SHAPEWORLD: A new test methodology for multimodal language understanding

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Abstract

We introduce a novel framework for evaluating multimodal deep learning models with respect to their language understanding and generalization abilities. In this approach, artificial data is automatically generated according to the experimenter’s specifications. The content of the data, both during training and evaluation, can be controlled in detail, which enables tasks to be created that require true generalization abilities, in particular the combination of previously introduced concepts in novel ways. We demonstrate the potential of our methodology by evaluating various visual question answering models on four different tasks, and show how our framework gives us detailed insights into their capabilities and limitations. By open-sourcing our framework, we hope to stimulate progress in the field of multimodal language understanding.

1 Introduction

Deep learning methods have had a major impact on research in natural language processing and raised performance substantially in many of the standard evaluations. Moreover, multimodal tasks like image captioning (Karpathy and Li, 2015) or visual question answering (VQA) (Antol et al., 2015) can now be tackled with great success. Such systems seem to solve the problems entirely on a sub-symbolic level, based only on raw image (and text) input, whereas previous approaches required a hand-crafted combination of various higher-level components.

There is, however, concern about how deep neural networks learn to solve such tasks. Investigations for image recognition (Szegedy et al., 2014; Nguyen et al., 2015; Zhang et al., 2017) have shown surprising behavior very different from what would be expected of their “surpassing human-level performance” (He et al., 2015). Deep networks for language tasks may exhibit similarly odd behavior (Sproat and Jaitly, 2016; Arthur et al., 2016). Moreover, it was recently found that datasets – for instance in VQA – contain various unexpected biases and peculiarities, which systems can exploit to answer complex questions, sometimes even without looking at the image at all (Goyal et al., 2016; Agrawal et al., 2016; Zhang et al., 2016). Such results cast doubt on whether deep learning systems actually acquire appropriate generalizations. However, given the recursive nature of language and the potentially enormous problem space of VQA and similar tasks, acquiring the ability for reliable generalization will eventually be essential.

A more theoretical issue is the ability of network architectures, in principle, to learn certain classes of structure. For instance, it has been shown that LSTMs possess the ability to handle long-range dependencies (Hochreiter and Schmidhuber, 1997; Gers and Schmidhuber, 2001). However, the formal experiments that have been done along such lines are limited, particularly in the multimodal domain of vision and language. While recent work indicates that the information encoded in image embeddings might be rich enough for good captioning results, it is an open question whether current architectures are able, in principle, to combine visual information effectively to handle the full range of linguistic constructions.

This paper introduces a new test methodology for multimodal deep learning models. SHAPEWORLD is a framework for specifying VQA-style datasets. An instance here consists of an image and a caption, and the evaluated model has to decide about their agreement, hence a form of yes/no
question answering which we call image caption agreement (ICA). Figure 1 illustrates the task and nature of the data with some example instances.

A SHAPEWORLD dataset differs from standard VQA evaluation datasets in three main ways. Firstly, a SHAPEWORLD dataset defines a process for generating artificial data consisting of abstract colored shapes, which is randomly sampled during training/testing according to constraints specified by the experimenter. Secondly, the evaluation focus is on linguistic understanding capabilities of the type investigated by formal semantics. The visual complexity and open-class vocabulary size is reduced to a minimum, while potentially allowing indefinitely complex syntactic constructions. Finally, the distribution of the evaluation data is deliberately kept different from the training distribution. Controlled data generation enables us to introduce previously unseen instance configurations during evaluation, which require the system to recombine learned concepts to be able to understand these novel instances (see figure 1) – hence a form of zero-shot learning. We think of the SHAPEWORLD tasks as unit-testing multimodal systems for specific linguistic generalization capabilities, in a similar way to the bAbI tasks (Weston et al., 2015) for text-only understanding.

We also present results for various VQA models on four SHAPEWORLD datasets targeting different multimodal language understanding abilities. The artificial data allows for a detailed analysis of the models’ strengths and weaknesses, and reveals unexpected shortcomings. As such, it offers a significantly different and interesting resource to complement standard evaluation practice. By exposing problematic instance patterns where these systems fail (e.g. spatial relations), and by providing a configurable, extensible testbed for systematic, detailed and comparable evaluation, we hope to stimulate progress in the field.

2 Related work

With the increasing popularity of deep learning approaches, artificial data of various kinds is again seen as a valuable tool in experimentation. Recently, the simulation paradigm has been argued to be a promising driver for artificial intelligence research (Kiela et al., 2016). Various platforms following this paradigm have been released, mostly aimed at reinforcement learning: the Arcade Learning Environment / Atari 2600 games (Bellemare et al., 2013), OpenAI Gym (Brockman et al., 2016), DeepMind Lab (Beattie et al., 2016), Project Malmo (Johnson et al., 2016), to name a few of the most popular. An important advantage of simulated data is its infinite availability, particularly in light of the need of many deep learning models for huge amounts of data. Automatically generating data greatly reduces the cost, time and human effort. Moreover, it allows researchers to focus on specific problem situations, isolated from a noisy and complex real-world environment.

When focusing on language tasks, the simulation paradigm faces the problem that interesting language generation is a difficult task in its own right, and that the difficulty increases with the complexity of the underlying world. The bAbI tasks (Weston et al., 2015) are generated by internally simulating a short scene and extracting a few simple sentences from it. A similar approach is taken by Narasimhan et al. (2015), but here the simulation is more complex, comprising a text-based role-playing game. The MazeBase game environment (Sukhbaatar et al., 2015) uses language as a mean to represent the game world. However, the descriptions are in an abstract, formulaic format, and the focus of the simulation is much more on the planning than the language component. The long-term research proposal of Mikolov et al. (2015) also simulates a world where
an agent learns to solve tasks by communication with a teacher module. At least for a start, this module is supposed to be scripted to automatically generate appropriate responses, given its internal knowledge of the world state.

Automatically generated data is common for tasks specifically focusing on the ability to efficiently process data of a certain formal structure. Here, data is deliberately stripped of any real-world connection to create an abstract capability check. Recent work in the context of deep learning has investigated sequence patterns (Joulin and Mikolov, 2015), combinatorial problems (Vinyals et al., 2015), or executing programming language code (Zaremba and Sutskever, 2014), amongst others. This kind of task is particularly common for neural network models (see, for instance, Bengio et al. (1994) more than twenty years ago). The reason for interest in abstract capability checks is that the learning process and decisions of deep networks are more difficult to interpret than shallower machine learning methods. Bowman et al. (2015) and Sorodoc et al. (2016) are more similar to our work in focusing on specific linguistic aspects. Both generate artificial data automatically based on abstract models for tasks targeting logical semantics and quantifiers, respectively.

The multimodal tasks of image captioning and VQA are closely related to our evaluation goal, but usually consist of “repurposed” real-world photos and human-written descriptions. However, there have been experiments in which parts of the data are artificial and/or generated automatically, for instance, automatic question generation from annotation (Ren et al., 2015) or systematic modification of captions (Hodosh and Hockenmaier, 2016). Abstract Clipart scenes have been used for image captioning (Zitnick et al., 2016; Zitnick and Parikh, 2013) and to balance existing VQA datasets (Zhang et al., 2016). Most similar to the SHAPEWORLD framework is the CLEVR dataset (Johnson et al., 2017). It contains images of rendered abstract 3-dimensional scenes and complex questions generated from a variety of templates. As with our work, they propose that their artificial dataset complements evaluation on real-world VQA datasets.

Our own work is based on automatically generated, fully artificial data. This data is not specifi-}

1 Although we contrast such “real-world” data with artificial simulations, it should be clear that this is very unlike the visual experience of an entity situated in the real world.

ically designed to address only a single structural problem, but is a testbed able to cover a whole range of linguistic phenomena. In fact, our generation system closely resembles classical work in formal semantics, where a statement corresponds to a logical expression which can be evaluated against an abstract world model (Montague, 1970). We utilize semantic representations based on Minimal Recursion Semantics (Copes-take et al., 2005) and broad-coverage, grammar-based realization driven by the English Resource Grammar (Flickinger, 2000) to make the internal world model compatible with language. However, while SHAPEWORLD uses these abstract representations internally, the external representation presented to the system under evaluation does not involve any abstract formalization of visual and textual input. It nevertheless presents the intended problems clearly, without any uncontrolled noise, biases or hidden correlations, which can obfuscate results when using real-world images and text (Goyal et al., 2016; Agrawal et al., 2016).

3 The SHAPEWORLD framework

The SHAPEWORLD framework is based on microworlds – small and self-contained artificial scenarios – which guide the data creation process. The SHAPEWORLD microworlds simply consist of colored shapes. This closed-world domain allows for exhaustive coverage of the space of possible microworlds and associated captions. The vocabulary used has an emphasis on closed-class words – the open-class vocabulary is currently far less than 100 words. In the following we explain the details of the data generation process inside the SHAPEWORLD framework. A schematic illustration of the process is shown in figure 2.

3.1 Image caption agreement task

In this paper we focus on the task of image caption agreement (ICA). The system to be evalu-

2 The SHAPEWORLD code is written in Python 3 and is available on GitHub (https://github.com/AlexKuhnle/ShapeWorld). The generated data is returned as NumPy arrays, so that it is possible to integrate it into Python-based deep learning projects using common frameworks like TensorFlow, Theano, etc. In our experiments, we use TensorFlow and we provide the models in this paper as part of the package. For the internal DMRS-based caption generation, the Python package pydmrs (Copes-take et al., 2016), as well as a reduced version of the English Resource Grammar (Flickinger, 2000) and of Packard’s Answer Constraint Engine (http://sweaglesw.org/linguistics/ace/) is included.
Figure 2: The generation process for ICA data, showing the alternative pathways depending on whether a correct instance (i.e., a true statement about the world) or an incorrect instance is to be generated.

Compared to the classic image captioning task, ICA emphasizes the understanding rather than the synthesis part of language use. We therefore avoid the problem of evaluating the appropriateness of a caption. The setup allows us to control the content of both modalities and consequently force a system to cope with difficult types of captions while obtaining a clear indicator of successful understanding. Although very similar to the VQA setup (i.e., yes/no questions), it neither requires the evaluated model to generate answers nor to rephrase the problem to fit it into a classification task of some sort – for instance, over the 1000/3000 most common answers, as is common practice recently (Lu et al., 2016; Fukui et al., 2016). ICA most closely corresponds to the work of Jabri et al. (2016), who present VQA as a binary classification of image-question-answer triples.

One further motivation for the task is that human performance could be measured using the same setup. We would expect close-to-perfect human performance on the tasks described here, assuming time is not tightly constrained. Interesting comparisons are potentially possible where human performance depends on presentation: e.g., quantifiers such as most (Pietroski et al., 2009). However, we will not discuss this further in the current paper.

3.2 World and image generation

At the core of each microworld instance lies an abstract world model. The internal representation of a microworld is simply a list of entities, given as records containing their primary attributes, such as position, shape, color, which are considered to be high-level semantic aspects reflected in captions. In addition, an entity has secondary attributes and methods which control, for instance, details of visual appearance, visual noise infusion, or the collision-free placement of entities. Importantly, all these ways of infusing noise can be controlled as well, which is useful particularly since noise is often seen as important for successful training of deep models.

The generator module automatically generates a world model by randomly sampling all these attributes from a set of available values. Both these values and other aspects of the generation process can be specified and adjusted appropriately for each dataset. The internal abstract representation is then used as a basis to extract a concrete microworld instance consisting of image and caption. The image (of size 64×64 in this work) is just a straightforward visualization of the world model. The table below gives an overview of the primary and secondary attributes, together with the value ranges and sampling details used for experiments in this paper (“distortion” here means width divided by height for rectangles and ellipses).

| Attribute   | Distribution                                                                 |
|-------------|------------------------------------------------------------------------------|
| shape       | choose(square, rectangle, triangle, pentagon, cross, circle, semicircle, ellipse) |
| color       | choose(red, green, blue, yellow, magenta, cyan, white)                      |
| location    | uniform(a = 0.0, b = (64, 64))                                              |
| object size | uniform(a = 0.15, b = 0.3)                                                   |
| distortion  | uniform(a = 2.0, b = 3.0)                                                    |
| rotation    | uniform(a = 0.0, b = 1.0)                                                    |
| shade        | trunc_normal(μ = 0.6, σ = 0.5)                                              |
| pixel noise  | trunc_normal(μ = 0.6, σ = 0.1)                                              |
Most squares are green and there are some circles which are blue.

\[ \approx \left[ \frac{\# \{ s_1 \in \text{World} : \text{square}(s_1) \wedge \text{green}(s_1, \text{color}) \}}{\# \{ s_2 \in \text{World} : \text{square}(s_2, \text{shape}) \}} > \frac{1}{2} \right] \wedge \exists s_3 \in \text{World} : \text{circle}(s_3, \text{shape}) \wedge \text{blue}(s_3, \text{color}) \]

Figure 3: An example of a DMRS graph corresponding to a more complex caption, with compositional components colored. The logical formula gives the formal semantic interpretation over a world model.

### 3.3 Caption generation

We currently provide an implementation of the SHAPEWORLD captioner interface using a grammar-based approach. More specifically, Dependency Minimal Recursion Semantics (DMRS) (Copestake et al., 2016) is an abstract semantic graph representation designed for use with high-precision grammars, such as those distributed by the DELPH-IN consortium.\(^3\)

A semantic representation like DMRS is particularly suited for the SHAPEWORLD framework, since it essentially mirrors the internal world model and hence acts like a (partial) language-specific annotation. Here, noun nodes correspond to entities, adjective nodes add attributes, and verb phrase nodes/sub-graphs specify relations between entities. The semantics of words like "square" or "red" is interpreted as iteratively filtering a subset of agreeing entities, while transitive relations like "to the left of" act similarly on pairs of entity sets, and quantifiers compare the cardinality of two entity sets. Below an example of a DMRS semantic graph with its compositional components colored:

![DMRS Graph Example](image)

**There is a blue circle.**

**Compositionality** of the semantic representation is a useful property and an important reason for our use of DMRS. Given compositionality, it is enough to specify the semantics of words – or, more precisely, of the linguistic atoms in the SHAPEWORLD context, which potentially are sub-graphs with multiple nodes and inner link structure – to be able to obtain the corresponding semantics of composed sub-graphs, and so generate a wide range of different captions.

Figure 3 shows an example of a more complex compositional caption, which contains the DMRS graph above as sub-graph. It also illustrates how various details are automatically inferred by the English Resource Grammar, including number-agreement between subject and verb, and between quantifier and noun, and realization of an adjective as relative clause. This greatly facilitates the generation of a combinatorially large amount of captions and makes the DMRS graph patterns reusable. Finally, figure 3 gives a formal semantic interpretation of the caption meaning as logical formula over a world model. This indicates how the agreement of a caption with a microworld is computed in the SHAPEWORLD framework.

Similar to the generator module, the **captioner module** randomly samples from a set of dataset-specific DMRS graph patterns, which are then applied to a world model to construct an agreeing **caption object** (see figure 2). The DMRS graph can be turned into an MRS representation, from which a corresponding English sentence can be generated with a bi-directional grammar like the English Resource Grammar and a parser-generator like Packard’s Answer Constraint Engine.

The captioner module’s ability to check whether another world model would agree with the semantics of this caption is important for the generation of negative instances, i.e., caption/microworld pairs that do not agree. These instances are obtained by either sampling a second, false world model, or by producing a false caption object via modification of the agreeing caption. In either case, the system ensures that false microworld and caption object do not accidentally agree.

\(^3\)Although we currently use the English Resource Grammar (Flickinger, 2000), other DELPH-IN grammars use a compatible approach, so SHAPEWORLD can easily be ported to other languages.
3.4 Training and testing on SHAPEWORLD datasets

Since SHAPEWORLD datasets are actually data generation processes, training and evaluation work differently from classic datasets. Where usually one has a fixed set of instances, here models are trained and tested on a fixed set of higher-level generator configuration constraints. In particular, the constraints for evaluation differ from the training constraints, hence requiring true generalization abilities. For instance, a certain shape-color-combination, a specific number of objects, a spatial location or a caption type can be held-out and never generated during training, such that concepts need to be recombined at test time. It is thus possible for a system to achieve optimal performance during training, but completely fail the evaluation.

Another important property of the SHAPEWORLD datasets, particularly for future extensions, is their compositionality. Instead of having to define a dataset from scratch every time, we can specify atomic datasets and then combine them in a mixer dataset, which tests for various different aspects of multimodal language understanding simultaneously. Reusability in fact applies even further down in the component hierarchy. For instance, we use the same generic world generator module for all four datasets. This is also useful for caption generation where, for instance, a logical combinator dataset can reuse different world captioner modules to generate simple statements which then are merged by logical connectives.

4 Experiments

4.1 Datasets

In this paper we look at four datasets, each designed to investigate an aspect of the capability to understand language in a multimodal setup. Figure 4 gives further information about these datasets. Note that since we first sample a microworld model and subsequently a caption, we cannot always easily control the generation process to sample each possible caption perfectly uniformly. This is in particular the case when focusing on more specific captions which might not apply to a microworld and hence require resampling.

4.2 Network architecture

We evaluate several multimodal deep neural network architectures that were recently proposed for VQA (Goyal et al., 2016; Agrawal et al., 2016; Jabri et al., 2016; Antol et al., 2015; Ren et al., 2015). Figure 5 shows the general architecture underlying all of these models. Implementations in TensorFlow, adapted for the ICA task, are included as part of the GitHub repository\(^4\). Each model is trained end-to-end on the task, including the CNN module and the word embeddings, as opposed to using pre-trained, general-purpose versions. We train for 5000 iterations\(^5\) with a batch size of 128, using Adam optimization (Kingma and Ba, 2014) with learning rate 0.001.

\(^4\)https://github.com/AlexKuhnle/ShapeWorld

\(^5\)We tracked the validation performance and found that learning essentially plateaus after at most half the iterations.
**LSTM-only** and **CNN-only** are simple unimodal baselines. **CNN+{BoW,LSTM,GRU}:Mult** obtain the caption embedding via BoW, LSTM or GRU, respectively, then fuse visual and textual information via pointwise multiplication. **CNN+LSTM:Add** and **CNN+LSTM:Concat**, i.e., pointwise addition and concatenation, are alternative basic ways of combining image and caption embeddings. Instead of concatenating the image embedding with the output of the LSTM, in **CNN:LSTM** it is concatenated with each word embedding before being processed by the LSTM. Finally, hierarchical co-attention (Lu et al., 2016) combines visual information on word-, phrase- and sentence-level with the language input, which is processed by a CNN. **CNN+CNN:HCA-\{par,alt\}** implements this approach with the two proposed co-attention mechanisms, parallel and alternating.

In the near future, we plan to also adapt the technique of multimodal compact bilinear pooling (Fukui et al., 2016), neural module networks (Andreas et al., 2016a,b) and potentially also relation networks (Raposo et al., 2017) to the ICA task, and upload implementations to the GitHub repository.

### 4.3 Results

Figure 6 reports the train\(^6\)/validation/test performance of four models. In addition to the overall accuracy, it contains a detailed analysis of the models’ ability to handle certain instance types. The accuracies for these **dataset partitions** were obtained by restricting the dataset generator to sample an evaluation set of only one instance type.

Due to space limitations, we do not report detailed numbers for the other models. Essentially, they all show the same (or worse) behavior as the **LSTM-only** model, apart from **CNN+GRU:Mult** which is similar to **CNN+LSTM:Mult**.

A number of conclusions from these results:

- The consistently low performance (best: 60%) indicates that all models essentially fail to learn spatial relations, in line with the findings of Johnson et al. (2017).\(^7\)
- The numbers for the **HCA** models on the **QUANTIFICATION** dataset indicate that quantifiers are not fully learned. They may be approximated by a rough number/existence/majority estimate – something we plan to investigate further.
- Unsurprisingly, **LSTM-only**, **CNN-only** and also **CNN+BoW:Mult** are not able to learn actual multimodal understanding, in contrast to their good performance on real-world data (Jabri et al., 2016). In our data, the failure in learning clearly shows in the tendency of these models to fall back to **always-correct** or **always-incorrect** predictions.
- Although sometimes lower than training accuracy, the above-chance-level validation/test accuracy indicate that in some cases the models are able to generalize (to some degree).

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\(^6\)Note that training accuracy here represents an interesting measure on its own, since no exact same instance is ever seen twice.

\(^7\)Contrary to what they report, our instances almost always require relational spatial reasoning.
| Dataset configuration | LSTM-only | CNN+LSTM:Mult | CNN+CNN:HCA-par | CNN+CNN:HCA-alt |
|-----------------------|-----------|---------------|-----------------|-----------------|
| ONESHAPE              | 51 / 46 / 50 | 81 / 70 / 66 | 90 / 77 / 78 | 92 / 71 / 77 |
| C: no hypernyms       | 90 / 70 / 100 | 95 / 64 / 57 | 98 / 71 / 73 | 97 / 68 / 66 |
| C: only hypernyms     | 100 / 100 / 100 | 52 / 34 / 30 | 96 / 78 / 82 | 95 / 75 / 73 |
| I: changed shape      | 6 / 5 / 7 | 70 / 81 / 82 | 60 / 63 / 58 | 73 / 78 / 78 |
| I: changed color      | 8 / 15 / 10 | 100 / 100 / 99 | 100 / 92 / 96 | 100 / 97 / 89 |
| I: changed both       | 7 / 5 / 6 | 96 / 97 / 98 | 87 / 85 / 84 | 93 / 92 / 89 |
| MULTISHAPE            | 62 / 67 / 67 | 72 / 71 / 72 | 72 / 71 / 69 | 71 / 68 / 68 |
| correct instances     | 48 / 49 / 50 | 76 / 64 / 54 | 81 / 68 / 65 | 71 / 59 / 55 |
| I: random attr.       | 58 / 63 / 68 | 67 / 74 / 79 | 64 / 67 / 68 | 70 / 73 / 78 |
| I: random existing attr. | 100 / 100 / 100 | 78 / 86 / 95 | 55 / 71 / 79 | 72 / 87 / 95 |
| SPATIAL               | 52 / 51 / 50 | 57 / 52 / 54 | 63 / 65 / 64 | 54 / 52 / 55 |
| C: no hypernyms       | 85 / 85 / 69 | 45 / 44 / 41 | 83 / 83 / 86 | 92 / 62 / 100 |
| C: only hypernyms     | 95 / 95 / 97 | 47 / 46 / 4 | 60 / 59 / 65 | 49 / 40 / 52 |
| I: swapped direction  | 11 / 13 / 16 | 98 / 97 / 98 | 36 / 39 / 30 | 50 / 61 / 47 |
| I: object random attr. | 15 / 12 / 16 | 88 / 88 / 91 | 69 / 68 / 68 | 63 / 66 / 60 |
| I: subject random attr. | 13 / 12 / 17 | 87 / 88 / 89 | 69 / 71 / 70 | 61 / 64 / 56 |
| QUANTIFICATION        | 57 / 51 / 36 | 56 / 36 / 38 | 76 / 71 / 78 | 74 / 77 / 78 |
| correct instances     | 23 / 22 / 18 | 25 / 30 / 26 | 74 / 71 / 72 | 70 / 71 / 75 |
| incorrect instances   | 94 / 93 / 93 | 88 / 90 / 88 | 81 / 83 / 88 | 78 / 82 / 82 |
| instances with no     | 52 / 51 / 48 | 61 / 60 / 61 | 56 / 56 / 51 | 55 / 55 / 58 |
| instances with the (=1) | 53 / 58 / 61 | 55 / 59 / 58 | 59 / 59 / 55 | 63 / 63 / 63 |
| instances with a (≥2) | 34 / 35 / 36 | 34 / 36 / 37 | 49 / 50 / 51 | 48 / 52 / 50 |
| instances with two (≥2) | 53 / 48 / 48 | 50 / 50 / 49 | 70 / 69 / 62 | 72 / 67 / 58 |
| instances with most    | 49 / 50 / 49 | 48 / 48 / 49 | 69 / 68 / 60 | 60 / 52 / 51 |
| instances with all     | 52 / 54 / 50 | 48 / 50 / 51 | 47 / 52 / 51 | 49 / 50 / 51 |

Figure 6: Accuracy in % (train/validation/test) of four selected models on our datasets, with a detailed evaluation of their ability to correctly understand specific instance types. Cell color indicates whether the corresponding instances were relatively harder or easier in comparison to the overall accuracy on the dataset, or whether the tendency is inconsistent across train/validation/test accuracies.

- Object recognition itself is not an issue – the CNN-only model trained for shape-color classification obtains ~98% accuracy.

There are many more interesting aspects that could be discussed, including learning curves, transfer learning and so on. However, the main point here is that a detailed investigation and error analysis like the one in figure 6 would be very difficult, if not impossible, to conduct with real-world data. It consequently shows the potential of artificial data as basis for a complementary evaluation methodology for multimodal language understanding systems.

### 4.4 Future work

The basic SHAPEWORLD framework can be elaborated in many ways. We plan to add new datasets addressing other aspects of language, as well as integrating options to enhance the language generation module, with the aim of providing more varied and natural image descriptions. For instance, we expect to integrate a subsequent step applying paraphrase rules after caption generation – Copestake et al. (2016) describe how this can be implemented on the level of DMRS graphs.

### 5 Conclusion

We have presented a new evaluation methodology and framework, SHAPEWORLD, for multimodal deep learning models, with a focus on formal-semantic style generalization capabilities. In this framework, artificial data is automatically generated according to predefined specifications. This controlled data generation makes it possible to introduce previously unseen instance configurations during evaluation, which consequently require the system to recombine learned concepts in novel ways, i.e., true generalization.

We evaluated various VQA models on four image caption agreement datasets, where the system has to decide whether a statement applies to an image. We showed how the SHAPEWORLD framework can be used to investigate in detail what these models learn with respect to multimodal language understanding. By exposing specific multimodal scenarios where current multimodal systems fail (e.g. spatial relations), and by providing a configurable, extensible testbed for systematic, detailed and comparable evaluation, we hope to stimulate progress in the field of multimodal language understanding.
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