What do models learn from training on more than text? Measuring visual commonsense knowledge

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Abstract

There are limitations in learning language from text alone. Therefore, recent focus has been on developing multimodal models. However, few benchmarks exist that can measure what language models learn about language from multimodal training. We hypothesize that training on a visual modality should improve on the visual commonsense knowledge in language models. Therefore, we introduce two evaluation tasks for measuring visual commonsense knowledge in language models[1] and use them to evaluate different multimodal models and unimodal baselines. Primarily, we find that the visual commonsense knowledge is not significantly different between the multimodal models and unimodal baseline models trained on visual text data.

1 Introduction

Language models (LMs) trained on large amounts of textual data have shown great performance on several textual tasks (Devlin et al., 2019; Brown et al., 2020). However, recent work has illuminated limitations with text-only training of LMs. These limitations arise from a lack of meaning (Bender and Koller, 2020) and experience (Bisk et al., 2020), together with the problem of reporting bias (Gordon and Van Durme, 2013). Multimodal training has been identified as one way to create models that do not suffer from the aforementioned limitations (Paik et al., 2021). While several multimodal models have been developed (Tan and Bansal, 2019; Li et al., 2019, 2020), few evaluation methods exist that can tell us whether multimodal training mitigates text-only training limits.

If we wish to successfully create multimodal LMs that learn from more than text, we need a way to evaluate them for what we expect them to have learned from their multimodal training.

[1] A link to a GitHub repo with the evaluation tasks and code necessary for reproducing our results will be placed here. For reviewing purposes, we add it as supplementary material.

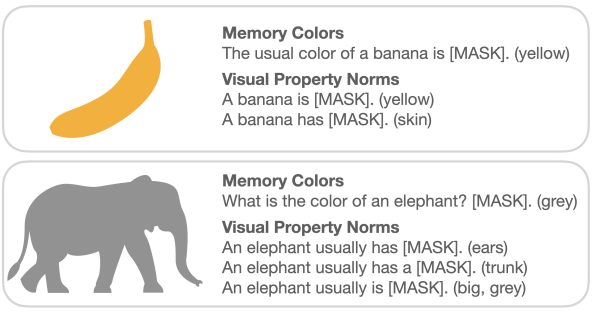

Figure 1: We introduce the two evaluation tasks Memory Colors and Visual Property Norms for measuring visual commonsense knowledge in a LM.

One hypothesis is that multimodal training should aid LMs in learning commonsense knowledge (Zhang et al., 2021). There are several text-only evaluation tasks that aim to measure the commonsense knowledge in LMs (Zellers et al., 2019; Zhou et al., 2020), but none of them focus explicitly on the commonsense knowledge learned through training on more than text.

We propose a simple method for measuring the visual commonsense knowledge of a model using two zero-shot masked language text-only tasks, depicted in Figure 1. The first task is the Memory Colors evaluation task (Norlund et al., 2021) and the second we create based on the visual features in the Centre for Speech, Language and the Brain (CSLB) concept property norms dataset (Devereux et al., 2014). We refer to the latter task as the Visual Property Norms evaluation task. We complement our work with the results of four vision-and-language models and four baselines on these two tasks.

2 Evaluation tasks

Our aim is to evaluate models for visual commonsense knowledge. To do this we make use of the existing Memory Colors evaluation task described in section 2.1, and introduce a new evaluation task, Visual Property Norms in section 2.2.

Common for both tasks is that they contain queries in English relating to visual properties of tangible concepts and that these queries are based on the knowledge of multiple human participants. Therefore, the tasks can be considered to evaluate visual commonsense knowledge.

Also common for both tasks is that they use textual templates containing a `[MASK]` token to be predicted by a model in a cloze-style fashion. The advantages with querying the models in this fashion is that most LMs[2] already have been exposed to this type of query format, including most multimodal models. We can then evaluate any model in a masked language modelling fashion on these tasks without additional training or having to make model-specific adaptations, enabling easy evaluation for researchers who may wish to use these evaluation tasks.

2.1 Memory Colors

The Memory Colors evaluation task is a text-only zero-shot cloze test that evaluates a model for its knowledge of memory colors. It queries a model for the color of 109 typical objects using 13 different query templates. The task has been created with the help of 11 human participants, so to some extent it encodes human visual commonsense knowledge limited to colors. Some examples of queries can be seen in Figure 1.

We use the same evaluation metric as specified by Norlund et al. (2021), i.e. the accuracy score after masking the model output for the 11 possible colors black, blue, brown, green, grey, orange, pink, purple, red, white and yellow.

2.2 Visual Property Norms

We also introduce a new cloze task to evaluate for visual commonsense knowledge, denoted Visual Property Norms. It is the largest query-based pure-language evaluation task capable of evaluating LMs for visual commonsense knowledge, containing 6,541 visual conceptual features produced by human participants.

We base it on the CSLB concept property norms dataset (Devereux et al., 2014) that contains the conceptual knowledge of 30 human participants for each of 541 concrete objects, with 123 participants in total. This knowledge is represented as a set of features per object, for which each feature is specified with a production frequency (PF)[3]. All features are also categorized as either *encyclopaedic*, *functional*, *other perceptual*, *taxonomic* or *visual perceptual*. Table 1 contains some examples of visual perceptual features in the dataset.

Concept	Relation	Feature	PF
Cherry	has a	stalk	17
Fern	is	green	29
Hair	is	thin	22
Plum	has	flesh	9

Table 1: Some concepts and their visual perceptual features in the concept property norms dataset.

We create our evaluation task from the concept property norms dataset in a set of steps. Firstly, since our goal is to measure visual commonsense knowledge, we only make use of the *visual perceptual* features. Since we wish to perform cloze tests through masked language modelling, only feature alternatives describable by one wordpiece from the BERT base uncased tokenizer are included.

Furthermore, we only include the four most common feature relations in the task. These are *has*, *has a*, *made of* and *is*. We then part the data into five different segments based on production frequency. This is done by thresholding the features for each concept such that only features with a PF above the set threshold for a certain data segment are included as gold labels in that segment. Features with higher PFs can be considered to be more apparent. The segments and their PF thresholds are listed in Appendix B.

Lastly, we create queries from the concepts in each data segment using 8 different query templates, seen in Appendix C. This is necessary to get a robust estimate of the performance of the evaluated LMs, since LMs are sensitive to query format (Jiang et al., 2020). Some examples of Visual Property Norms queries can be seen in Figure 1.

Similarly to Weir et al. (2020) we use the mean average precision (mAP) as our evaluation metric, since there may be multiple correct answers for each query in our evaluation data. We calculate this score for each concept and relation, per query template and production frequency segment. We then get a final score for each production frequency segment by taking the average score over all query templates and concepts per segment. This metric is measured over a vocabulary that has been masked to only contain the 614 possible answer alternatives in the Visual Property Norms evaluation data.

[2] Excluding autoregressive LMs.

[3] I.e. how many of 30 participants produced that feature.

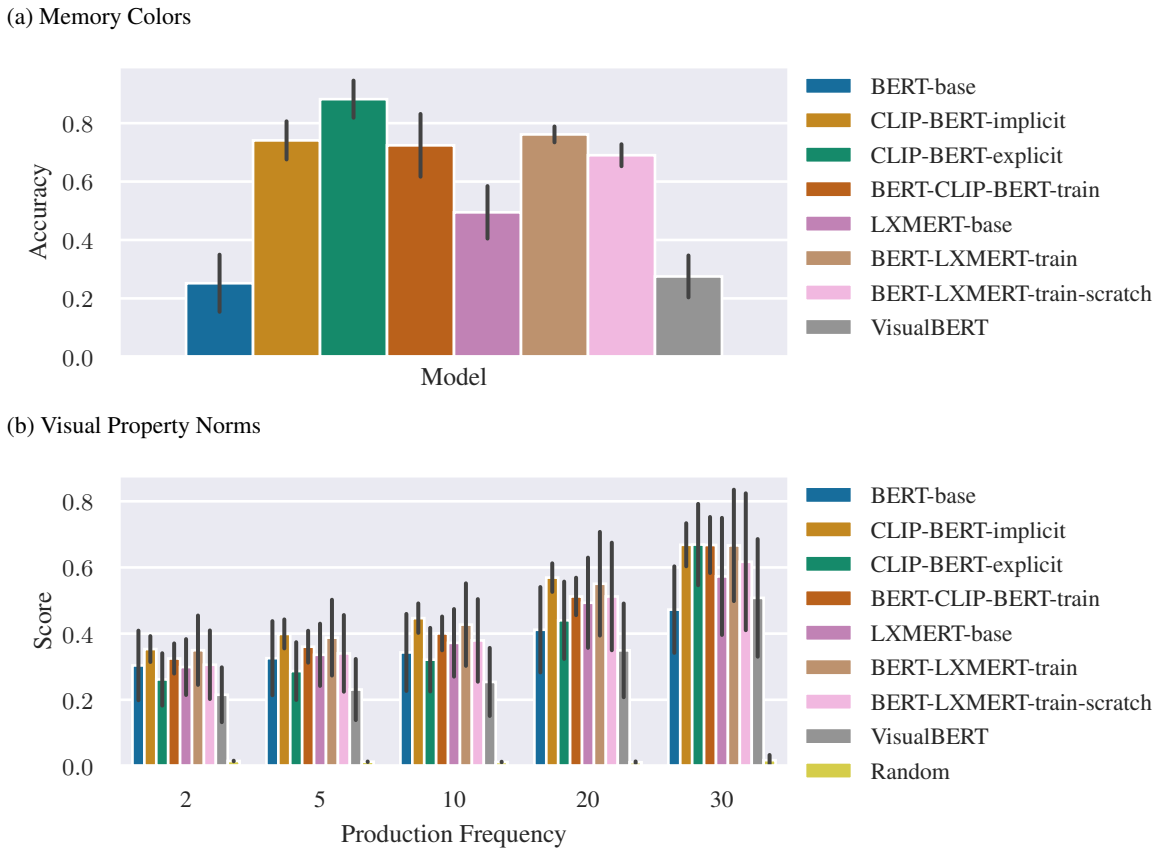

Figure 2: The model accuracy on Memory Colors and model scores on Visual Property Norms per production frequency segment. The error bars indicate the standard deviation of the model performance over the different query templates. The score has been calculated by masking the vocabulary of the models to only contain the possible answers of the task.

3 Models

We evaluate four multimodal pre-trained models for their visual commonsense knowledge. These are CLIP-BERT both with and without imagination[4](Norlund et al., 2021), a LXMERT base uncased (Tan and Bansal, 2019) and VisualBERT (Li et al., 2019). We also evaluate four unimodal baseline models. These are a BERT base uncased pre-trained on English Wikipedia and BookCorpus, a BERT base uncased further trained on the pure-text part of the CLIP-BERT training data (BERT-CLIP-BERT-train) and two BERT base uncased models trained on the pure-text part of the LXMERT training data, one from scratch and one initialized from pre-trained BERT weights (BERT-LXMERT-train-scratch and BERT-LXMERT-train).

All models are to some extent based on the BERT base architecture and consequently share the same vocabulary and tokenizer. They are also of similar sizes with $\sim$ 110M trainable weights, the exception being LXMERT with $\sim$ 230M trainable weights. Additional information about the models can be found in Appendix A.

Adapting the models for pure-text queries The majority of current multimodal models have not been developed to be queried only with text. In this case, both CLIP-BERT and VisualBERT should work well with only removing their visual features input, since they are single-stream models. However, LXMERT is a dual-stream model that requires a visual feature input. We handle the removal of visual information by simply removing the visual processing chain in LXMERT, making the language input the only input given to the Cross-Modality Encoder in the model. This would not work if we still wanted to use the model in a multi-modal fashion, but we can make this adaption since we are only interested in querying the model for visual commonsense knowledge via language.

[4]The explicit version has the ability to "imagine" visual features when queried with text.

4 Results

The results of the models on our two evaluation tasks can be seen in Figure 2. We format the analysis of the results around a set of questions.

Do the multimodal models display more memory colors knowledge? The multimodal CLIP-BERT-explicit model has the best performance on this task. So to some extent, yes. But it is worth noting that the unimodal BERT model trained on LXMERT training data is second best on the task, outperforming both LXMERT and VisualBERT, indicating a small multimodal advantage.

Is performance on Memory Colors indicative of performance on Visual Property Norms? The ranking visible in Figure 2a does not entirely differ from that in Figure 2b. The main exception being CLIP-BERT-explicit, which has the best performance on Memory Colors, but is outperformed by most other models on Visual Property Norms. We perform a closer analysis of how these results compare by extracting Visual Property Norm results for colors in Appendix C.

Do the models perform better when evaluated on more apparent concept features? We can observe how the model performance unanimously increases with increased production frequency threshold in Figure 2b. Thus, it appears as though the models agree more with concept features that can be regarded as more apparent.

Do the multimodal models contain more visual commonsense knowledge? The results in Figure 2b do not really indicate clear advantage of either unimodal or multimodal models. The multimodal model CLIP-BERT-implicit may generally have the best performance on the task, but the unimodal models trained on visual text data do not differ much in performance. For example, the unimodal BERT-LXMERT-train performs almost on par with CLIP-BERT-implicit.

However, we cannot exclude the possibility that the multimodal models suffer in performance due to a lack of visual feature input. Future work investigating this would be valuable.

Are the models sensitive to how they are queried? Prevalent for all models is that their performance varies greatly with how they are queried. BERT-LXMERT-train may have the best performance on Visual Property Norms if queried differently. We evaluate the model performances depending on query template in Appendix C.

Does fine-tuning on visual language develop visual commonsense knowledge? In both Figures 2a and 2b it is visible that unimodal model performance greatly improves with fine-tuning on visual text corpora. Potential explanations for this are that the models become more attuned to the task with fine-tuning, or that corpora from VQA and image captioning do not suffer as much from reporting bias compared to more common corpora.

5 Related Work

Weir et al. (2020) also use the CSLB concept property norms to probe LMs for commonsense knowledge. Our work differs from theirs in that we focus on visual commonsense knowledge and evaluate several multimodal models for whether their multimodal training grants them additional visual commonsense knowledge.

Norlund et al. (2021) also query a multimodal model for visual commonsense knowledge but with a focus on memory colors. Paik et al. (2021) present similar work but with more focus on probing and reporting bias. In our work, we include general visual commonsense knowledge concepts and evaluate several multimodal models.

6 Conclusions

We introduce new evaluation methods for measuring the visual commonsense knowledge in LMs and evaluate a number of multimodal LMs on these benchmarks. We find that there are no significant differences in performance between models trained on pure-text and models trained on images and text. Most prominently, we find that a unimodal LM trained on image captions and VQA queries can attain a visual commonsense knowledge on par with that of a multimodal model.

We also confirm the results by Jiang et al. (2020), that LMs are sensitive to query format even when querying for commonsense knowledge. This casts some doubts on what is really measured in a model for a cloze task and if we can reason about LMs as having knowledge. An interesting future step would be to investigate this further and if it would be more applicable to use e.g. probing or some other evaluation method.

Nonetheless, this is a first step towards measuring the visual commonsense knowledge in multimodal as well as unimodal LMs. We hope that the evaluation tasks introduced here may aid other researchers in their aim to create models that learn from more than text.

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A Additional model information

Additional information about the models used in our work can be found in Table 2. We can observe that VisualBERT has been trained on a data

amount that is quite small compared to those of CLIP-BERT and LXMERT.

It is also worth noting on the different backbones of the models. CLIP-BERT is a single-stream multimodal model with a CLIP backbone for visual processing. LXMERT is a dual-stream multimodal model with a Faster R-CNN detector backbone. While VisualBERT is a single-stream model that also utilizes Faster R-CNN detector backbone. Since CLIP has been trained on the immense WIT dataset, the backbone data sizes differ greatly between CLIP-BERT and the other multimodal models.

B Additional information on Visual Property Norms

Information about the different segments and number of entries per segment in the Visual Property Norms can be seen in Table 3.

C Additional results on Visual Property Norms

Additional model results on the Visual Property Norms can be found here.

Figure 3 indicates model performance per feature relation across the production frequency segments. We can observe how the models show the best performance for the *is made of* relation, which arguably can be associated more with visual perceptual properties.

Figure 4 shows model score per query template across all production frequency segments, indicating that CLIP-BERT-implicit benefits from being more robust to different query templates. Additionally, these results indicate that BERT-LXMERT-train would have the best overall score on Visual Property Norms if the queries containing "q: a" were to be removed.

Lastly, Figure 5 contains the results of the models on the color part of Visual Property Norms which has been filtered to only contain queries with gold labels describing colors. Here, we see some indications of a better performance of CLIP-BERT-explicit for colors. Potentially, the imagination capacity of this model is more helpful for queries with answers relating to more basic visual properties, such as color.

Model	Text	Visual text	Images+Text	Backbone	Training objectives
BERT	80M				MLM, NSP
CLIP-BERT-implicit	80M		4.7M	400M	MLM
CLIP-BERT-explicit	80M		4.7M	400M	MLM
BERT-CLIP-BERT-train	80M	4.7M			MLM
LXMERT			9.2M	0.1M	MLM, RFR, DLC, ITM, IQA
BERT-LXMERT-train	80M	9.0M			MLM
BERT-LXMERT-train-scratch		9.0M			MLM
VisualBERT	80M		1.7M	0.1M	MLM, ITM

Table 2: An overview of the pre-trained models, the sizes of their training datasets and their pre-training objectives. The sizes are measured in number of training samples. The backbone column indicates the training data sizes for the image processing backbones of the models. For the training objectives, ITM refers to Image-Text Matching, RFR to RoI-Feature Regression, DLC to Detected Label Classification, MVM to Masked Visual Modeling and IQA to image QA.

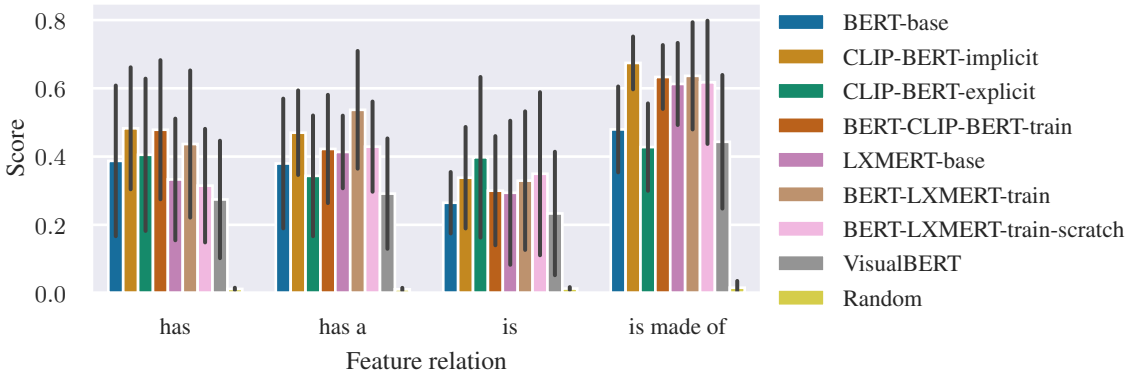

Figure 3: The model scores on Visual Property Norms per feature relation. The error bars indicate the standard deviation of the model performance over the different query templates. The score has been calculated by masking the vocabulary of the models to only contain the possible answers of the task.

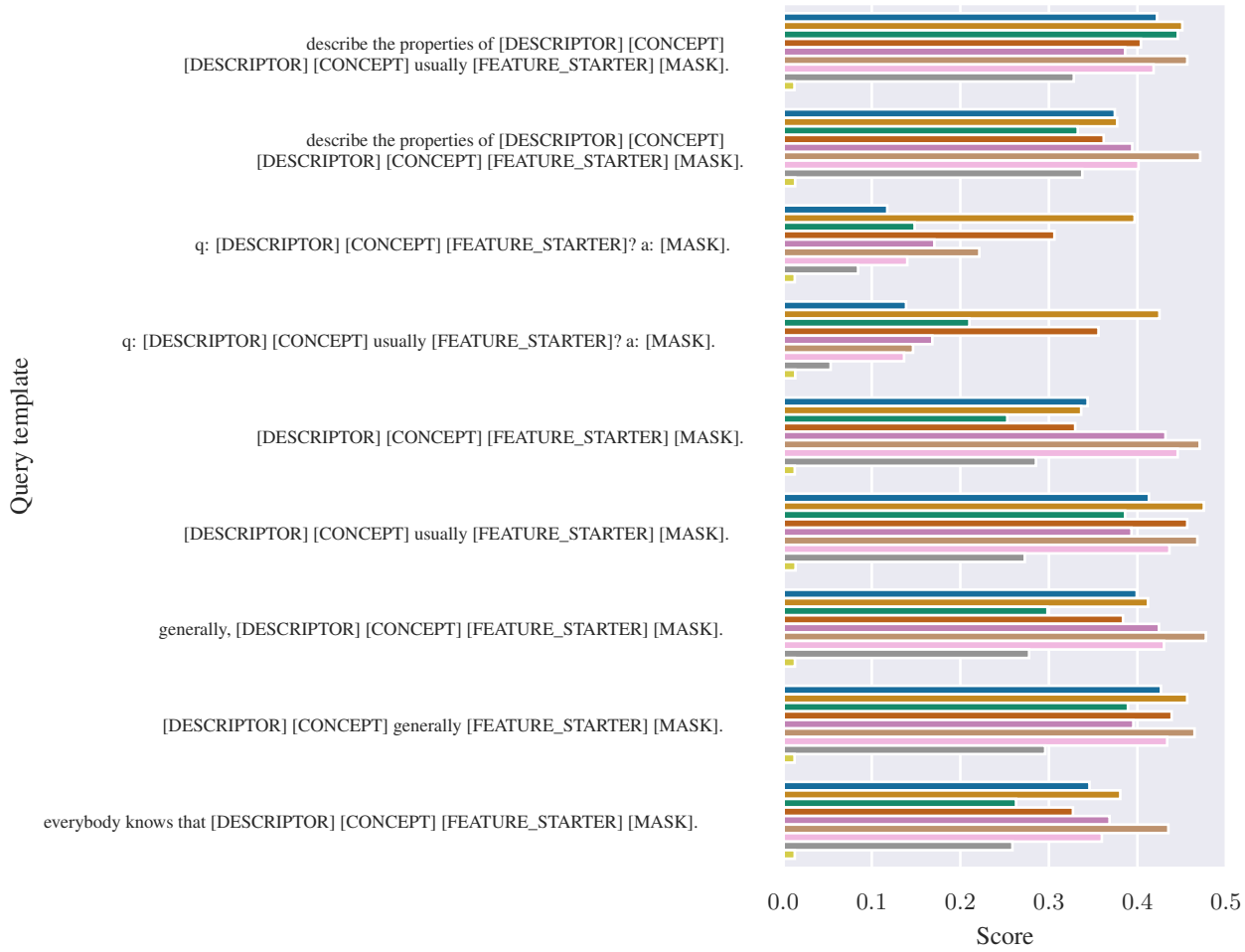

Figure 4: The score for each model on Visual Property Norms per query template. The score has been calculated by masking the vocabulary of the models to only contain the possible answers of the task.

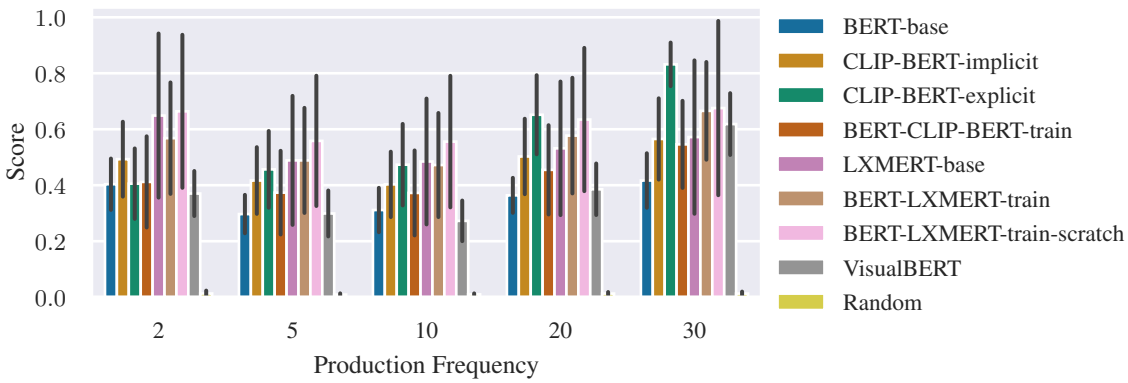

Figure 5: The score for each model per production frequency segment on Visual Property Norms that has been filtered to only contain samples for which the correct answer is one or more out of 11 possible colors. The score has been calculated by masking the vocabulary of the models to only contain the possible answers of the task.

PF	entries	*has*	*has a*	*made of*	*is*
2	6,541	1,675	1,190	1,176	2,500
5	3641	1,016	642	760	1,223
10	2001	583	347	509	562
20	613	169	88	209	147
30	27	5	2	10	10

Table 3: The data segments segmented based on production frequencies together with their number of entries. The entries are calculated as the number of feature-concept-label entries, where there can be several features belonging to the same feature and concept. The PF column indicates the production frequency threshold for each segment, all features with a production frequency higher or equal to this threshold are included in the segment. We also list the number of labels per feature relation type.