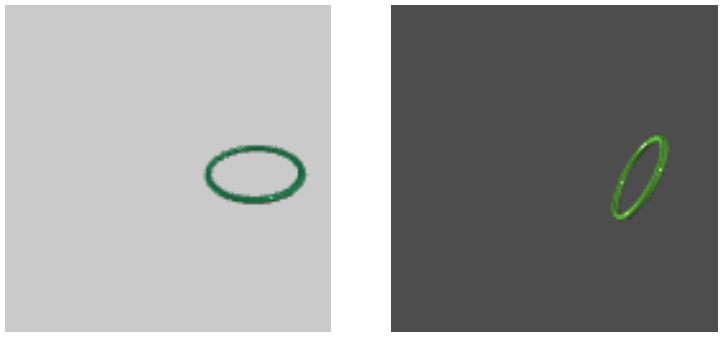

Images of the same category

- The sender has to convey the values of the 5 features

Baking in inductive bias

LSTMs are not biased towards compositionality (Liška et al., 2018)
We compare four pretraining regimens:

- no pretraining
- category-wise classification: predict the category of the presented image
- feature-wise classification: predict the value of each feature independently (one classifier per feature)
- auto-encoding: learn to reconstruct the full image.

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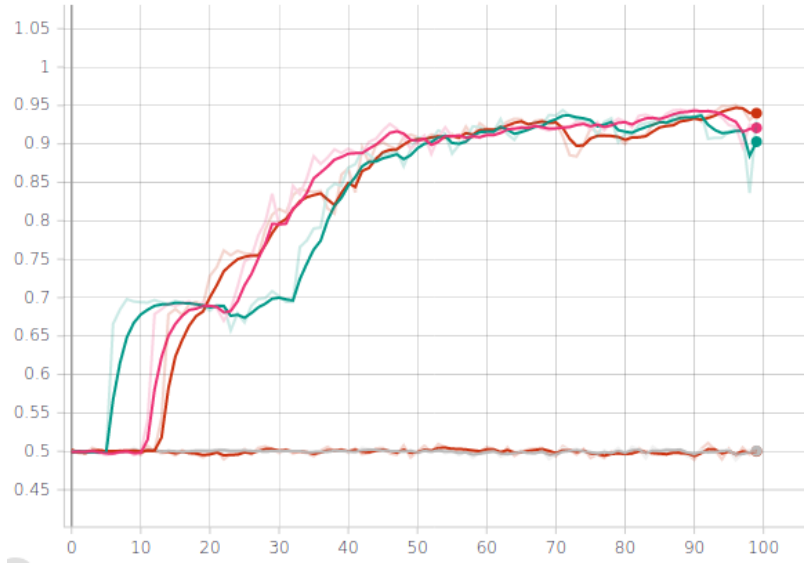
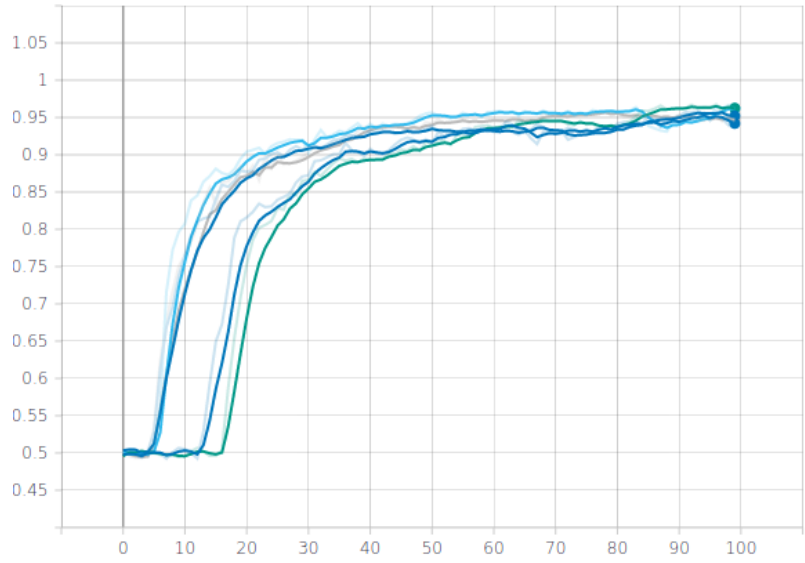
Computational details: CNN + LSTM agents. Hyperparameters are explored by grid. We also study whether to freeze CNN weights after pretraining, or whether further adaptation is required.

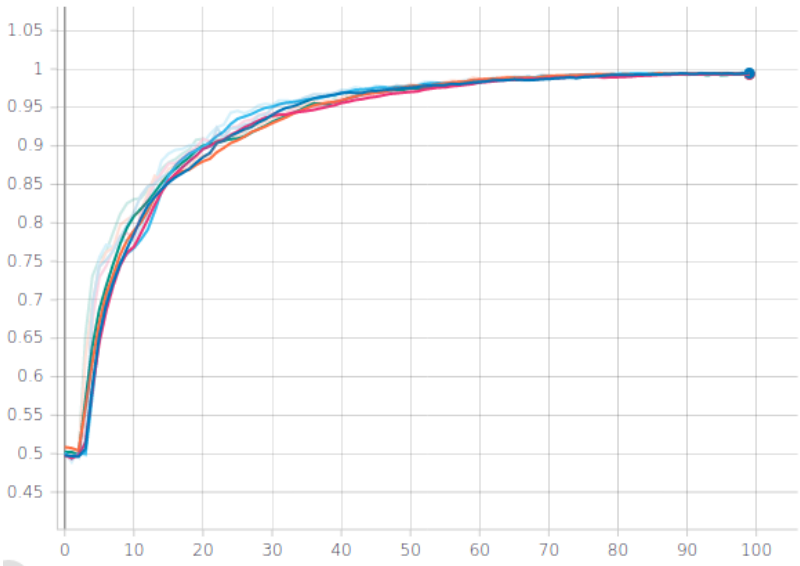
Results: Accuracy



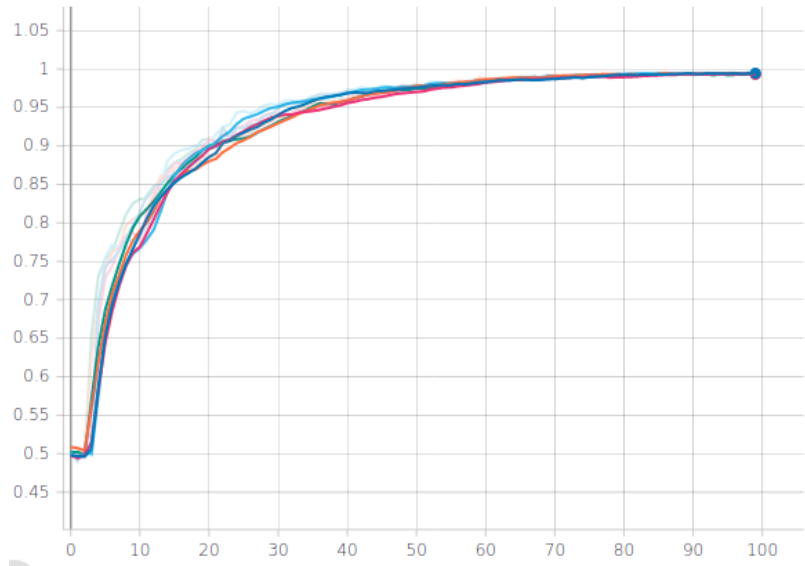
No pretraining



Auto-encoder



Feature-wise (Frozen)



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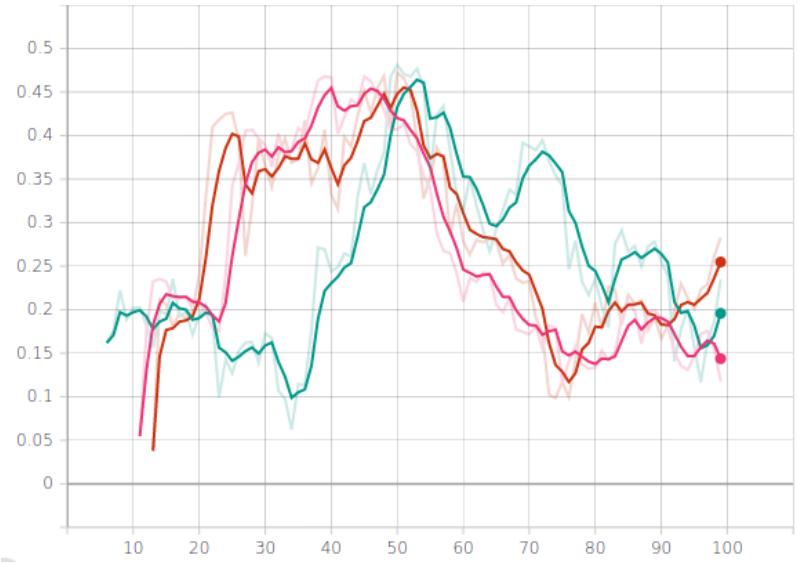
Results: Compositionality



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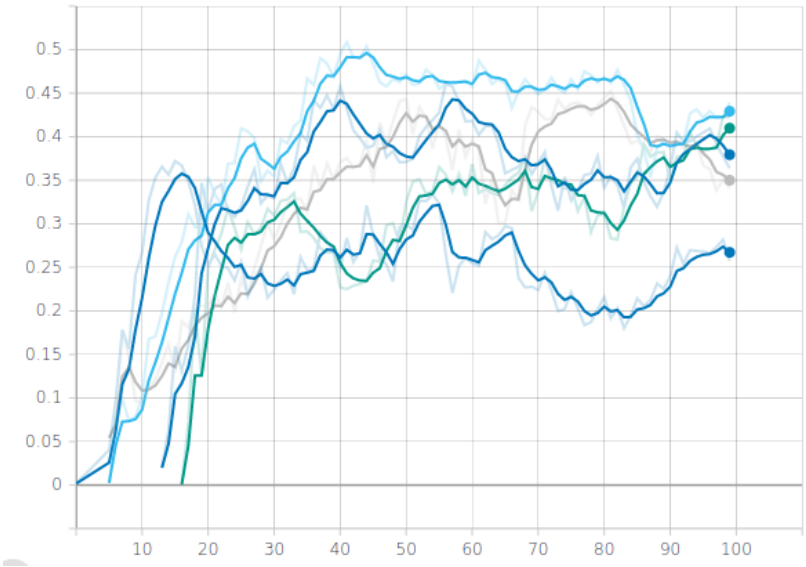

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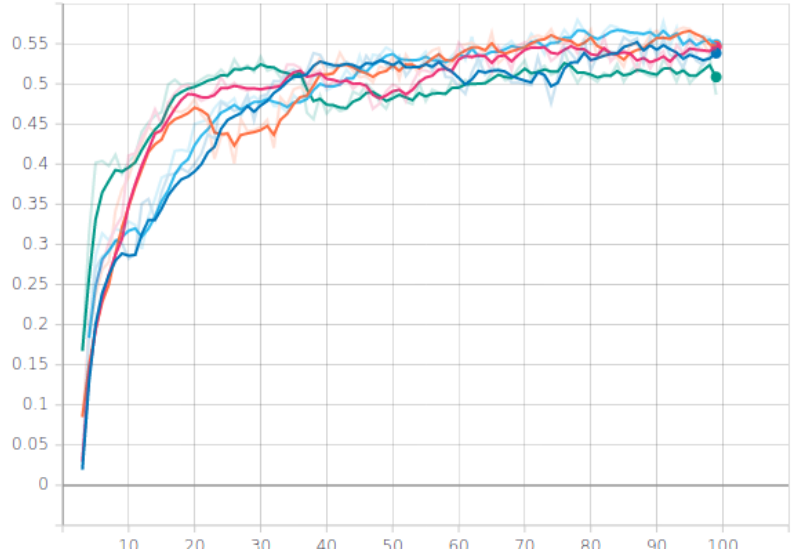

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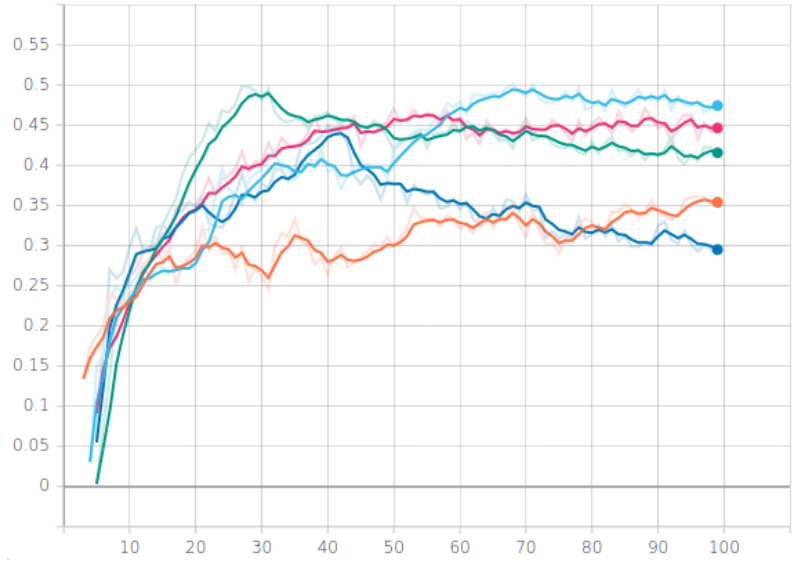

Category-wise (Frozen)

In short

- Any pretraining helps

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- More direct supervision helps more

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- Can we induce compositionality less directly?

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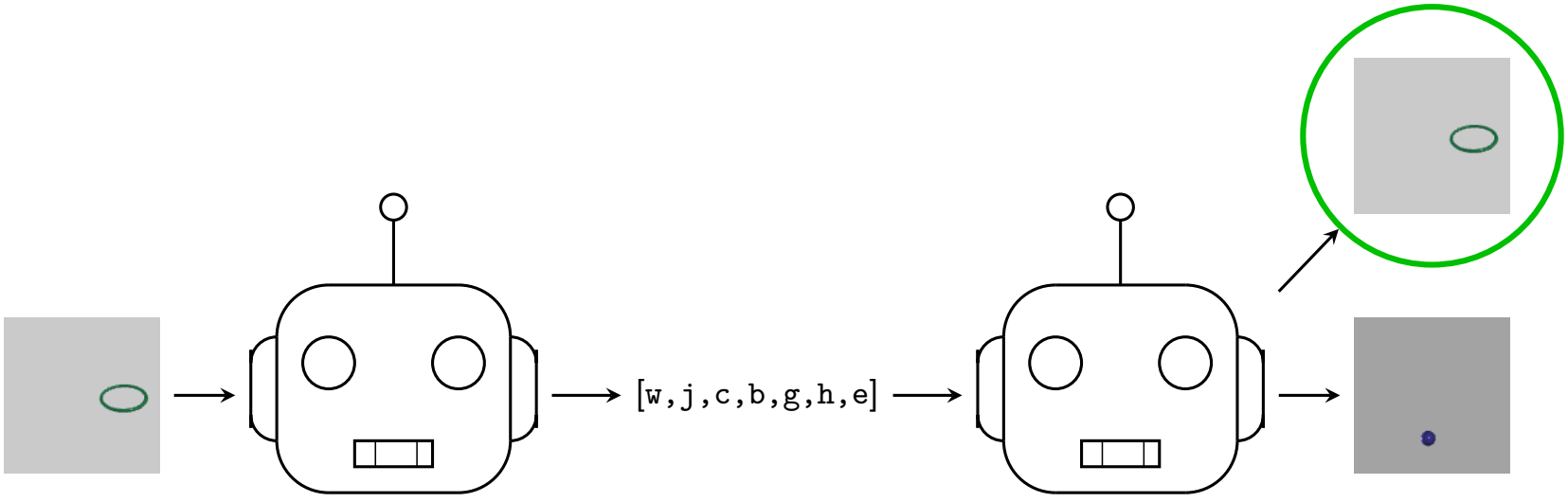
Meet Charlie

- Signaling game with a tweak



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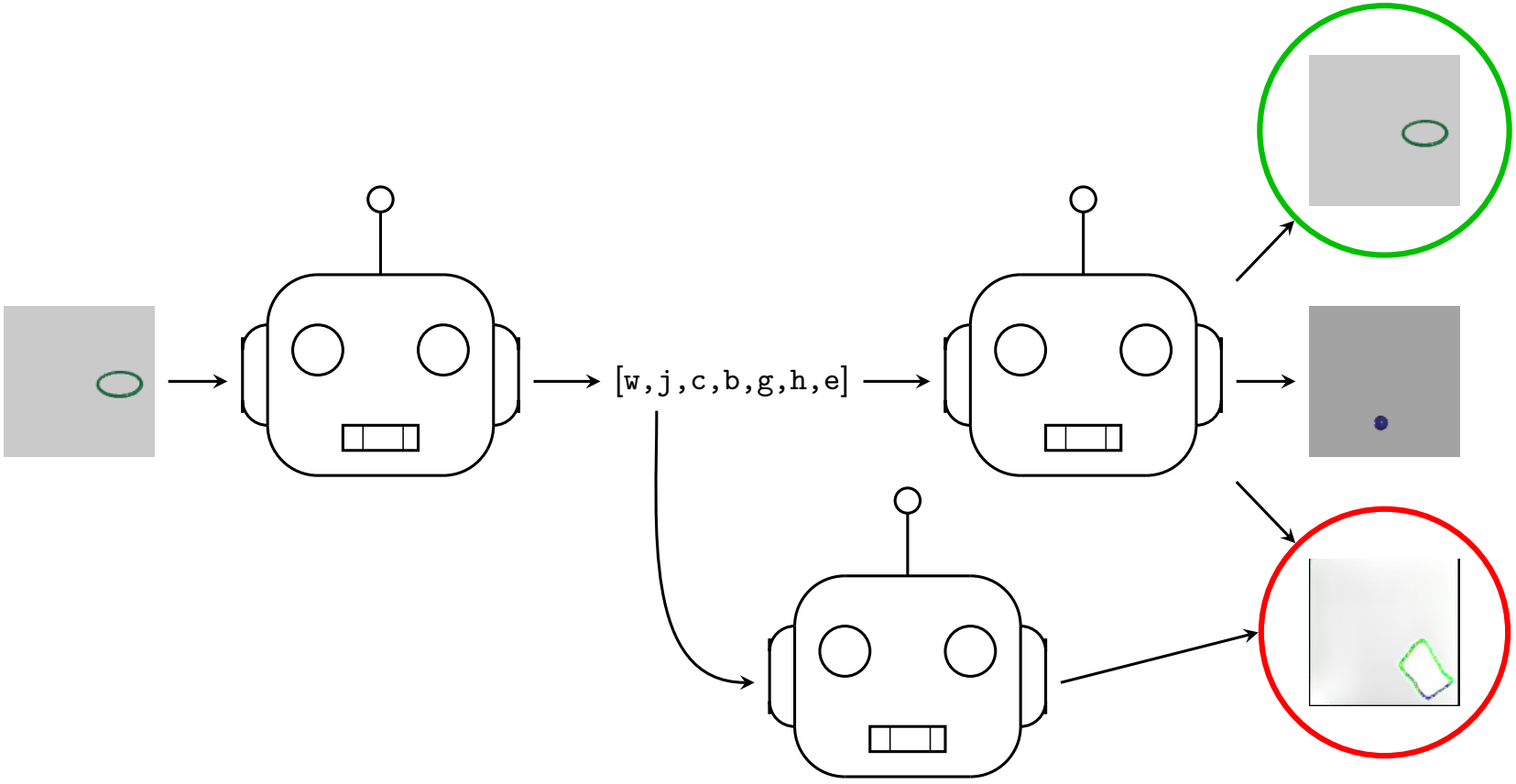

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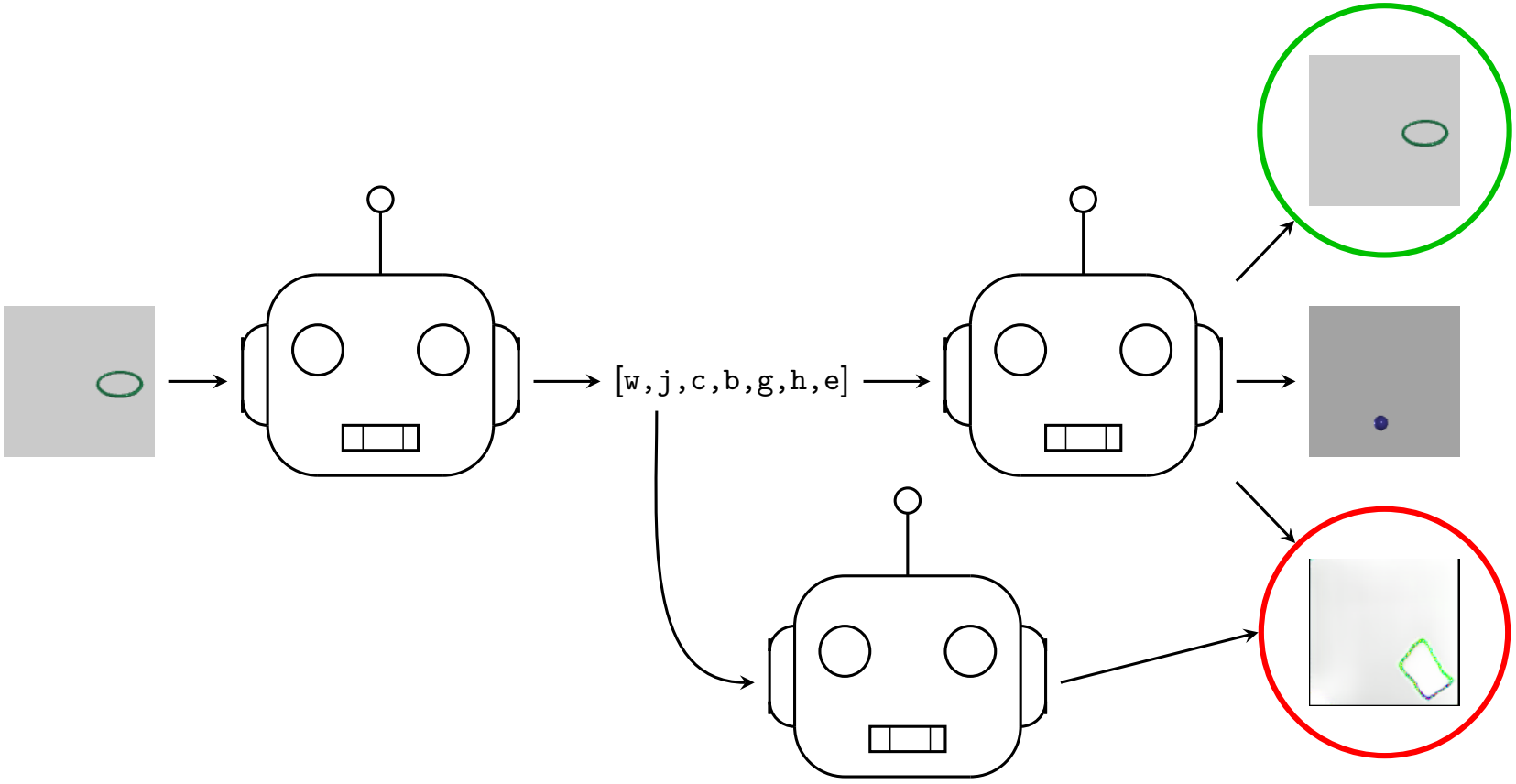
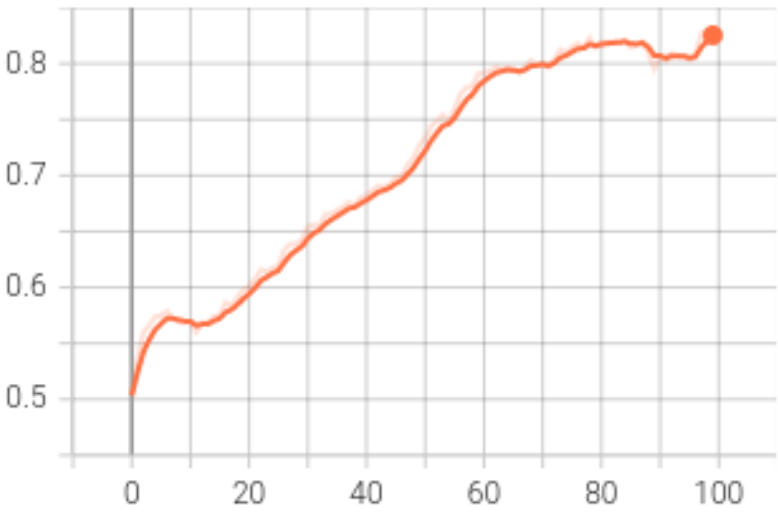
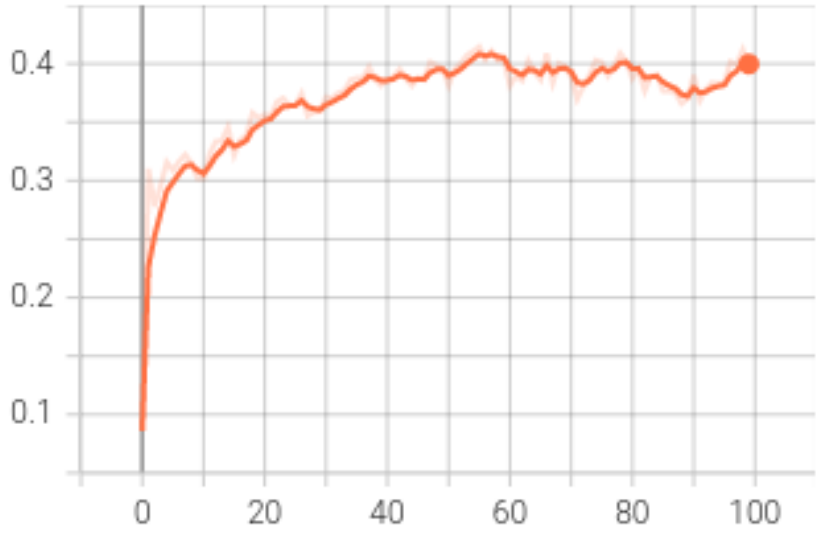


- Feature values are no longer the sole plausible meaning

Early results

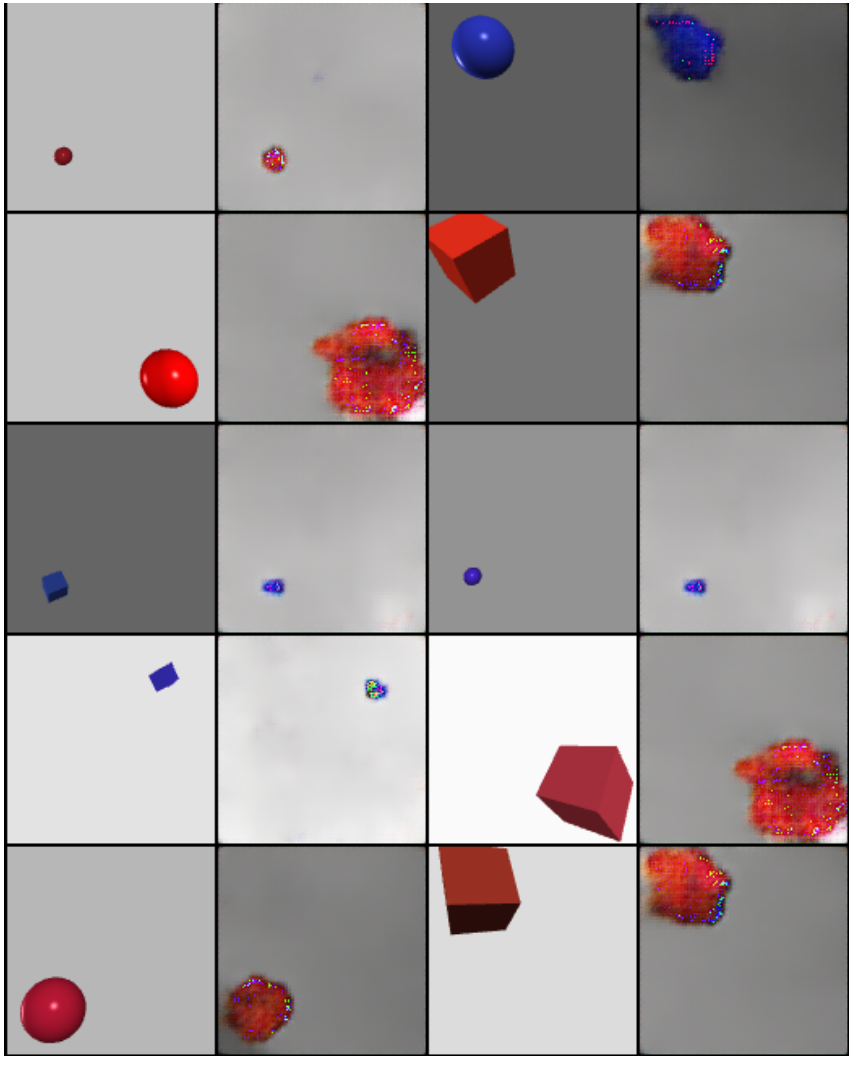


Accuracy

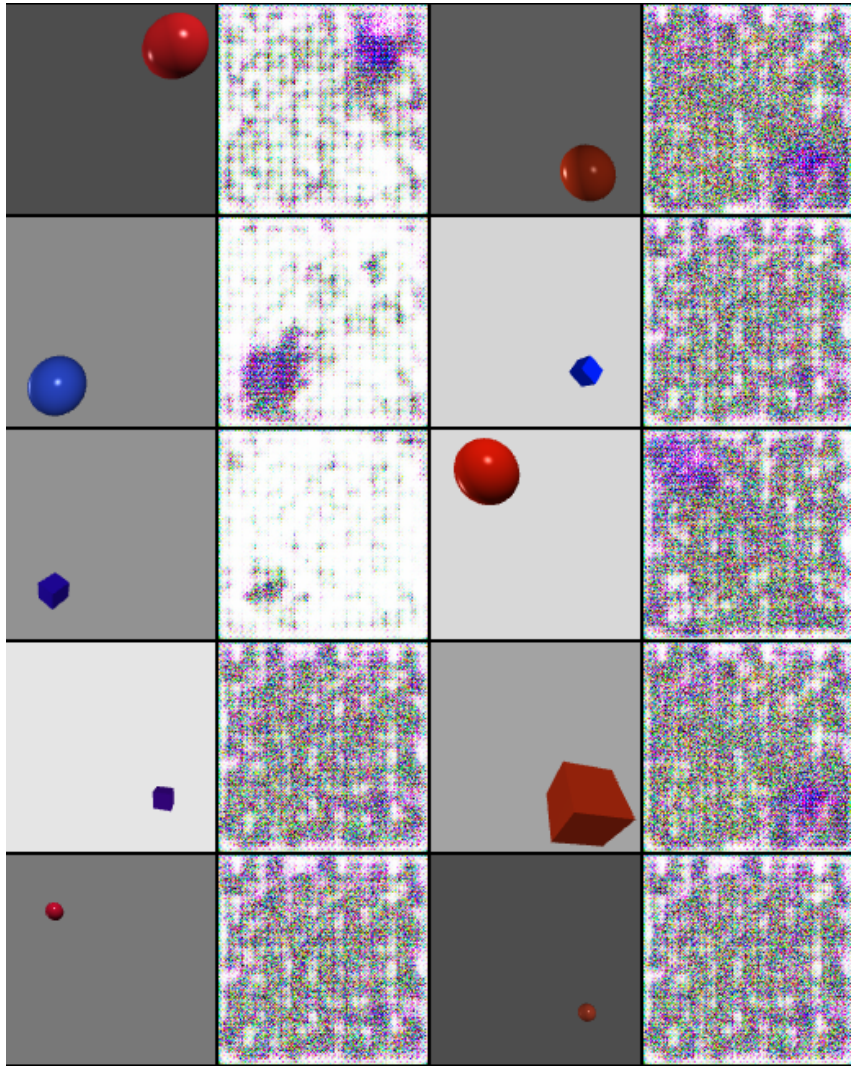


Compositionality

Having a look at the images



Pretraining



No pretraining

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- More work to be done!

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- Not all tasks are equally complex, nor equally likely to yield compositional languages
- How to (pre-)train a model is crucial

- Metrics for compositionality are unsatisfactory
- Many other fators to consider: dataset? reward function?