### DEPARTMENT OF PHILOSOPHY, LINGUISTICS AND THEORY OF SCIENCE

# SPATIAL RELATIONS IN EMERGENT LAN-GUAGES

This is the subtitle

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## **Abstract**

## Preface

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## 1 Introduction

### [Dominik Künkele] 2 pages

- 1.1 Research Question
- 1.2 Motivation
- 1.3 Contribution
- 1.4 Scope

#### **Background and Related Work** 2

[Dominik Künkele] 7 pages

#### 2.1 Language Games

### [Dominik Künkele]

- EGG
- Resnet

#### 2.2 Dataset

#### [Dominik Künkele]

- CLEVR
- 3D objectssimple objects
- CLEVR baselines

### 3 Experimental Setup

#### [Dominik Künkele] 15 pages

#### [Dominik Künkele]

- what is ambiguity?
- unambigous dataset:
- target group = non-target group
- all attributes shared, except for the color
- -- -> describable with one 'word'

In this section I will describe which experiments were conducted to answer the <u>questions from the previous</u> sections as well as the setup of these experiments. This will be done in two parts. The first part contains the creation of the datasets that will be used in the experiments. In the second part I will go deeper into discussing each experiment, including the necessity of the experiment, the specifities of the dataset, as well as the final architecture of the models.

[Dominik Künkele]

#### 3.1 Creation of the dataset

The basis for my dataset is the CLEVR dataset (Johnson et al. (2016)). This dataset includes 3D-generated images depicting scenes with different kind of objects. Each of these objects has different combinations attributes, such as *shape*, *color*, *size* and *material*. The possible values of these attributes are listed in Table 1. Three to ten objects are randomly placed into the scene and assigned with random attributes. To enhance realism and reduce ambiguity, objects do not intersect, have a certain distance from each other, and are at least partially visible. Figure 1 shows an example of a generated image in the CLEVR dataset.

shape	color	size	material
cube	gray	small	rubber
sphere	red	large	metal
cylinder	blue		
	green		
	brown		
	purple		
	cyan		
	yellow		

Table 1: Attributes of objects in the CLEVR dataset

Furthermore, the dataset contains information about each scene. This includes the selected attributes for each object as well as the exact position of the centers of all the objects, both 3D-coordinates in the 3D scene and 2D-coordinates in the final rendered image. In addition, simple spatial relations (in front of, behind, left, right) between the objects are calculated and stored. These are simply based on the 3D-coordinates of the objects from the perspective of the camera position.

#### [Dominik Künkele] ambiguity

This research investigates how agents communicate about the relations of objects seen in images. For that reason the original CLEVR dataset offers too little control over how the objects are created and in which relation they stand to each other. Following, I extended the source code to generated images for the CLEVR

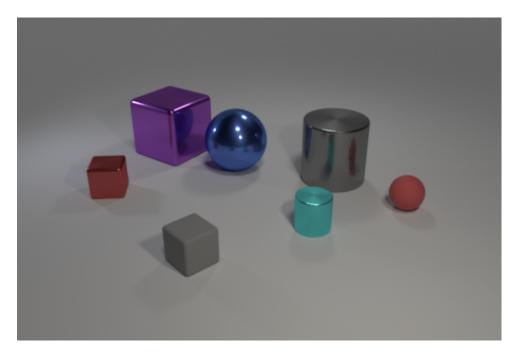


Figure 1: Example of a generated image in the CLEVR dataset

dataset.<sup>1</sup> To simplify the generation, I only focused on the attributes *shape*, *size* and *color*. The *material* is always the same for all objects in a generated image. There were three main extensions to the code:

First, objects in the scene were separated into three categories: one *target object*, objects in a *target group* and *distractor* objects. The target object is the main object in the scene that should be identified and communicated by the agents. All other objects and their relations are based on this target object. The target group contains similar objects to the target object. These are objects that the agents need to discriminate the target object from. Finally, the distractors are objects that add noise to the scene and should make it more complex and are expected to teach the agents more precise descriptions. The number of the objects in both group can be controlled.

In a second step, when generating the images it is possible to define the relations between *target object/target group* and *target object/distractors*. The relation is defined as **how many** attributes of the target object are identical with objects in the target group and distractors respectively. For example the target object is a *small red cube*. If two attributes are shared between target object and target group, objects in the target group could include *small blue cube*, *big red cube* or *small red sphere* but couldn't include another *small red cube* or a *small blue cylinder*. The number of shared attributes can also be set to a range to make the discrimination task more challenging.

Lastly, it is also possible to define exactly **which** attributes should be shared between the target object and the groups. For example, it can be defined to have the same size for objects in the target group, but have randomly selected different shapes and color. This allows a very controlled generation of relations between the objects in the scene. Figure 2 shows one generated image with this extended source code. Here, the target object is the large purple cylinder. The target group contains four objects that share zero to a maximum of two attributes. It is not controlled, which attributes are shared (they are selected randomly). There are no distractor objects.

<sup>&</sup>lt;sup>1</sup>The extended source code can be found on GitHub: https://github.com/DominikKuenkele/MLT\_Master-Thesis\_clevr-datasetgen

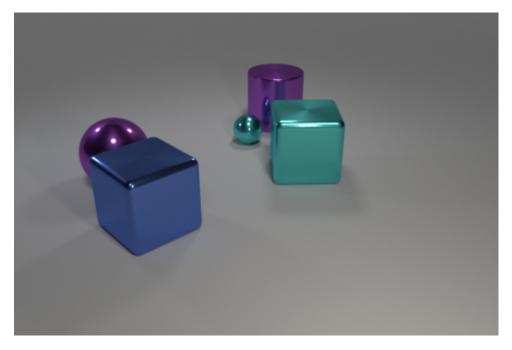


Figure 2: Example of a generated image with the extended code

For all generated datasets in the following sections, the general constraints and settings are as close as possible to the original CLEVR dataset. The size of the generated images is 480x320 pixels. 10.000 images are created for each of the datasets. Each image contains a maximum of 10 objects, that are not intersecting, have the same minimum distance and are partially visible.

### 3.2 Description of experiments

Language games are very complex setups for machine learning models. The models need to solve multiple tasks at the same time to solve the overall problem. For instance in a simple setup of a game two agents are involved. The first agent, the sender is shown a scene with objects and needs to communicate on target object to the other agent, the receiver. The receiver is shown the same scene and needs to identify the target object with respect to the message of the sender. In this case, the sender first needs to learn to encode the scene as well as the information about the target object into its own space. In a next step it needs to learn how to translate this encoding into a message that is sent to the receiver. The receiver then needs to learn to decode this message, after which it needs to learn how to combine the decoded message with its own encoding of the scene. And finally it needs to learn how to identify the target object with this information.

[Dominik Künkele] ?

For this reason I decided to divide the main problem and let the models learn simpler subtasks and increase the complexity step by step. This will give me a very detailed overview, where the models struggle to learn and in which ways they can be improved. Mainly, I separated the tasks into language games with two agents (final experiments) and classical machine learning tasks without any communication, namely only one 'agent' that solves the task alone (pre-experiments). With this division, I can analyze the learning of the encodings of the scenes separately from the learning of producing and decoding messages.

#### 3.2.1 Pre-experiments without language games

coordinate predictor

### [Dominik Künkele]

- pretrained ResNet/VGG
- scratch
- encoding of attributes (one-hot)
- encoding of attributes (dale)
- encoding of locations
- masking

bounding box classifier

caption generator

### [Dominik Künkele]

- dale
- masked

### 3.2.2 Language games

## 4 Results and Discussion

[Dominik Künkele] 15 pages

## **5 Ethical Considerations**

[Dominik Künkele] 1 pages

[Dominik Künkele] 1 big model vs. many task specific models

## 6 Critiques and Limitations

[Dominik Künkele] 3 pages

[Dominik Künkele] combine with future work

## **7 Future Work**

[Dominik Künkele] 2 pages

## 8 Conclusion

[Dominik Künkele] 2 pages

## References

Johnson, J., Hariharan, B., van der Maaten, L., Fei-Fei, L., Zitnick, C. L., & Girshick, R. (2016). Clevr: A diagnostic dataset for compositional language and elementary visual reasoning. *CoRR*, abs/1612.06890.

## A Resources