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SPATIAL RELATIONS IN EMERGENT LANGUAGES

This is the subtitle

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In this section I will describe which experiments were conducted to answer the questions from the previous 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, which datasets the model is trained on, as well as the final architecture of the models.

[Dominik Künkele] ?

3.1 Creation of the dataset

The basis for my datasets is the CLEVR dataset (Johnson et al., 2016). This dataset includes 3D-generated images depicting scenes with different kinds 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 all 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 in relation to the position of the camera.

[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 generate images for the CLEVR dataset.[1] To simplify the generation and the later learning of the models, I only focused on the attributes with a high impact on the appearance of the object, namely the *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:

[Dominik Künkele] referring expressions

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

[1] https://github.com/DominikKuenkele/MLT_Master-Thesis_clevr-dataset-gen

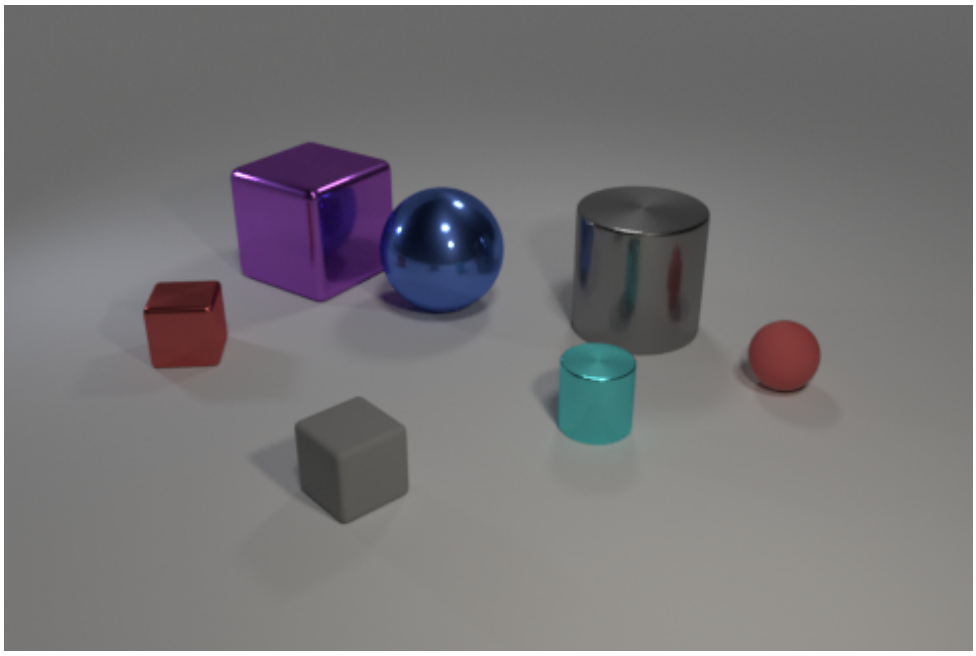


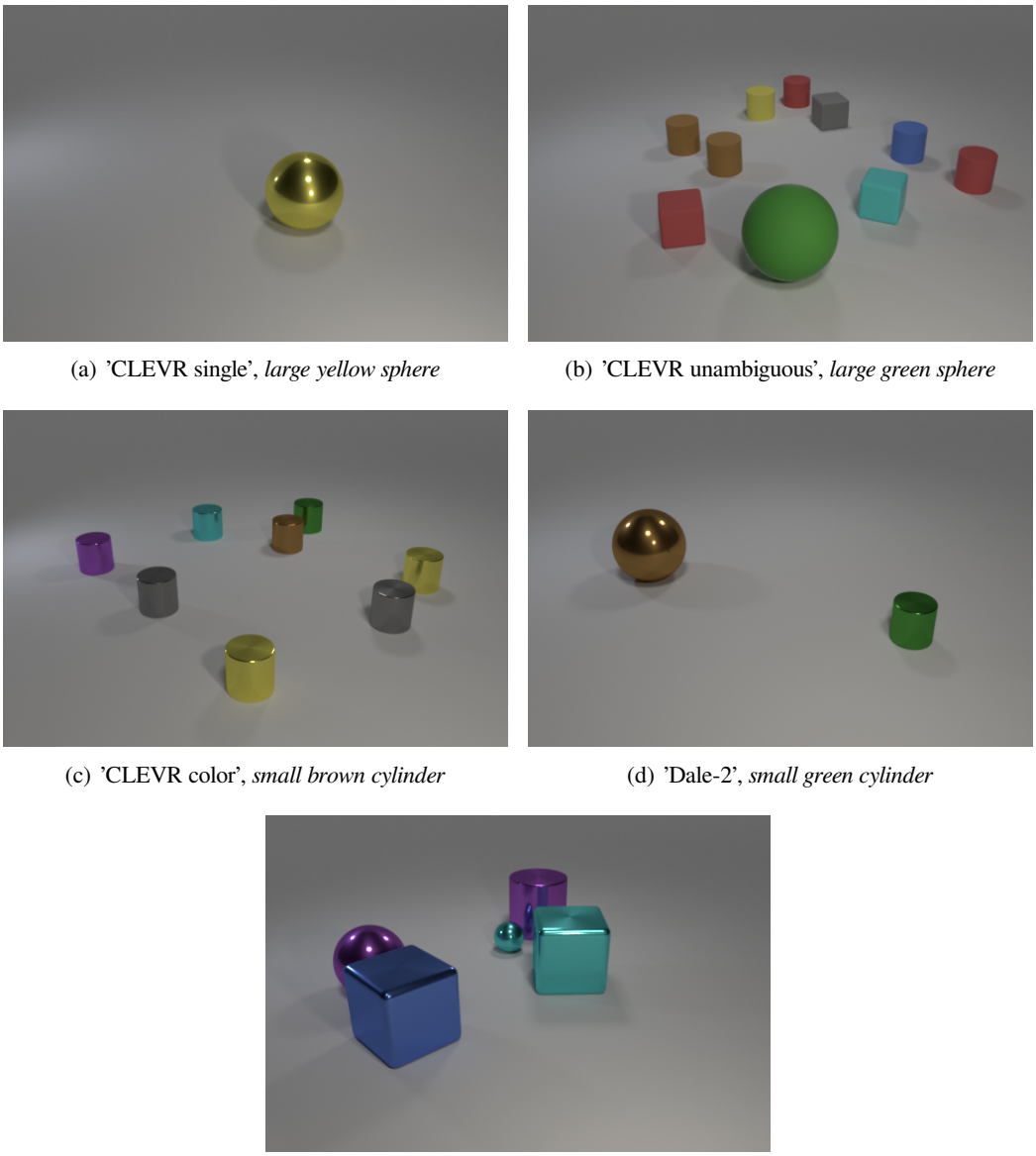
Figure 1: Example of a generated image in the CLEVR dataset

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. They expected to teach the agents more precise descriptions of the target object. 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 the attributes of a single object 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 different, randomly selected shapes and colors. This allows for a very controlled generation of relations between the objects in the scene. Figure 2(e) 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). The large purple cylinder shares the same color and size with the large purple sphere, the same size with both cubes and no attribute with the small turquoise sphere. There are no distractor objects.

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 between objects and are partially visible from the camera.



(a) 'CLEVR single', *large yellow sphere*

(b) 'CLEVR unambiguous', *large green sphere*

(c) 'CLEVR color', *small brown cylinder*

(d) 'Dale-2', *small green cylinder*

(e) 'Dale-5', *large purple cylinder*

Figure 2: Example images of each dataset, with the target object specified

CLEVR single

The simplest dataset is called 'CLEVR single'. This is a very simple dataset and has the purpose to simplify the problem the model needs to learn as much as possible. Each scene in the dataset contains only one single object, the target object. There are neither objects in the target nor in the distractor group. All attributes are assigned randomly to the target object. The differences across the whole dataset are the locations and rotations of the objects. With this dataset, neural models can focus on only the features, as well as the locations of this single object. There are no objects that distract the model from extracting features from the target object. This helps to understand if the models are actually able to assign features or learn locations of these features in an image. Figure 2(a) shows an example with the only object being the *large yellow sphere*.

CLEVR unambiguous

The second dataset that is created is called 'CLEVR unambiguous'. The purpose of this dataset is to create scenes, where the target object is completely unique and as easily identifiable as possible. For this reason, there exist only two groups in the scene, the target object and distractors. The distractor group can contain in between 6 and 9 objects. The target object doesn't share any attributes with the distractors. Namely, if the target is for instance green, no other object in the scene is green as well. This also applies to the other attributes. When referring to this target object, it is therefore enough to only describe one of the attributes.

Consider the scene in Figure 2(b). The target object can be completely described as the *large green sphere*. On the other hand, also descriptions like the *green object*, the *large object* or the *sphere* would be unambiguously referring to the target object.

CLEVR color

This task could on the other hand be difficult to learn for neural models. Although the target object is unique in the scene with resect to the distractors, the description isn't. Considering all unordered combinations of the three attributes and a composite referring expression, there are $\binom{3}{3} + \binom{3}{2} + \binom{3}{1} = 7$ possible descriptions of the target object. This can propose a difficulty, when the models try to converge towards one representation. For this reason, I created the 'CLEVR color' dataset. It has a similar setup as the previous dataset, containing between 6 and 9 distractors. But instead of the target object sharing no attribute with the distractors, they share exactly two attributes. Furthermore, to simplify the relation between target object and distractors over the whole dataset, it is also controlled which attributes are shared. The distractors have always the same size and shape as the target object, but the color is always different. The reason for choosing the color as the only discriminating attribute is that it is assumed that the color is easier to learn for neural models as opposed to for instance abstract shapes.

As seen in Figure 2(c), the *small brown cylinder* is unique. The number of possible descriptions is lowered to three, since the color *brown* needs to be part of it. Notice as well that this restriction doesn't apply to the distractors, where multiple objects with the same color are allowed.

CLEVR Dale datasets

Both of the above described datasets are very restrictive on the disambiguating relations between the target object and the rest of the objects. Either no attribute or only one attribute is shared. More realistically would be if objects can share a variable number of attributes. In real situations, there is no restriction at all, how objects or things relate to each other. Natural language emerged that can refer to distinct attributes of these objects to discriminate them from each other. This emergence of referring attributes and their combination is studied deeper in this work.

For this, I created a dataset that allows almost any relation between a target object and the distractors. The relations are only restricted by the incremental algorithm for the Generation of Referring Expressions (GRE) described in Dale & Reiter (1995). This algorithm ensures that every scene contains a unique object in respect to its and the distractors' attributes. Using the algorithm, one can refer to an object using its attributes to discriminate it from all other objects as efficiently as possible. In other words, the object is described unambiguously using the lowest number of words. For the dataset that means that zero, one or two attributes can be shared between the target object and distractor objects. This ensures the uniqueness of the target object. On the other side, it is not controlled which attributes are shared. These are assigned randomly. There is again no control over the relations between distractors, which means that distractors can appear multiple times.

Two datasets, following these rules are created. The Dale-2 dataset contains one target object and one distractor (see Figure 2(d)), while the Dale-5 dataset contains one target object and exactly four distractors. Consider Figure 2(e), with the target object being the *large purple cylinder*. The large purple sphere shares the size and color, the two cubes only share the size, and the small turquoise sphere doesn't share any attribute.

These two datasets allow a more realistic look in how models can acquire knowledge about attributes of objects. More specifically how models learn to discriminate objects from each other, since the model may only need to learn discriminative features of objects and not all features of the whole object.

[Dominik Künkele] probabilities of shared attributes for both Dale-2 and Dale-5

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 one 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, all objects and their attributes, 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 objects. 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. [2] 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 Feature extractors

To extract features from the images, I make use of different deep neural network architectures that are developed for this task. First, I use the VGG19 (Simonyan & Zisserman, 2015) which is an architecture based on many convolutional layers. After the convolutional layers, the data is passed first through an average pooling layer which outputs 512x7x7 dimensions. Next follow three linear layers with *ReLU* non-linearities in between. After flattening the input, these classification layers output 4069, 4069 and 1000 dimensions respectively.

[Dominik Künkele] why ResNet/VGG

Secondly, I include the ResNet-101 (He et al., 2016) that tries to overcome problems of very deep networks, using residual blocks. There are four blocks that output 256x56x56, 512x28x28, 1024x14x14 and 2048x1x1 dimensions. A following average pooling layer outputs 2048x1x1 dimensions as well. The final linear layer reduces the flattened data to 1000 dimensions, corresponding to the ImageNet classes.

[Dominik Künkele] needs to be explained deeper?

Both architectures are available pretrained on an image classification task on the ImageNet dataset. Since the task in this research is very different from a classification, multiple different adaptions of these architectures are compared. Table 2 lists the different adaptions for both VGG19 and ResNet-101 that will be used in this research. In the later chapters, it will be referred to these adaptions using the name in the table.

[Dominik Künkele] deeper discussion about different layers of these

[2] https://github.com/DominikKuenkele/MLT_Master-Thesis

	description	output dimensions
VGG-0	contains only the convolutional layers	512x7x7
VGG-avg	contains an additional average pooling layer	512x7x7
VGG-cls1	contains an additional one classification layer, including its non-linearity	4069
VGG-cls2	contains another additional classification layer, including its non-linearity	4069
VGG-cls3	the original VGG19 architecture	1000
ResNet-1	contains one residual block	256x56x56
ResNet-2	contains two residual blocks	512x28x28
ResNet-3	contains three residual blocks	1024x14x14
ResNet-4	contains four residual blocks	2048x1x1
ResNet-avg	contains an additional average pooling layer	2048x1x1
ResNet-cls	the original ResNet-101 architecture	1000

Table 2: Different adaptions of VGG19 and ResNet-101 used in this research

Furthermore, I experimented with both the pretrained models as well as with the architectures trained from scratch with a random initialization for the weights. This reason for this was to test if the success of an experiment was actually making use of the pretrained knowledge incorporated in the models. If that was not the case, the agents were likely not using image features, but instead relying on some other underlying patterns to solve the task. Basically, this approach works as an indicator to determine the actual success of the agents aside from measures as the accuracy or precision.

3.2.2 Pre-experiments without language games

The final objective of this thesis is to find out, how agents can communicate about relations of objects spatially as well as based on their attributes. Because of that, the first experiments focus on extracting information from images and combining them with structured knowledge. Here, I structured the experiments into three levels. In the first level, the model are trained to learn the position of objects in the image and attend to specific regions of the image. In the second level, the models are trained to differentiate objects in the scene from each other. The last level adds language to the experiment, more specifically the models learn to caption and describe objects in the image. These combined experiments should lay the basis for how to build up the agents in the language games.

Level 1 - Coordinate predictor: This level should help to analyze, how the final task of the language game should look like, in especially what the receiver is tasked to predict. As described before, the sender should communicate an object in the image and the receiver needs to identify it. The challenge lies in how the receiver refers to the identified object. There are multiple possibilities, how it can be done. One of them could be to describe the target object with human language, using the attributes. The main goal however is to let the language of the agents emerge as natural as possible. Including human knowledge into the task would bias also the emerged language towards attributes and words, humans are using. For this reason, the final task of the receiver will be to 'point' to the target object. Since also positional information of the objects should be part of the discrimination, the image will not be separated into several bounding boxes around the objects, but instead the whole image is the basis. The models are therefore tasked to predict the center coordinates of the target object. With this approach, the models receive few human knowledge, but are still able to rely on all information present in the image to discriminate the objects.

To achieve this goal, multiple setups of models are tested. In the simplest setup, the model receives only the image as an input and produces two numbers as an output, the predicted x- and y-coordinate of the target object. Here the image is first passed through one of the *feature extractors*. Next, the extracted feature vector is flattened and passed through two linear layers with a *ReLU* non-linearity between. These reduce the dimensions first to 1024 and finally to 2.

[Dominik Künkele] preprocess image

To determine the loss, the euclidean distance between the resulting predicted point on the image and the ground truth point are calculated. This distance is learned to be minimized. By doing that, the model learns to focus and attend on a specific part in the image, in a perfect model the center of the target object.

With this simple setup, the model is in theory able to focus on an object in the image. The problem arises as soon as multiple objects are present in the image. There is no information available for the model to understand which one of these objects is the actual target object, except for the final calculation of the loss. Since there is not necessarily a pattern for which object in the image is the correct target object over the whole dataset, the models will likely fail to generalize. Therefore, the models need to receive more information. Here, I try out four different ways to encode the target object.

[Dominik Künkele] go deeper, why

In the first method, I encode the attributes of the target object as **one-hot encodings**. There is a three-dimensional vector encoding the *shape*, an eight-dimensional vector encoding the color and a two-dimensional vector encoding the two different sizes. The dimensions of these vectors can either be zero or one, depending on the attributes of the target object. These three encodings of the attributes are then concatenated. The image is again passed through a feature extractor, before the flattened vector is reduced to 2048 dimensions with a linear layer. The result is concatenated with the encoded attributes and passed to a final linear layer to predict the coordinates.

In an extension to this method, I also include the **center coordinates of all objects** in the image. This should help the model to identify all possible options to chose from, when predicting the target object. All the center coordinates are simply extracted and shuffled. Since there are varying numbers of objects in the image, this vector of variable length is padded to 10 objects, resulting in a vector with a length of 20. The padding objects have zeros for both coordinates, which no other real object can have. For this model, I also made use of a more complex way to encode the image. Here, I based the approach on code that implements baselines for the CLEVR dataset (Johnson et al., 2017). The image is first passed through the feature extractor. Afterwards, a 2-dimensional convolutional layer, reduces the channels from 2048 to 512 channels with a kernel size of 1. After applying the *ReLU* function, the resulting matrix is max pooled over two dimensions with both a kernel size and a stride of 2. The resulting matrix is flattened and concatenated with both the attribute encodings and the shuffled coordinates of all objects. This is then passed again through a final linear layer to predict x- and y-coordinates.

[Dominik Künkele] why?

The third method encodes the attributes of the target object with human language using the **incremental algorithm for the Generation of Referring Expressions (GRE)** described in Dale & Reiter (1995). This opposes the idea described before, to share as few human knowledge as possible with the model. Still, this approach can help to understand and analyze if the model was able to extract information about the objects and more specifically their attributes from the image. If the model is able to match parts of the image with human words it would show that the model learned this attribute. If the model in a next step can learn this over the whole dataset, this would mean that it could generalize over these attributes and assign them to certain regions in an image. This insight could help then to design another model that makes use of these learnings without human language.

Using the algorithm, one can describe an object using its attributes to discriminate it from other objects as efficiently as possible. In other words, the object is described unambiguously using the lowest number of words. The algorithm assumes that there is an order of importance for attributes, such as shape, color

and size. This order defines, which attributes can be left, while still identifying the object uniquely. For our research, we rely on the following order from most important to least important: shape, color, size Given for example the scene from 2(e) with the target object being the *big purple cylinder*. Using all three attributes, this description identifies the object perfectly and uniquely. Following the algorithm, we could make the description shorter by removing the least important attribute *size* without loosing unambiguity, describing it as the *purple cylinder*. This can be taken even one step further by removing also the *color*. Describing it as the *cylinder* still doesn't describe any other object, since the target object is the only cylinder in the scene.

For the experiments, each every image is captioned, by a description of the target object using the described algorithm. To use it in the model, the caption needs to be padded to an equal length, in this case to a length of 3, which is the maximum number of attributes that can be used. For this, as standard practice in captioning tasks, the captions are padded at the end with a specified padding token.

The model is made up of three parts: The first part extracts features from the image. Here, the setup is similar to the previous model. The image is passed through a feature extractor, before it is passed through two 2d convolutional layers, both reducing the channels to 128 with a kernel size of 1. A *ReLU* function is applied, after both convolutional layers. As before, the resulting vector is pooled, using max pooling with both a kernel size and stride of 2. In the second part, the caption is encoded, using an LSTM. Here, the learned embeddings of each token are parsed by the LSTM and its final hidden state is then used as a summary of the complete caption. The third part is again the predictor of the coordinates of the target object. Both the processed image and the final hidden state of the LSTM are flattened and concatenated. The resulting vector is passed through three linear layers reducing to 1024, 1024 and 2 dimensions respectively. Between each linear layer, the *ReLU* function is applied. This architecture is also inspired by the baselines described in Johnson et al. (2017).

The forth method, to encode the target object utilizes **masking** of the image. For this, the image is separated into a fixed size squared area containing the target object and the rest of the image. The side of the square is always two fifth of the image width, in this case 192 pixels. This size always includes the whole object if it is large or small, while not being cut of if the target object is too close to the border of the image. The square is filled in white, while the rest of the image is filled in black. This approach has the advantage of providing as few as possible human bias to the model. While even the one-hot encodings contain human knowledge by explicitly encoding human chosen attributes, masking the image will only point the model towards the target object without giving more information. It therefore can only rely on its own extracted visual features when looking at masked images.

[Dominik Künkele] can just rely on masked image when predicting coords, more useful for captioning or language game

The model is presented with both the original image and the masked image. Both are passed through a feature extractor and afterwards passed through a linear layer, reducing the dimensions to 2048. The resulting vectors are concatenated and passed through another linear layer that predicts the coordinates.

The test dataset is again evaluated on the euclidean distance of the predicted coordinates to the ground truth coordinates. This distance needs to be minimized. The mean of all calculated distances is calculated across the whole epoch, which results in a mean distance score per epoch. Since this score only takes the average of all predictions into account it can't evaluate every prediction individually. If for instance the prediction of one object is getting more precise with growing number of epochs, but the precision of another object gets worse, the mean distance will stay the same. It doesn't reflect this change. For that reason, I also introduced an accuracy score. For that I defined a fixed size circle with a radius of 20 pixels around the center of each object. If the model's prediction lies in this circle, it will be counted as a correct prediction, if it lies outside, it is a false prediction. These scores are averaged for the epoch and result in an accuracy score, where 100% means that all predictions were very close to the center coordinates and 0% means that no predictions were close to the center coordinates. This of course doesn't give a perfect representation since the size of the objects varies, but it will still show, how precise each individual prediction is. A high accuracy may indicate

that the model could identify this specific object better.

The coordinate predictors are trained on the 'CLEVR single' as well as on both 'Dale' datasets. The 'CLEVR single' dataset should test the model if it can actually learn locations of an object. Since the model relies on the extracted features of either VGG or ResNet, locational information about the image could have gone lost. Training on this dataset should make sure that the model can converge towards the correct pixels, utilizing these features. In a next step, the 'Dale' datasets provide the actual problem of discriminating objects from each other and afterwards pointing to the correct one. Here, the models should make use of the additional given information about the scene, as one-hot encodings of the attributes, descriptions using the GRE-algorithm or the encoded locations. 'Dale-2' and 'Dale-5' provide two different difficulties for the model, where it needs to discriminate a target object from one or four distractors. Latter task is assumed to be significantly harder.

Level 2 - Bounding box classifier:

[Dominik Künkele] better to call it discriminators?

One problem that arises, when only predicting the coordinates is that the models may not be able to predict locations of objects from just visual features. Feature extractors like VGG or ResNet are trained on extracting visual information. In this process, absolute locations of these features in the images may get lost in the resulting vectors, since they are not important for this task. To address this challenge, I restructured the task in this experiment. Instead of predicting two coordinates of a target object, the model now needs to classify between all available objects. This will take all positional information out and just focus on the attributes and discriminating factors between the objects. To do this, fixed-size bounding boxes are extracted around each of the object in the image. As for the masking, the bounding boxes are a square of 192x192 pixels, to capture the complete object. The bounding boxes of all objects are padded to a number of 10 bounding boxes, the maximum number of objects in an image with a matrix of zeros. These bounding boxes are shuffled.

[Dominik Künkele] pre-process bounding box

The model passes each of the bounding boxes through a feature extractor. The resulting vectors are concatenated, which basically is a concatenation of the extracted features of each object. This long vector is passed through a linear layer with 4096 with a subsequent *ReLU* function. Afterwards, a linear layer reduces the dimensions to 10, corresponding to the 10 bounding boxes in the input. With a final *softmax* function, the model then points to one of the bounding boxes as the target bounding box. The loss is calculated using cross entropy.

The bounding box classifier is trained on all datasets excluding the 'CLEVR single'. The 'CLEVR unambiguous' and 'CLEVR color' datasets are directly comparable to each other for the similar setup of their creation. Especially interesting is the effect of the number of shared attributes. Does it help the model if the target object is unique in every attribute or does it help if there is only one specific attribute that is shared? A similar assumption can be made for the 'Dale' datasets. How big is the effect of increasing the number of distractors and the growing number of attributes that are needed to discriminate the objects.

Level 3 - Caption generator: As the bounding box classifier, the caption generator only acts as a learning step towards understanding, how the model can learn the attributes of objects. It is used the same way to create the captions for each image as in the section above with the GRE-algorithm. This method focuses even more on human knowledge and structure of language than the experiment above, since it is even the final task of the model. There are some minor additions concerning the padding of the caption. As before, the caption is padded to a number of three tokens, corresponding to the maximum of three attributes.

However, there are three different ways how the padding is applied. First, the captions are, as usual in

captioning tasks padded at the end with a specified padding token. A problem could arise when the caption is not viewed as a natural language sentence, but as slots filled with tokens. More specifically, following the GRE-algorithm, the last token in the caption is always the shape. The second last token if existing describes the color, while the third last token if existing describes the size. As soon as this sequence is padded at the end, these slots suddenly disappear. A caption that only describes the shape, such as *cube* will be padded to *cube* <*pad*> <*pad*>, where the third last slot is filled up with the shape instead of the size. Since in this task we are not focussing on producing natural language with a correct grammar, but focus instead of extracting attributes, having a slot structure could help the model to express the extracted attributes correctly. For this reason, the second method of padding the caption is prepending the caption with padding tokens. By this, the positions of the slots are preserved and if not specified just filled with a padding token. The last variation concerns the order of producing each token. When the captions are prepended, the model would need first produce two padding tokens, before it finally can produce a much more meaningful token for the shape. This could be difficult to learn for a model, as the longer a sequence of tokens is, the more information about the beginning of the sequence gets lost. Even though a sequence of just three tokens may not be long enough for this factor to be a problem, I experimented to reverse the caption. Instead of producing for instance <*pad*> *green sphere* as correct in English, the model would now need to produce *sphere green* <*pad*>. Notice that the padding token is again at the end of the generation, but the order of slots as well as the amount of information in the caption are still preserved.

Nonetheless, this helps to understand more detailed if and how the model discriminates objects. Does it rely on the same attributes, humans are using, or does it find other important differences, or is it able to solve the task at all?

I compare two different models against each other. The first model just takes the image as the input. During training, also the ground truth caption is passed to the model. The image is processed as in the section before. First, it is passed through a feature extractor with two following 2d convolutional layers, reducing the channels to 128. After each convolutional layer the *ReLU* function is applied. The result is pooled using max pooling and then reduced to 1024 dimension using a linear layer. The such encoded image serves as the initial hidden state of an LSTM, which generates the caption. During training the input sequence for the LSTM at each time step are embeddings of the tokens in the ground truth caption. No teacher forcing is applied. The output of the LSTM is passed through a linear layer at each step to determine logits over the symbols of the vocabulary. The loss is calculated using cross entropy. When testing, the LSTM always generates three tokens, with a start-of-sequence token as first input to the LSTM. Each token in the sequence is determined, by selecting the highest logit in the output of each step in the LSTM.

Since with this approach, the model doesn't have any information about the target object, I extend it with a masked image. As in the section above, a masked version of the image is created and passed to the model. The model works exactly the same, except for the additional separate image encoder that encodes the masked image in the same way as the original image. Both encodings are concatenated and then used as the initial hidden state for the LSTM. This should point the model to which object to describe and discriminate from the other objects.

To test the success of the model, three measures are calculated. The first measure is the **accuracy** if the model predicted every word in the caption correctly. This gives a hint, how the model fares in general and also able to predict actually any of the attributes at all. However, a 'false' prediction doesn't give much insight into why the model predicted a wrong caption.

It could be the case that the model predicted the correct shape, but wrong color. Even worse, the model could have predicted more attributes than necessarily to uniquely identify the target object and didn't follow the rules of the GRE-algorithm. For instance, consider the scene in Figure 2(e). The correct caption is *cylinder*. If the model would predict *purple cylinder*, the accuracy determines it as false as captioning *large*

purple cylinder as well *small green cube*. The first two descriptions identify the target object perfectly, but the model only didn't learn yet to leave unnecessary attributes out. To mitigate this, I also include a **word-by-word accuracy**. This measure calculates the accuracy not on sentence level, but on word level. The first predicted caption of the model would yield a word-by-word accuracy of 66% (including padding tokens), the second 33%, while the third prediction would yield 0%. This can give a better understanding of the errors the model makes.

With the **non-target accuracy**, I identify if the model described another object, which is not the target image. This is basically an inverted accuracy score; the lower the score, the better the model fares. For this I generated captions for all the non-target objects and distractors in the images using the GRE-algorithm. If the generated description of the model describes an object that is not the target object, it gets assigned 100%. If not, independently of describing the target object, no object, or one of the objects insufficiently, it gets assigned 0%. Using this measure, I can get a quick overview if the model's problem lies in extracting and relating attributes or in understanding which of the presented objects is the target object.

The caption generator models are trained on both 'Dale' datasets. Again, each of these datasets increases the complexity of the description. While the referring expression for the 'Dale-2' datasets are generally shorter, expressions of the 'Dale-5' datasets need to be more specific and use more attributes. Furthermore, the model needs to attend to many more locations in the image at the same time to find discriminating factors between those.

[Dominik Künkele] align 'description', 'caption' and 're-ferring expression' over the whole section

3.2.3 Language games

The experiments that are executed using language games have a similar structure as the pre-experiments, since those lied the basis for the language games.

The language games in this research have an asymmetric setup. One agent, the sender is shown some information and needs to generate a message. This message is received by the second agent, the receiver. The receiver needs to parse this message and combine it with the information they are given as well. The receiver then makes a prediction, which is compared to the ground truth. The game is set up prosocial, which means that both agents receive the same loss based on the receiver's prediction. All weights of the agents are adapted in the same way.

[Dominik Künkele] Gumbel-Softmax vs RE-IN-FORCE

All language games are set up and run in the EGG framework (Kharitonov et al., 2019), developed in PyTorch. This framework consists of heavy configurable core that controls the generating and parsing of the message, the calculation of the loss and the rules, for how the weights of all neural models are trained. The configuration includes for example a choice between single symbol and sequence messages with varying RNNs, a choice between Gumbel-Softmax relaxation and REINFORCE algorithms to learn neural models containing discrete symbols or an easy switch between different loss functions. Furthermore, runs of games can be saved to analyze the used messages of the agents and how they change over the duration of the learning.

[Dominik Künkele] better in the-oretical back-ground?

The framework is hereby setup in three levels. Part of the lowest level are the *agents* themselves. The agents are neural models that need to be developed from scratch and define how, the agents process their input and combine it with the message (in case of the receiver) and what they output. The second level are *wrappers* that take care of generating and parsing the message. The sender wrapper uses the output of the sender agent, to produce a message. The receiver on the other hand parses the message received by the sender and passes the result as an additional input to the receiver agent. The third level, the *game* links all described parts together. It provides the agents with the input and passes the message from the sender to the receiver. Furthermore, it uses the output of the receiver and calculates the loss, which is then the basis for the adaption of the weights for both wrappers and agents.

[Dominik Künkele] vocabu-lary?

For the following language games, the sender will always produce a sequence of symbols as a message, which the receiver will parse. Gumbel-Softmax relaxation is applied to produce discrete symbols. This is done using two LSTMs, an encoder LSTM in the sender wrapper and a decoder LSTM in the receiver wrapper. The output of the sender agent is used as the initial hidden state for the encoder LSTM. This LSTM is then producing symbols until it generates an end-of-sequence symbol. This sequence is then passed to the receiver wrapper with its decoder LSTM. Its hidden state is initialized randomly. The received message sequence is processed symbol by symbol. After each time, a symbol is processed by the LSTM, the resulting new hidden state is passed to the receiver agent as the parsed message. The receiver agent is combining it with its representation of the image input and predicting an output. The *game* is afterwards calculating a loss for each of these outputs separately. These losses are summed up to a total loss that is used to adapt the weights in both agents as well as in both LSTMs.

First, I will discuss *discrimination games*, because they have the simplest setup. Furthermore, other language games that research this topic use a very similar setup. In the next step, I will look into caption generators that are set up as a language game. Here, the sender describes the scene, while the receiver needs to generate a caption. In the last step, I try to lose as much human bias as possible and the models are trained on just 'pointing' towards the target object, by again predicting its center coordinates.

Discrimination games: In a discrimination game, the agents are presented with two or more images, one of these being the target image. The sender needs to communicate this target image to the receiver by discriminating it from the other distractor images. The receiver then needs to decide based on the message, which of the images is the target image.

The discrimination games in this research have a very similar setup as described in Lazaridou et al. (2016). The agents in this research resemble their *agnostic sender* as well as their *receiver*. One central difference is the production of the message. The main goal of their language game was the identification of the concept that and image was related to. Therefore, the sender communicated only single-symbol messages to the receiver, which should describe the concept of the target image. Opposed to that in this research, the agents are tasked to discriminate objects from each other based on their attributes. It is therefore assumed that the sender will communicate these discriminative attributes. For that reason, the sender is allowed to generate sequences as a message.

Both 'Dale' datasets are used to train the agents in this mode. Similarly to the bounding box classifier, bounding boxes around each of the objects are extracted and fed to the game. As in Lazaridou et al. (2016), the sender receives the bounding box of the target object as the first image, while the rest of the bounding boxes are shuffled. The sender is assumed to learn which of the input images is the target images by this approach. The receiver receives the images in completely shuffled order.

For the sender, the images are passed through a feature extractor and a following linear layer that reduces the dimensions to an embedding size e_s. All embedded images are concatenated and passed through another linear layer to reduce the dimensions to the hidden size h_s. This is then used as the initial state of the encoder LSTM in the sender wrapper.

The receiver also encodes all images using a feature extractor with a following linear layer, reducing it to e_r. The sequence, received by the sender is the input for its decoder LSTM, where the hidden state with a dimension of h_r is randomly initialized. As mentioned above, the receiver combines this image representation with the hidden state of each symbol separately. This is done by passing the hidden state through a linear layer to scale its dimensions to the same e_r. This allows the calculation of the dot product between it and the image representation. If the message describes an object well, the resulting dot product should be higher. The receiver then 'points' to one of the images by applying the *softmax* function over the

results of the dot products. The loss is calculated using the NLL-loss.

During the experiments, five variables are adjusted to compare their effects: (1) the image embedding size for the sender e_s, (2) the LSTM hidden size for the sender wrapper h_s, (3) the image/message embedding size for the receiver e_r, (4) the LSTM hidden size for the receiver wrapper h_r and (5) the size of the vocabulary $|V|$.

Caption generators:

Coordinate predictors:

4 Results and Discussion

[Dominik Künkele] 15 pages

4.1 Pre-experiments without language games

4.1.1 Coordinate predictor

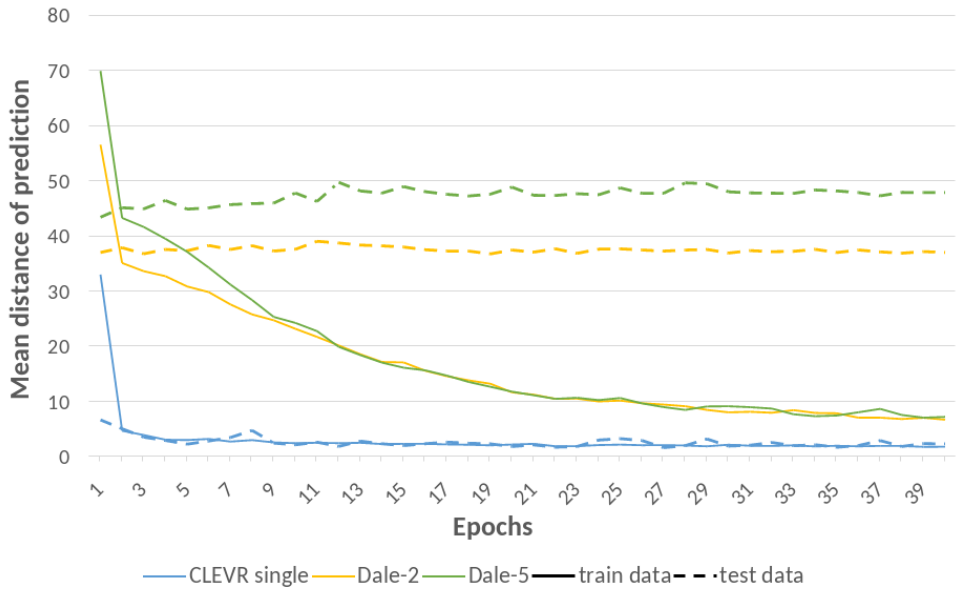


Figure 3: Mean distance between predicted coordinates and ground truth in pixels on different datasets

Figure 3 shows the results of the coordinate predictor that doesn't include any information about the target object. The used feature extractor for these results is *Resnet-3*, but the results don't differ significantly with other feature extractors. As can be seen, the success between the different datasets differ significantly. The more objects are present in an image, the worse the model performs. The model converges for the CLEVR single dataset after around 20 epochs to a mean distance of around 2 pixels. This prediction even though not perfectly on the center point is always on the object. Opposed to that, using the Dale-2 dataset with two objects, the mean distance is from the first epoch between 37 and 38 pixels. With five objects in the Dale-5 dataset, the model only predicts a mean distance of around 45 pixels in the beginning, which worsens with a rising number of epochs to 48 pixels.

An interesting observation is the difference of the mean distances between training and testing data. The training distance is constantly approaching zero, while the testing loss is staying constant or even getting higher. This points to the fact that the model is not generalizing the task and learning abstract patterns that can be applied to unseen data, but instead learning the training data by heart. That is especially visible for the Dale-5 dataset, where learning the patterns of the training data looses even the ability to interpret some patterns in the testing data. Applying a higher dropout didn't have an impact on the results.

This behavior is indeed not very surprising. First, these results show that the model is able to derive geometrical information from abstract feature, extracted by a feature extractor. Geometrical information therefore doesn't get lost during this abstraction, but the model is able to point to a specific object, as long as only one object is part of the image. Secondly, more than one objects present in an image confuse the model, and it is not able to consistently point to one of them. This can have multiple reasons, for instance that models lacks the ability to separate objects in the extracted features. But even given, the model is able to do that and

could determine the location of each object in the scene given the feature, it would not be able to tell, which of these is the actual target object. The guess is then more or less random. This especially applies to the Dale-2 dataset, where an identification of the target object just based on one distractor is impossible; both of the present objects are unique. For the Dale-5 dataset, the model could in theory learn that the target object is always the one object which is unique in respect to its and the distractors' attributes. This task on the other hand seems very difficult to learn. In conclusion, the models are able to predict geometrical coordinates, but need more information about the target object to identify it.

When the target object **attributes are encoded as one-hot vectors** and added to the input, the results don't improve. One factor that now has a much higher impact is the feature extractor that is used. Table 3 compares the mean distances the models predict for the different feature extractors. The results are shown for the models trained on the Dale-2 and Dale-5 datasets for training and test data. First, a big difference can be seen between the datasets. The model doesn't converge on the correct coordinates for the Dale-5 dataset at all, looking at the test data. All resulting mean distances are in a similar range around 50 pixels. Using the Dale-2 dataset, the behavior is a little different. All ResNet extractors with four residual blocks and optionally additional average pooling and classifier layers reach similar scores as the experiments before without any one-hot encodings. Interestingly, using less residual layers, the model doesn't converge at all and the mean distances jump up and down between the epochs. This effect also applies when using less residual blocks. Using the VGG, both using VGG-avg and VGG-cls2 achieve a similar performance, while the others predict coordinates between 43 and 46 pixels away.

[Dominik Künkele] compare to scratch

	Dale-2		**Dale-5**	
	train	test	train	test
VGG-0	30,26	46,2	**10,81**	48,33
VGG-avg	**9,96**	36,9	32,17	54,40
VGG-cls1	37,99	43,28	46,57	50,75
VGG-cls2	34,95	**36,32**	47,63	**46,38**
VGG-cls3	39,99	44,32	47,26	46,77
ResNet-3	92,07	91,12	11,52	48,52
ResNet-4	**8,09**	**36,78**	**9,05**	46,84
ResNet-avg	29,21	38,94	37,10	48,71
ResNet-cls	33,29	38,83	41,57	**46,57**

Table 3: Mean test losses for different feature extractors with one-hot attribute encodings after 20 epochs

[Dominik Künkele] wrong numbers

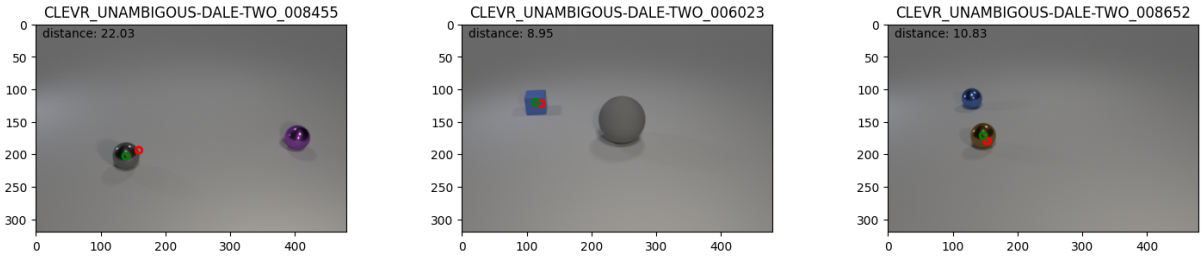
Secondly, the training loss now looks also different. In almost no cases, the models converge to a very low mean distance, meaning a high precision in their predictions, as they did in the experiment before. There are only exceptions when ResNet-4 is used or respectively VGG-avg for Dale-2 and VGG-0 for Dale-5. In other words, that means that the models are again not able to generalize, but in specific cases to learn the patterns in the train data by heart. This hints to the fact that only specific layers of the feature extractors contain information that is generally usable to identify and discriminate objects. Especially high layers, like the classifier layers and in the case of ResNet also the average pooling layers seem to already encode to task specific knowledge that was learned during the pre-training of these deep neural models. This information can't be utilized for the tasks in this research and earlier layers with more abstract information need to be used. The experiments in the following sections are set up using these lower layers as ResNet-3, ResNet-4, VGG-0 and VGG-avg.

Adding **information about the center coordinates** of all objects should have helped the models to get a list of possible predictions. In theory, the model could learn to choose between these coordinates by relating them to the extracted features of the image. This hypothesis doesn't hold. All results for both datasets

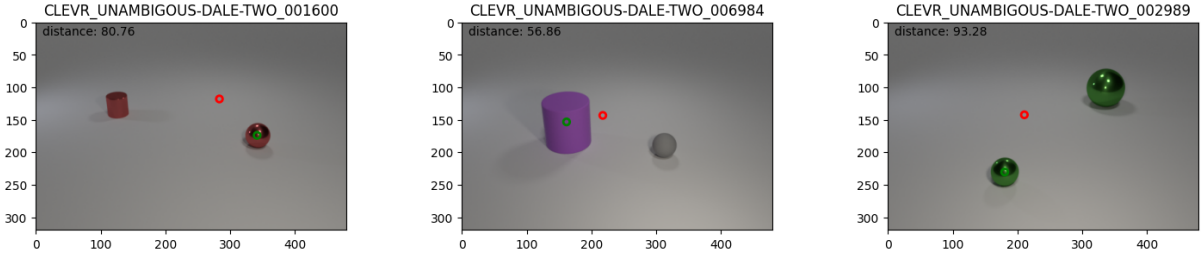
Dale-2 and Dale-5 are the exact same as without included information about the locations. The problem therefore doesn't seem to lie in predicting coordinates in general, but predicting the coordinates of the target object. The model is still not able to understand, which object is the target object. For that reason, a better representation of the target object is necessary.

In a next step, information about the attributes is included using the *GRE-algorithm* from Dale & Reiter (1995).

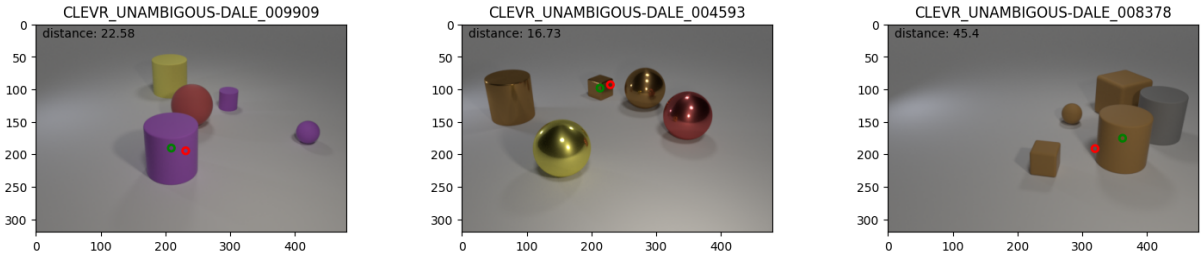
[Dominik Künkele] change



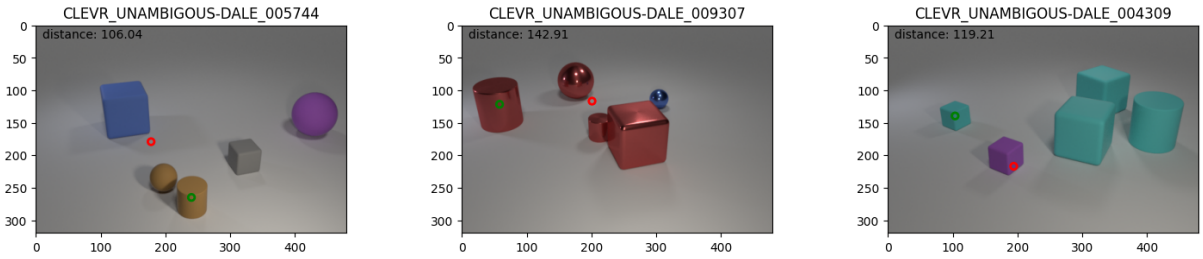
(a) 'Dale-2', train split



(b) 'Dale-2', test split



(c) 'Dale-5', train split



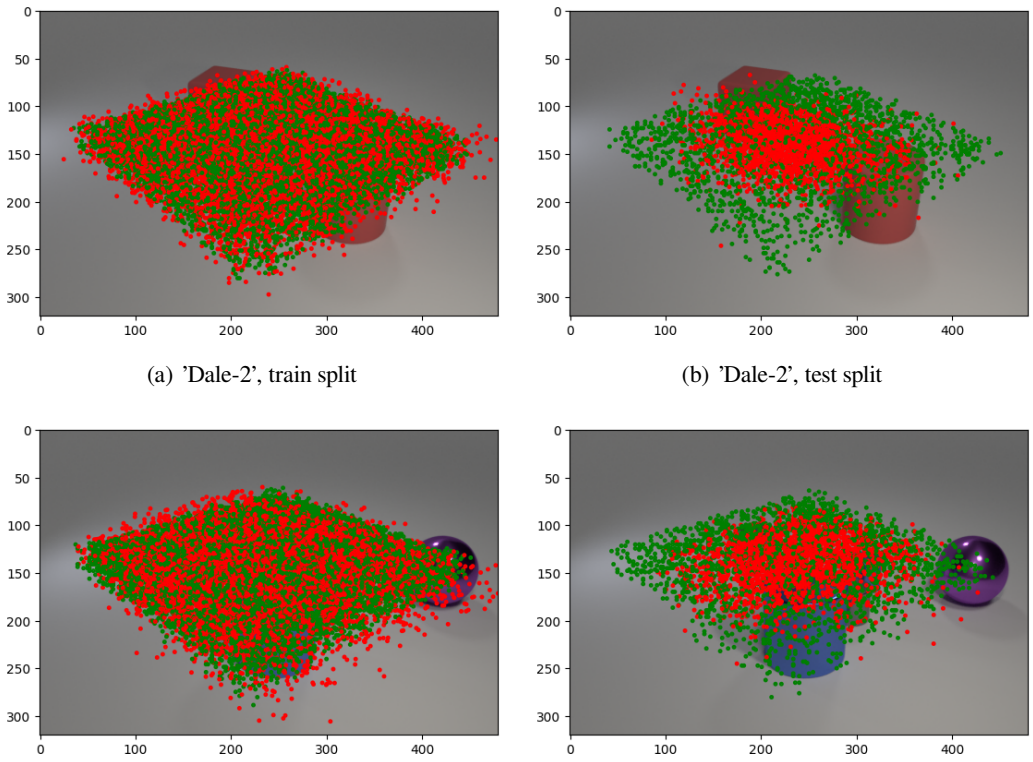
(d) 'Dale-5', test split

Figure 4: Visualization of the models' predictions in the 'Dale' datasets

An interesting pattern appears when doing a qualitative analysis of the models' predictions. Here, I visualized the predicted coordinates compared to the ground truth coordinates. Figure 4(a) shows random examples of predictions for images in the train dataset of Dale-2. The green circle shows the ground truth center coordinates of the target object, while the red circle shows the prediction of the model. As can be seen, the prediction are very precise. Figure 5(a) combines the predictions and ground truths across all images in the

train dataset. Here, all predicted coordinates are placed as red circles into the image, while all ground truth coordinates are places as green circles. The resulting shape is a rhombus, which reflects that all objects are placed usually central into the scene. As expected the green and red rhombus align mostly in the same area for the train split of the 'Dale-2' dataset.

The results look very different for the test split. As can be seen in Figure 4(b), the three randomly selected predictions don't align with the ground truth coordinates. For all the images, the predictions don't lie on any object. In the left image as well as in the central image, the predictions are closer to the target object than towards the distractor, but are still quite imprecise. These findings align with the mean distance scores, described in the sections before. However, it seems that the model's predictions are all towards the center of the image. This can be seen clearer in Figure 5(b). Again, the green circles form the shape of rhombus. In contrast, the predictions in red almost all cluster in the center of the image. They form roughly the shape of a smaller rhombus. This behavior can be observed for all datasets and architectures of the model. Figures 4(c), 4(d), 5(c) and 5(d) show the results for the 'Dale-5' dataset. Here, the model more likely predicts the center coordinates of a distractor object as seen in the right image, which is also reflected in the lower score of the mean distance. Also the combined visualization shows the same clustering of predictions in the center of the scene, but pattern of the smaller rhombus is better visible.



(a) 'Dale-2', train split

(b) 'Dale-2', test split

(c) 'Dale-5', train split

(d) 'Dale-5', test split

Figure 5: Visualization of the models' predictions in the Dale datasets

These results allow two conclusions. First, the models are biased to predict

Second, even though the models are biased towards the center of the image, the predictions are still often leaning in the direction of the target object. This indicates that it is still able to

4.1.2 Bounding Box classifier

4.1.3 Caption generator

In the next paragraphs, the results of the caption generator will be discussed. Table 4 shows the different scores of the models, when trained on 'Dale-2' and 'Dale-5'. ResNet-3 produced the best results, when it was used as a feature extractor. The results are shown after 50 epochs, but the scores already start to converge after 20 epochs and changed only very in the following epochs.

	Accuracy	**Word-by-word accuracy**	**Non-target accuracy**
Dale-2	49%	82%	48%
Dale-2 masked	72%	90%	25%
Dale-5	21%	45%	40%
Dale-5 masked	21%	54%	45%

Table 4: Results of the caption generator, based on ResNet-3

The sum of the *accuracy* and the *non-target-accuracy* adds to 97%, when trained on the 'Dale-2' dataset. This means that the models produce almost always correct descriptions of an object in the image. Moreover, these descriptions are also efficient in the way that they follow the GRE-algorithm of Dale & Reiter (1995) and only use necessary discriminative attributes. Features of both objects are therefore extracted perfectly and related to the vocabulary. As expected, the model has difficulties to decide, which of both objects is the target object, since no information is passed to the model. With 48% of the images describing the target object and 49% of the images describing the distractor, the model uses a random guess. This changes, when also the masked image is presented to the model. Then, the accuracy for the target object is with 72% well above chance. Still, the wrong descriptions describe almost every time the distractor object. This indicates that the problem doesn't lie in extracting features of objects, but only in deciding which object in the image to describe.

When the model is trained on the 'Dale-5' dataset, the results are much worse. Now, without masking only in 61% of the images, the model describes any of the objects in the image. With 21% of these descriptions being a description of the target object, the model again uses a random guess. Interestingly, passing the masked image to the model doesn't help it to identify the correct object. The accuracy stays at the same value. In contrast, the non-target accuracy is increased by 5% points. The model is more likely to identify a wrong object. Furthermore, the word-by-word accuracy increases from 45% to 54%. This increase is likely due to the fact that the description of the target object often shares some attributes with distractor objects. For instance an image with a target object being a *small red cube* was identified as a *<pad> <pad> cube* when the model didn't receive the masked image. After also the masked image was passed to the model, it generated the description *small blue cube*. This was the correct description of a distractor and because of the overlap of the attributes, the word-by-word accuracy increased from 33% to 66%.

The approach, how the padding is produced and in which order the attributes are concatenated didn't have an effect on the described metrics. When the order was reversed and the padding appended, it seemed like the model was converging slightly faster and reaching the limit around tow to three epochs earlier. The final peak stayed exactly the same and the effect was therefore not studied deeper if there is an actual significant difference.

There are two main possible explanations for the big difference between the two datasets. First, as already seen in the experiments before, the bigger number of distractors confuses the model more, where to focus on. In the 'Dale-2' dataset, there are only two possibilities, while the four distractors in the 'Dale-5' dataset give the model a bigger choice. The second explanation lies in the used GRE-algorithm. When only two random objects are placed in a scene, the probability that only the shape is enough to discriminate the objects

is at 66,6%, namely the caption is only one word long. For shape and color, the probability lies at 29,2% and that all three attributes are necessary is 4,1%. Opposed to that the probabilities with four distractors are 19,8%, 47% and 33,2% respectively. With four distractors the algorithm is much more likely to produce longer captions. These are harder to generate for the model, since it needs to take more attributes into account to discriminate the target object from the distractors.

4.2 Language games

4.2.1 Discrimination games

There are five variables in the experiments that are adjusted: (1) the image embedding size for the sender e_s, (2) the LSTM hidden size for the sender h_s, (3) the image/message embedding size for the receiver e_r, (4) the LSTM hidden size for the receiver h_r and (5) the size of the vocabulary $|V|$.

Table 5 shows the accuracy of the models calculated on the success of communication if the receiver can identify the target object. A random guess corresponds to 50% in the *Dale-2* dataset and 20% in the *Dale-5* dataset.

Dataset	h_s	e_s	h_r	e_r	$\|V\|$	**Acc.**
Dale-2	10	10	10	10	10	95%
Dale-2	50	50	128	128	10	50%
Dale-5	10	10	10	10	10	23%
Dale-5	10	10	10	10	20	23%
Dale-5	10	10	10	10	100	41%

Table 5: Results: h are different hidden sizes, e embedding sizes and $|V|$ vocabulary sizes.

For the *Dale-2*, a clear correlation between the hidden sizes, embedding sizes and the size of the vocabulary can be identified. A hidden/embedding size as high as the vocabulary size is beneficial for identifying the correct object. The receiver identifies almost every sample correctly when all sizes are 10. When the hidden and embedding sizes are increased, the guesses by the receiver are random with 50% accuracy. Interestingly, a vocabulary size of 10 is enough to communicate a meaningful message when the model is trained on the *Dale-2* dataset.

The results change, when using the *Dale-5* dataset with four distractors. With four distractors and with low hidden, embedding and vocabulary sizes, the agents barely pass the random baseline with 23%. Only increasing the vocabulary size to 100 raises the accuracy by almost 20% points to 43%. This is still considerably lower than the 95% of the *Dale-2* dataset.

[Dominik Künkele] calculation of loss?

Two conclusions can be drawn. First, the hidden as well as the embedding sizes need to be close to the vocabulary size. This even applies for very low vocabulary sizes, which means that the image encodings need to be compressed to the same low dimensions. The reason for this is very likely that neural models have difficulties to upscale from lower dimensions (e.g. from low h_r to high e_r) as opposed to learn how to extract the important information from a vector with many dimensions.

The second conclusion that can be drawn looks at the differences between the two datasets. Unsurprisingly, the agents have a much higher difficulty to discriminate a target object from four instead of one distractor. Since we discriminate objects based on properties that are also distinguished in human cognition (color, size, shape), we expect that the vocabulary onto which the agents converge reflects these categories and is therefore close to human vocabulary. There are 48 possible combinations of attributes. Still, for Dale-2, a vocabulary size of only 10 is enough for an almost perfect accuracy with two objects. This hints to the fact that the agents don't describe the complete target object, but only rely on discriminative attributes

between the objects. The need for a more detailed description of discriminative attributes is higher when more distractors are involved. Therefore, the models need to learn more combinations of symbols in order to attest to this higher level of detail and especially how to relate them to features in the images.

[Dominik Künkele] look at language

[Dominik Künkele] test different sizes

[Dominik Künkele] similarity to bounding box classifier

4.2.2 Caption generators

4.2.3 Coordinate predictors

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

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A Resources