ILLUME: Rationalizing Vision-Language Models by Interacting with their Jabber

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Abstract
Bootsrapping from pre-trained language models has been proven to be an efficient approach for building foundation vision-language models (VLM) for tasks such as image captioning or visual question answering. However, it is difficult—if not impossible—to utilize it to make the model conform with user’s rationales for specific answers. To elicit and reinforce commonsense reasons, we propose an iterative sampling and tuning paradigm, called ILLUME, that executes the following loop: Given an image-question-answer prompt, the VLM samples multiple candidate rationales, and a human critic provides minimal feedback via preference selection, used for fine-tuning. This loop increases the training data and gradually carves out the VLM’s rationalization capabilities. Our exhaustive experiments demonstrate that ILLUME is competitive with standard supervised fine-tuning while using significantly fewer training data and only requiring minimal feedback.

1 Introduction
Recent vision-language models (VLM) are predominantly build on pre-trained (foundational) large language models (LM) (Tsimpoukelli et al. 2021; Eichenberg et al. 2021; Wang et al. 2022; Li et al. 2022; Saharia et al. 2022). As both Eichenberg et al. (2021) and Li et al. (2022) argue, this reduces the reliance on noisy vision web data while enabling a wider range of downstream tasks. However, while LMs show remarkable capabilities on tasks requiring commonsense knowledge (Shwartz et al. 2020), transferring these capabilities with standard supervised fine-tuning from the foundational LM to the VLM still requires large amounts of human-generated and annotated data.

In this work, we argue that those capabilities inherent to large-scale LMs transfer to downstream VLMs. In particular, leveraging existing knowledge enables a more efficient tuning approach using significantly less training data and requiring only minimal human interaction. In order to transfer the ability of commonsense rationalization between different modalities, we propose ILLUME (Interactive Ly Rationaliz ing Vision-Language Models), cf. Fig. 1. During this interactive process, the model’s performance improves based solely on self-generated samples (see Step 1) selected by human feedback (Step 2), interactively aligning the model to human preferences and gradually carving out rationalization capabilities (Step 3). Our empirical evaluation demonstrates that ILLUME uncovers and amplifies latent capabilities while balancing the benefits of human feedback against labor intense generation of ground truth data.

Specifically, we contribute: (i) evaluating commonsense reasoning—language as well as vision—of three recent pre-trained VLMs, (ii) analyzing the transfer (language to vision) of their commonsense rationalization capabilities, and (iii) introducing a novel iterative tuning paradigm.

We proceed as follows. First, we briefly discuss related work. Subsequently, we describe the task and our proposed ILLUME approach to transfer reasoning capabilities between modalities. Before concluding and discussing the benefits as well as limitations, we present our experimental evaluation showing indeed LMs can transfer their rationalization capabilities to VLMs using the ILLUME paradigm, achieving competitive performance on several open-ended visual reasoning benchmarks.

2 Related Work
Recent works have extended upon visual question-answering (VQA) tasks by considering natural language rationales to further elaborate on answer-reasoning. For instance Zellers et al. (2019) provide a dataset for visual commonsense reasoning that includes rationale explanations for a VQA task. However, the task is not posed as open-ended generation; instead, both answers and the explanation must be selected from a predefined set of possible options.

In contrast, the Pointing and Justification Explanation model (PJ-X) by Park et al. (2018) generates open-ended textual explanations for VQA and visual heatmaps pointing towards the evidence of an answer. Similarly, Wu and Mooney (2019) proposed the Faithful Multimodal Explanation model (FM), which relies on a pre-existing answering model that is fed a combination of textual and visual representations. These architectures are complex and tailored explicitly to perform that one task. In this work, we propose utilizing a pre-trained multimodal VLM instead, offering a more versatile approach and allowing to leverage capabilities of the underlying LM.

ILLUME is also closely related to fine-tuning large models from human feedback. Recently, InstructGPT (Ouyang et al. 2022) has demonstrated tuning language models with
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Let us start off by describing the task at hand in more detail before introducing our ILLUME approach.

3.1 Problem Statement

Recent state-of-the-art vision approaches build models on pre-trained (foundation) LMs (Tsimpoukelli et al. 2021; Eichenberg et al. 2021; Wang et al. 2022; Li et al. 2022; Saharia et al. 2022). Here, we aim to transfer rationalization capabilities from LMs to multimodal VLMs. The majority of current VLM architectures adhere to the same fundamental principles. Two encoders for vision and language project images and text into a joint embedding space. Subsequently, a transformer-based decoder performs autoregressive, open-ended text generation on the encoded multimodal inputs. Often the architecture is based on a pre-trained language encoder-decoder turned into a multimodal model through slight adjustments to the architecture and additional pre-training. We consider the task of transferring rationalization capabilities inherent to the underlying LM to the corresponding VLM. Therefore, we make efficient adjustments to the decoder in order to elicit the desired behavior.

In this context, we do not treat reasoning as a multiple-choice answer task (Kafle and Kanan 2016) but as an open-ended text generation (Tsimpoukelli et al. 2021). We consider VQA tuples \((i, q, a)\) consisting of an image \(i\) and a respective pair of text sequences for the question \(q\) and answer \(a\). We employ the model to perform a function \(f(i, q, a) = e\) that elaborates on the visual question answering and provides a textual explanation \(e\).

An explanation refers to an explicitly generated textual sequence \(e\) and does not target the interpretability of the model’s output. In line with previous research, we use the terms reasoning and explanations to describe the generation of rationales for VQA and use these terms interchangeably.

3.2 Self-talk Prompting

Our proposed approach is closely related to the self-talk (Shwartz et al. 2020) prompting paradigm. Instead of transferring capabilities between modalities, the self-talk approach focuses on improving reasoning via self-generated clarifications. However, we assume that LMs achieving a solid performance on this task are predestined for multimodal (vision-language) reasoning via VLMs. Therefore, we first establish a baseline for commonsense reasoning in natural language using the self-talk approach to evaluate and, in turn, select fitting LM candidates.

More precisely, self-talk aims to elicit world knowledge encoded in the model through a multi-step prompting scheme. The model is guided towards generating explicit clarification context for the original question that results in more faithful answers. Both clarification and context are prompted to the model to predict the final answer. Further details can be found in Appendix A.

3.3 ILLUME: Tuning by Interacting with Jabber

For vision-language rationalization, we now introduce ILLUME, a tuning framework that leverages a model’s capabilities in one modality and enables transferring these skills to multimodal applications with minimal supervision. To that extent, we apply iterative sampling, human feedback, and fine-tuning, as depicted in Fig. 1. In short, at each iteration, we sample explanations from the training data using the tuned model of the previous iteration. Minimal human feedback is provided to the model through marking fitting explanations. We envision this feedback to be provided through interaction with a human user, making this an interactive learning approach.
Sampling The first step of ILLUME is sampling rationale explanations given an input (image-question-answer) prompt. Expressive sampling techniques for LMs have been a long-standing point of discussion in the scientific community. On the one hand, just choosing the most probable token at each position in the sequence may lead to dull outputs. On the other hand, the tail of the distribution of token probabilities might still hold a significant portion of the total probability mass. This makes it inadvertently likely to predict completely unrelated tokens. The most prominent approaches to combat these issues are temperature sampling, top-$k$ sampling, and top-$p$ aka nucleus sampling.

Throughout this paper, we rely on the following sampling approach, which combines top-$k$ and temperature sampling. Firstly, we apply top-$k$ sampling to limit the generated sequence to the most probable tokens. On these filtered tokens, we apply temperature sampling as follows. Consider the logit $l_i$ of the output probability $p_i$ assigned to a token $i$. Temperature sampling scales the logits by temperature $T$ before applying softmax and samples from the resulting distribution:

$$\hat{l}_i = \text{softmax}_1 \left( \frac{l_i}{T} \right) = \frac{e^{l_i/T}}{\sum_j e^{l_j/T}}.$$  

Low temperatures push the models towards selecting the most probable tokens, whereas higher temperatures lead to low probability tokens being chosen more often. Subsequently, we keep $k$ fixed and generate multiple outputs at different temperatures $T \in (0, 1)$ to receive a diverse yet syntactically and semantically more sound set of samples.

Additionally, we aid the sampling process through prior prompt engineering. Initially, we test multiple suitable explanation prompts for each combination of model and dataset. An explanation prompt is the sequence of tokens appended to the image, question, and answer to elicit textual explanations. We evaluate multiple sound options and identify the best scoring prompt(s), which we then use in later sampling. The diversity of samples can be increased even further by repeating the process with multiple explanations prompts. Nonetheless, this comes at the cost of substantially increased computing requirements, and our results indicate that using only the best prompt is sufficient in most cases.

Human Feedback A significant portion of generated explanations is likely to be of poor quality, especially in the first iterations. Therefore, we refer to the unfiltered set of samples as jabber. Subsequently, we identify and reinforce those portions of the generated jabber conforming to human intent. Following sampling, in the second step, a critic labels each explanation as either fitting for the image-question-answer pair or not fitting. Thus, attenuating the generation of jabber towards on-point explanations. This process can easily be performed by human annotators, making our approach closely related to explanatory interactive machine learning (XIL), in which the human user provides feedback to the training process by interacting with the model’s explanations (Friedrich et al. 2022).

It is noteworthy that at this stage, the iterative feedback can be automated by comparing the generated candidates to existing human-generated ground truth explanations using task-specific metrics. For instance, in our experiments, we leverage the ROUGE-L score (Lin 2004) to benchmark our approach, i.e., for each explanation candidate, we calculate the sample-wise score between the generated hypotheses and ground truth reference(s). However, this requires prior, labor-intensive human labeling and is limited by well-known shortcomings of these approaches. We discuss this further in the empirical evaluation and limitation sections.

Tuning The final step of an ILLUME iteration is fine-tuning the VLM based on the selected self-generated samples. As a parameter-efficient approach toward fine-tuning a large neural network, we use bottleneck adapters (Houlsby et al. 2019). More precisely, we optimize the parameters $\theta$ of small adapter layers inserted at each attention and fully connected module of the decoder instead of tuning the complete model’s weights. We train the VQA and explanation generation task simultaneously, with the training loss

$$\mathcal{L}(X, \theta) = \mathcal{L}_{vqa}(X^A, X^E, \theta) + b \cdot \mathcal{L}_{exp}(X^E, \theta)$$  

being the sum of the language modeling loss for the next token prediction of the answer $\mathcal{L}_{vqa}$ and explanation $\mathcal{L}_{exp}$. $X \supseteq X^A \cup X^E$ (where $X^A \cap X^E = \emptyset$) is the training set and $\theta$ the set of optimized parameters of the VLM. The training set $X^E$ is increased before each feedback iteration $i$. These samples are generated by the VLM’s parameters $\theta_{i-1}$ and subsequently filtered by human users or a pre-defined reward function and threshold.

We observed that adding additional training data from the original VQA task makes the tuning process more robust and also leads to better explanations. Therefore, we add VQA samples without explanation ($X^A$) to the training data. In total, the VQA task consists of the VQA pairs of the self-generated training data $X^E$ as well as a randomly drawn subset $X^A$ of $X \setminus X^E$. We scale the VQA and explanation loss to balance out the disproportional number of samples with $b = \frac{n(X^A)}{n(X^E)}$, where $n(X)$ is denoted as the number of elements in set $X$.

The language modeling loss reflects the assumption that the probability $P$ of every token $t_i$ in a sequence can be expressed as the conditional probability of that token given all previous ones:

$$P(t_1, t_2, ..., t_n) = \prod_{i=1}^n P(t_i | t_{<i}).$$

In an autoregressive neural network, the probability distribution of a token at time step $i$ can be expressed as softmax over all token logits. The loss for predicting this token is the cross entropy between these softmax logits and a one-hot encoding of the target token. Further details, if needed, can be found in (Radford et al. 2018).

4 Experimental Results

Here, our intention is to investigate the transfer of reasoning from natural language to multimodal VQA across three VLMs with distinctive architectural differences. Before evaluating the introduced ILLUME approach, we compare the rationalization capabilities of the underlying LMs
in natural language using self-talk prompting and establish a correlation with multimodal VQA reasoning.

4.1 Experimental Protocol

Let us first clarify the details of our experimental protocol.

Models We consider three recent VLMs which differ mainly in the choice of LM on which to build the multimodal model. 1) MAGMA (Eichenberg et al. 2021), whose LM-foundation is a large GPT model, 2) BLIP (Li et al. 2022), which uses BERT (a less powerful initialization), and 3) OFA (Wang et al. 2022), which is trained from scratch.

In Sec. 4.2 we investigate the underlying language models of each VLM. For MAGMA, we consider luminous-base, which itself is based on the GPT-J architecture. Further, we evaluate the base version of BERT as the underlying language model of BLIP. Since OFA is trained from scratch, no baseline language model exists to consider. Instead, we evaluated the large general pre-trained OFA checkpoint, using it only with natural language sequences.

Based on the experiments in Sec. 4.2 and 4.3, MAGMA has proven as most suitable for ILLUIME. Hence, we continue the subsequent evaluation solely on MAGMA. Subsequently, we refer to the zero-shot model as MAGMA_{base} to distinguish it from fine-tuned variants.

Datasets & Benchmarks We use six diverse commonsense reasoning benchmarks to evaluate the natural language self-talk approach. These datasets are CSQA (Talmor et al. 2019), COPA (Gordon, Kozareva, and Roemmele 2012; Roemmele, Bejan, and Gordon 2011), McTaco (Zhou et al. 2019), PIQA (Bisk et al. 2020), Social-IQA (Sap et al. 2019) and WinoGrande (Sakaguchi et al. 2020) which cover a wide range of reasoning tasks ranging from basic real-world concepts to physical and social interactions as well as temporal commonsense. All datasets provide multiple-choice answers, with a model’s performance being measured as its accuracy in choosing the correct alternative.

For the visual reasoning task we consider the three datasets, namely VQA-X (Park et al. 2018), ACT-X (Park et al. 2018) and CLEVR-X (Salewski et al. 2020). Contrary to the reasoning benchmarks in natural language, we treat multimodal reasoning as open-ended text generation without providing multiple-choice alternatives. Further details on the composition of these datasets can be found in Appendix B. Additionally, we provide benchmark results of MAGMA on these datasets compared to the current state-of-the-art in Appendix E.

Further, note that prompt engineering of the explanation prompt can significantly affect explanation quality. For comparisons between models, we evaluate each model with the same set of potential explanation prompts and report the scores for the best-performing one. Additionally, we consider a similar set of questions for ACT-X and evaluate every combination of questions and explanations for each model. In addition, similarly to Park et al. (2018), we observed that the quality of explanations depends on the answer given in the context prompt. Therefore, we used the ground truth answer instead of the model-generated one for all experiments to allow a fair comparison between the models.

ILLUME: Sampling We performed sampling using the VLM on the training data to generate five explanations, each at five different temperatures. We set $k = 5025$ to be equal to 10% of the vocabulary and select temperatures $T \in \{0.01, 0.1, 0.3, 0.6, 0.9\}$. In total, this yields up to 25 different explanations. For ACT-X, we additionally sampled with five questions per image resulting in 125 samples total. The explanations generated in this manner were very diverse, with most of the resulting jabber distinctly unsuitable for further fine-tuning. Nevertheless, this approach is intended to generate a large variety of samples to increase the likelihood of generating fitting ones. However, this also requires the generated explanations to be filtered rigorously.

ILLUME: Feedback For each explanation candidate, we calculated the sample-wise ROUGE-L score between the generated hypotheses and human-annotated ground truth (GT) reference(s). As the quality of an explanation is subjective to some extent (cf. Sec. 4.3 and 5) there exist no single correct explanation. Therefore, we empirically chose (cf. Appendix C) a threshold of ROUGE-L $\geq 0.7$ to be a good approximation of fitting explanations. We observed that explanations below that threshold are often too much jabber, in that they are semantically or syntactically incorrect, incomplete, or simply too different from the ground truth to be a fitting explanation.

Within the inherent limits of an automated metric, we deem this to be a reasonable trade-off between addressing differences in wording and filtering out ill-formatted text sequences, thereby turning jabber into sound explanations.

ILLUME: Tuning We tuned the VLM (MAGMA) by optimizing the adapter weights (see (Houltsby et al. 2019)) contained in the LM transformer of the network keeping the image prefix module frozen. For all experiments, we used the AdamW optimizer and a batch size of 256. The training was distributed over 8 A100 GPUs resulting in a per GPU batch size of 32. Regarding Eq. 1, we added roughly ten times more samples without explanation $X^A$ than $X^E$ to regularize optimization. Any additional hyper-parameter optimization was performed on the dedicated validation splits, with the test splits being evaluated only for reporting final scores. We provide further insights on the hyperparameter selection of fine-tuning using self-generated examples in Appendix D.

Evaluation Metrics We use automated natural language generation (NLG) metrics for text generation to assess a model's performance on explanation generation. For references, we rely on the provided ground truth explanations in the datasets. This approach is considered best practice in this area of research. However, these metrics have well-known limitations that should be considered when relying on them for evaluation (Sai, Mohankumar, and Khapra 2022). First, n-gram based metrics are generally incapable of bridging the semantic gap. Therefore, generated sequences that convey the same meaning but are phrased differently will receive low scores. Additionally, fitting explanations are not unique, and a model might generate a suitable explanation that is not included in the references and will therefore be discarded.
multiple-choice QA tasks. Higher scores are better. All models use self-talk as a knowledge source (Shwartz et al. 2020). The chance row represents the expected accuracy achieved by selecting a multiple-choice answer randomly. The best (*) and runner-up ("•") results are highlighted bold.

Table 1: Self-talk LM performances. Question answering accuracy (%) of models are reported on the dev. sets of 6 commonsense reasoning datasets. Please note that total scores are not directly comparable between datasets as they are heavily influenced by the number of provided references as well as their vocabulary size and sequence length (Salewski et al. 2020). Both of these factors vary significantly between the datasets making meaningful, direct comparisons impossible.

| Model                        | Chance | CSQA↑ | COPA↑ | MC-TACO↑ | PIQA↑ | Social-IQA↑ | WinoGrande↑ |
|------------------------------|--------|-------|-------|----------|-------|-------------|-------------|
| GPT-J-6B                     | 20.0   | 50.0  | 18.9  | 30.0     | 33.3  | 50.0        |
| BERT (BLIB)                  | 51.7   | 74.0  | 64.8  | 71.2     | 46.3  | 59.9        |
| OFA-LM (OFA)                 | 21.5   | 64.0  | 39.0  | 48.1     | 32.8  | 49.1        |
| Luminous-base (MAGMA)        | 17.8   | 53.0  | 43.6  | 51.9     | 34.0  | 50.7        |

Table 2: Zero-shot reasoning performance. Results are reported on the respective validation datasets. Scores refer to Bleu-4, Rouge-L & CIDEr where higher scores are better and best results are bold. Scores are reported for the best performing prompt for each combination of model and dataset. Please note that total scores are not directly comparable between datasets as they are heavily influenced by the number of provided references as well as their vocabulary size and sequence length (Salewski et al. 2020). Both of these factors vary significantly between the datasets making meaningful, direct comparisons impossible.

| Model     | VQA-X↑ | ACT-X↑ | CLEVR-X↑ |
|-----------|--------|--------|----------|
| OFA       | 0.3    | 9.1    | 3.3      |
| BLIB      | 0.0    | 5.5    | 0.0      |
| MAGMA     | 9.2    | 32.5   | 23.1     |

In addition to the commonsense abilities of VLMs’ underlying LMs, the VLMs’ zero-shot performances indicate the portion of reasonable rationales that can be expected among the generated jabber. Therefore, we require a pre-trained model to perform decently on these benchmarks in order to produce a sufficient number of fitting explanations that may be used for further fine-tuning. To this end, we now benchmark the initial, i.e., without additional fine-tuning, multimodal rationalization capabilities of the discussed VLMs.

4.3 Zero-Shot Visual Reasoning

In addition to the commonsense abilities of VLMs’ underlying LMs, the VLMs’ zero-shot performances indicate the portion of reasonable rationales that can be expected among the generated jabber. Therefore, we require a pre-trained model to perform decently on these benchmarks in order to produce a sufficient number of fitting explanations that may be used for further fine-tuning. To this end, we now benchmark the initial, i.e., without additional fine-tuning, multimodal rationalization capabilities of the discussed VLMs.

Tab. 2 depicts the zero-shot reasoning performance of all models. It is apparent that those VLMs whose language models perform weak on NLP reasoning also yield low-quality multimodal explanations. However, MAGMA, which is based on a GPT variant with good language reasoning capabilities, can generate decent multimodal explanations in a zero-shot fashion without any training for that particular task. An example highlighting these differences is depicted in Fig. 2. As is apparent for these inputs, OFA and BLIP tend to overfit on the VQA task, resulting in these models only repeating the answer if prompted for further outputs. On the VQA-X validation set, when prompted for a rationale, OFA and BLIP repeat the answer in 63% and 89% of all samples, respectively. Therefore, we use MAGMA for all subsequent experiments.

4.4 ILLUME

Affirmed by the zero-shot capabilities, we applied our ILLUME paradigm to the VQA-X and ACT-X datasets. The application of logical reasoning in the form of the CLEVR-X dataset remains challenging, which we discuss in further detail in the limitations (cf. Sec. 5).
Figure 2: Exemplary comparison of explanations generated on the VQA-X validation set by different models. VQA image, question, answer, and a generated explanation of each model with the ROUGE-L score wrt. ground truth. Explanations for MAGMA_{base}, OFA & BLIP are generated zero-shot. (Best viewed in color)

Tab. 3 shows the progress of ILLUME on VQA-X and ACT-X. Overall, ILLUME generalizes well to unseen data. At the initial iterations, especially on ACT-X, tuning for a single epoch on a small training set significantly increases the number of fitting explanations the model generates on new data. We can observe that explanation generation improvements are closely correlated to the number of new samples added to the training data. The number of samples and the NLG scores improve rapidly in the beginning and slowly converge in later iterations. Additionally, we can observe ILLUME to be more robust against overfitting than tuning with ground truth data. The latter approach suffers a significant drop in scores achieved on the validation set at a stage in the procedure at which the ILLUME variant still improves, cf. iteration 7 through 9 on ACT-X. For both experiments, we make the empirical observation that the best scores are achieved once the ratio of new samples drops below 5%, e.g., the number of samples for VQA-X from iteration 7 to 8 only increases from 3385 to 3541, equalling 4.6%. Therefore, this threshold might be a vital indicator for performance saturation in datasets without ground truth reference.

More precisely, in the case of VQA-X, the quality of explanations improves for eight iterations until the scores plateau. The resulting ILLUME model even slightly outperforms the model obtained through standard supervised learning on ground truth data. Additionally, ILLUME yields a model remaining competitive with MAGMA_{full} while using no ground truth explanations and less data.

In the case of ACT-X, we had to apply slight modifications to address the nature of the dataset. The number of fitting explanations generated in a zero-shot fashion is significantly lower than for the other datasets. We addressed this issue by sampling the training set with multiple question prompts and two different explanation prompts. For the initial sampling, this significantly boosts the number of fitting explanations. The benefit of using more than one explanation prompt for sampling diminishes with subsequent iterations as the model is conditioned on the prompt used in training. Therefore, we only employed it for the first sampling iteration. Nonetheless, the initial number of samples remains comparatively low, making up less than 1% of the ground truth training set. Further, while fine-tuning the VLM on the ACT-X ground truth data, we observed that training on only one fixed question might lead to unstable training behavior, especially on smaller subsets of the training set. Therefore, we chose to use five different—albeit similar—question prompts during the training of both the VQA and the explanation task. This adjustment makes the ILLUME self-generated data more diverse and leads to more robust training.

In summary, our empirical results clearly show that ILLUME achieves competitive performance and requires less human labor, making it a more effective approach for tuning foundation models than using truth data. Note that this only applies to tasks on which the model displays rudimentary capabilities through language or multimodal pre-training; see results on CLEVR-X in Sec. 5.

5 Discussion & Limitations

Before concluding, we discuss the transfer and progressive alignment of VLMs' reasoning capabilities in more detail. Furthermore, we touch upon limitations and observed short-comings of ILLUME.
Furthermore, we would like to reiterate the issues of automatic NLG metrics. Fig. 3 (middle) provides an example of metrics failing to bridge the semantic gap. The sentences ‘he has a smile on his face’ and ‘he is smiling’ are scored as substantially dissimilar, although they are semantically identical. Yet another example is shown in Fig. 3 (bottom). Here the generated explanation ‘they are standing and eating’ is rated significantly higher than ‘it has long legs and neck’, although the first one provides virtually no valid information on why the animal is a giraffe, whereas the second one identifies two of its most prominent features. This further illustrates the limited significance of comparisons between checkpoints and models using automatic NLG metrics. Nevertheless, as described, such metrics are a valid indicator to evaluate a method itself. Hence, we benchmarked ILLUME on several datasets utilizing ROUGE-L to simulate user feedback and a wide range of scores for evaluation. Yet, the above-discussed examples further motivate ILLUME’s intended use of direct human feedback in training and evaluation.

**Flaws in Logical Reasoning** One frequently observed shortcoming of large neural networks is their inability to generalize to logical reasoning. Zhang et al. (2022) recently demonstrated that BERT does not learn logical reasoning but instead captures statistical features in the training data. Therefore, the model remains unable to generalize to other distributions of the exact same problem. In the multimodal domain, DALL-E 2 (Ramesh et al. 2022) fails to construct logical relations between objects faithfully.

We also observe ILLUME to yield no satisfying results on the CLEVR-X dataset. Details in this regard can be found in Appendix G. Summarized, we attribute this behavior to the same observations made by Zhang et al. (2022) in that current LMs appear incapable of inferring logical reasoning from a few training examples. Therefore, VLMs bootstrapped from LMs struggle to transfer logical reasoning capabilities without major extensions. Instead, we argue that the approach of training and evaluating logical reasoning as a pure text generation task may be inherently flawed. Instead, logic-based methods (Shindo, Dhami, and Kersting 2021) that utilize differential forward-chaining using first-order logic could yield more coherent explanations.

## 6 Conclusion

We proposed an efficient rationalization approach for multimodal transformers called ILLUME. As our experiments demonstrate, ILLUME enables the transfer of commonsense reasoning from LMs to downstream VLMs. In particular, the ILLUME approach remains competitive with fine-tuning on ground truth data while using substantially fewer training samples that are also self-generated. Further, it paves the way toward lowering the workload on annotators and enables aligning the model to users’ rationales through interactive feedback in the training loop.

Our paper provides several avenues for future work, as already discussed. Probably the most important one is increasing transformers’ logical and commonsense reasoning capabilities.
Acknowledgement
This research has benefited from the Hessian Ministry of Higher Education, Research, Science and the Arts (HMWK) cluster project “The Third Wave of AI”.

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A Natural Language Self-Talk Prompting

Self-talk prompting aims to elicit world knowledge encoded in the model through a multi-step prompting scheme. The model is guided towards generating explicit clarification context for the original question that results in more faithful answers. Both, clarification and context are prompted to the model to predict the final answer.

An illustration of the self-talk prompting process is depicted in Fig 4.

Given a multiple-choice premise, the model is first prompted with the premise concatenated with one of multiple question prefixes. Prefixes are engineered for each dataset individually and depend on the type of posed questions. The language model completes several questions for each prefix, which are then used for extracting clarification answers. For each well-formed question multiple answers are generated through additional sampling. The prompt for the final answer generation consists of the original premise and the generated clarification.

B Visual Reasoning Benchmark Datasets

Here, we provide further details on the composition of the datasets used to evaluate visual reasoning based on VQA tasks.

The VQA-X dataset extends the COCO based VQA-v1 (Zitnick et al. 2016) and v2 (Goyal et al. 2017) datasets with human-annotated explanations. Similarly, ACT-X provides explanations for human activities and builds on the MPII Human Pose (Andriluka et al. 2014) dataset. Therefore, ACT-X is not originally a VQA task as the datasets contains an answer in the performed activity but no question. Nonetheless, the intended open-end activity classification is entailed by the VQA task with a question such as 'What is the person doing?'. Therefore, we construct a ACT-X based VQA task using question prompts similar to the one stated above. Lastly, the CLEVR-X dataset provides synthetically generated explanations for the CLEVR (Johnson et al. 2017) dataset. Although automatically generated, the contained ground truth labels are of similar quality as human generated once since they are generated from underlying CLEVR scene graphs using templates with varying wording.

We note that the VQA-X test split is not publicly available wherefore we randomly split the original validation set into a custom validation and test set.

C Threshold in Automated Feedback

Here, we perform a brief ablation study on choosing the right threshold for filtering generated samples. As discussed previously we establish a lower bound of $R-L \geq 0.7$ based on manual inspection of generated samples. As the model trained using $R-L \geq 0.7$ is only slightly worse than the one utilizing the respective ground truth explanation, increasing the ROUGE-L threshold is unlikely to yield any benefits in performance. With increasing threshold, the number of fitting explanations decreases rapidly, thus the trade-off between the number of samples and their closeness to the ground truth is non-beneficial. On the contrary, we argue that maintaining some variance with respect to ground truth alignment can result in a more robust training process.

Table 4 shows the results on the VQA-X validation set of 3 experiments that only differ in the threshold used for choosing fitting samples and thus the number of training explanations. The resulting explanation scores decrease with decreasing number of samples disregarding their closeness to the ground truth. Therefore, we used the threshold of $R-L \geq 0.7$ for all experiments. Nonetheless, this experiment also demonstrates that the model is able to generalize on small sample sizes. This demonstrates the approach to be applicable to applications where the initial number of fitting explanations is low.

D Training on Self-Generated Samples

MAGMA performing reasonably well on zero-shot reasoning enables generating training samples from the model itself to improve already existing capabilities. Next to the above ablation study justifying the sampling threshold ROUGE-L $\geq 0.7$, we describe and provide further evidence for the chosen sampling and tuning setup.

Sampling and feedback Initial sampling on the training datasets of VQA-X and CLEVR-X produced fitting explanations for roughly 4% and 10% of the training set, respectively. In the case of ACT-X, we received significantly fewer fitting explanations from the baseline model ($\leq 1\%$).

The feedback provided by selecting fitting explanations can be fed back into the model by performing finetuning on these explanations. We employed training as described in the paper on filtered, self-generated explanations. Next, we analyze the training behavior of one iteration of ILLUME for reasoning by comparing training on self-generated samples to training on ground truth data.

Self-generated vs. ground truth samples Tab. 5 shows how training on noisy, self-generated explanations compares to training on ground truth data. We ran three training setups on VQA-X with the same hyperparameters and number of training samples that only differ in how training data is sourced. The first experiment uses 1207 fitting explanations generated by the model. The second configuration considers the same 1207 samples as the previous one. However, it trains on the GT explanation instead. At the same time, the
The VLM generates fitting and evaluation loop. However, the subset of samples for extent that it might even be attributed to noise in the training set being closer in distribution using ground truth data. Presumably, this is due to the GT explanations of the validation set used for evaluation. Some intuition about MAGMA’s performance within the limits of evaluation with automated metrics.

Table 5: Comparison of training MAGMA on VQA-X with self-generated training data vs. ground truth (GT) explanations. Scores are reported on the validation set. Bleu-4, Rouge-L, & CIDEr score where higher is better. Training with self-generated explanations results in similar performance as training on the same GT explanations. However, other randomly drawn but equally sized subsets can lead to better scores.

| Training samples                  | B-4↑ | R-L↑ | C↑     |
|-----------------------------------|------|------|--------|
| Self-generated (w/ R-L ≥ 0.7)     | 15.38| 40.32| 48.88  |
| GT explanation (same as above)    | 17.80| 41.31| 50.68  |
| Random GT samples                 | 19.93| 44.28| 64.50  |

third setup randomly samples 1207 GT explanations.3

The results for training on self-generated samples instead of the same GT explanations are slightly favorable towards using ground truth data. Presumably, this is due to the GT explanations in the training set being closer in distribution to the GT explanations of the validation set used for evaluation. Nonetheless, the difference remains negligible to the extent that it might even be attributed to noise in the training and evaluation loop. However, the subset of samples for which the VLM generates fitting explanations appears not to be the optimal one concerning the generalization learned during training. Note that we drew multiple random samples of the same number of GT explanations from the training data, all of which resulted in a slightly better model than the sampled GT subset.

3Contrary to the iterative ILLUME tuning process, we did not include any additional VQA samples for this experiment.

E Benchmarking MAGMA for VQA Explanation Generation

In the main text of this work we evaluate ILLUME on MAGMA. However, MAGMA also proves to perform excellent on visual reasoning using the common setting of learning from ground truth explanations.

To demonstrate MAGMA’s performance, we provide a benchmark on the VQA-X, ACT-X and CLEVR-X datasets using ground truth data, and, importantly, compare the fine-tuned MAGMA models to current state-of-the-art (SOTA) architectures. To the best of our knowledge there exist two models for the task of VQA explanation generation which are PJ-X (Park et al. 2018) and FM (Wu and Mooney 2019).

We establish a baseline for MAGMA’s potential performance on these datasets by fine-tune the model for each of them using the ground truth explanations of the entire training split using the previously described training setup.

Our goal is to provide an estimate of MAGMA’s performance and not report new state-of-the-art results for relevant benchmarks. Therefore, we limited our hyperparameter tuning to a limited guided search of the hyperparameter space and did not perform any exhaustive grid searches. Consequently, the following results are solely intended to provide some intuition about MAGMA’s performance within the limitations of evaluation with automated metrics.

Tab. 6 shows the performance of MAGMA on the respective validation datasets fine-tuned for each of the VQA-X, ACT-X and CLEVR-X. Tab. 7 compares MAGMA’s performance to the current state-of-the-art models PJ-X and LM on the respective test splits. We sourced the scores of both models from the respective papers. As we are having to use custom validation and test splits, this results in us reporting scores for VQA-X on different splits than PJ-X and FM limiting the significance of these comparisons. Nonetheless, MAGMA remains competitive with both models across
Table 6: Evaluation of explanation MAGMA explanation generation after finetuning on the respective validation datasets. Scores refer to Bleu-4, Rouge-L & CIDEr (%) where higher scores are better.

Table 7: Comparison of MAGMA tuned for explanation generation against state-of-the-art models on respective test sets. Scores refer to Bleu-4, Rouge-L & CIDEr (%) where higher scores are better. MAGMA remains competitive with the much more specialized architectures of PJ-X and FM.

all three datasets. These results demonstrate the potential power of large-scale multimodal language models such as MAGMA, given that it is a general-purpose model for text generation on any multimodal inputs. Whereas PJ-X and FM were specifically designed to perform only this one task.

Here, we investigate the influence of increasing MAGMA’s capacity (as number of parameters) on the zero-shot performance of VQA explanation generation. Since the underlying language model of MAGMA extended only slightly outperforms the LM of the base model on natural language reasoning, we limit this comparison to VQA-X.

Table 8: Results of two iteration of ILLUME on CLEVR-X. Bleu-4, Rouge-L & CIDEr score reported on the a) validation split and b) training split.

F ILLUME – Extended Metrics

In Tab. 9 we provide our ILLUME results for VQA-X and ACT-X extended with further metrics.

G Flaws in Logical Reasoning

As mentioned in the main text, we frequently observed shortcoming of VLMs ability to generalize to logical reasoning. The following experiments provide further evidence in this regard.

Tab. 8(a) shows the progress over two iterations of ILLUME tuning on the CLEVR-X validation split. With each iteration of training the quality of textual explanations decreases instead of improving. This also results in fewer fitting explanations being generated, exacerbating this effect further. Furthermore, finetuning on the 5-10% subset of the training data used in self-talk fails to generalize explanations to the rest of the training set. Tab. 8(b) indicates that all but the CIDEr score drop significantly after fine-tuning on the training split as well.
Table 9: Iterative process of **ILLUME** on VQA-X (top) and ACT-X (bottom) until scores plateau on the validation set. Δ values next to the scores indicate the difference between training on self-generated samples vs. the same amount of GT samples, with positive scores indicating that ILLUME outperforms training on GT (**bold**) and vice versa. MAGMA_{base} refers to zero-shot (It 0) performance and MAGMA_{full} refers to the model tuned on the entirety of the GT training set. Additionally, RV displays the relative value wrt. total amount of samples in original training set. The bottom rows show scores on the test set. Bleu-1 through Bleu-4, Rouge-L, Meteor& CIDEr scores are shown (higher is better).