

# From Wrong To Right: A Recursive Approach Towards Vision-Language Explanation

Jixin Ge<sup>1,2\*</sup> and Sanjay Subramanian<sup>1</sup> and Trevor Darrell<sup>1†</sup> and Boyi Li<sup>1†</sup>

<sup>1</sup> UC Berkeley, CA, USA

<sup>2</sup> Peking University, Beijing, China

{gejixin, sanjayss, trevordarrell, boyili}@berkeley.edu

## Abstract

Addressing the challenge of adapting pre-trained vision-language models for generating insightful explanations for visual reasoning tasks with limited annotations, we present ReVisE: a **R**ecursive **V**isual **E**xplanation algorithm. Our method iteratively computes visual features (conditioned on the text input), an answer, and an explanation, to improve the explanation quality step by step until the answer converges. We find that this multi-step approach guides the model to correct its own answers and outperforms single-step explanation generation. Furthermore, explanations generated by ReVisE also serve as valuable annotations for few-shot self-training. Our approach outperforms previous methods while utilizing merely 5% of the human-annotated explanations across 10 metrics, demonstrating up to a 4.2 and 1.3 increase in BLEU-1 score on the VCR and VQA-X datasets, underscoring the efficacy and data-efficiency of our method.

## 1 Introduction

Explanations for visual reasoning are important in real-world applications (Anderson et al., 2018; Hendricks et al., 2016) like assistive technologies (Dognin et al., 2020) and interactive learning (Misra et al., 2018), but collecting human annotations for these explanations is expensive. The use of language models (LMs) and pre-trained vision-language models (VLMs) have shown promise in explanation generation (Sammani et al., 2022; Plüster et al., 2022). However, generating high-quality explanations remains a considerable challenge when annotations are scarce (Bayoudh et al., 2021; Suzuki and Matsuo, 2022).

Previous work has aimed to ameliorate this issue by focusing on enhancing model architecture and subsequent finetuning using large amounts of

human-annotated explanations (Sammani et al., 2022; Plüster et al., 2022). Nonetheless, such techniques, reliant on extensive fine-tuning, fall short in the face of limited annotations. Thus, we propose an approach to amplify the model’s own reasoning capabilities during inference to generate high-quality explanations. Recent research has demonstrated the efficacy of step-by-step reasoning in language and multimodal reasoning, particularly in contexts where samples are limited (Wei et al., 2022b; Lu et al., 2022; Zhang et al., 2023; Ge et al., 2023). As such, we adopt a phased approach, integrating visual and linguistic components for step-by-step vision-language explanation.

In this work, we introduce the **R**ecursive **V**isual **E**xplanation (ReVisE) — a method for generating visual reasoning explanations that surpasses previous methods while using merely 5% of the human-annotated explanations. Initially, we fine-tune BLIP-v2 (Li et al., 2023) to generate explanations on 5% of the dataset. During inference, we generate an initial explanation, then iteratively generate new explanations based on the preceding one. Each step involves computing new visual features, guided by the preceding sentence. This sentence and the new visual features then serve as inputs to generate a new sentence in the next step. Crucially, ReVisE serves as a dynamic, self-correcting mechanism by progressively redirecting visual attention on the image and regenerating the explanation over steps. Additionally, ReVisE generates pseudo-ground truth explanations for few-shot self-training, producing pseudo-labels that considerably aid self-improvement compared to traditional pseudo-labels.

We evaluate ReVisE on four vision-language natural language explanation (VL-NLE) tasks — e-SNLI-VE (Do et al., 2020), VQA-X (Park et al., 2018), AOK-VQA (Schwenk et al., 2022), and VCR (Zellers et al., 2019). Our results show improvements across ten evaluation metrics,

\* Work done while visiting UC Berkeley; Code Available at <https://github.com/para-lost/ReVisE>

† Equal advising.

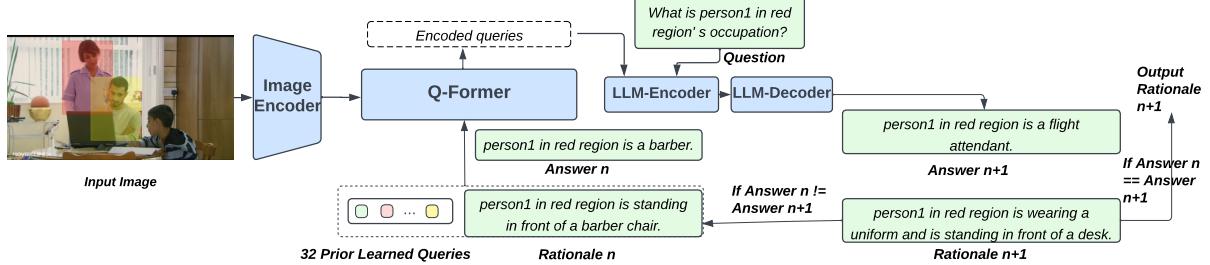


Figure 1: The pipeline of ReVisE. In each step, QFormer receives the concatenated input, consisting of  $K = 32$  pre-trained queries and the explanation generated from the previous step, to calculate cross-attention with the encoded image. The output from QFormer, processed further, pairs with the question to guide the frozen LLM in generating the next-step explanation.

with enhancements of up to 4.2 and 1.3 in the BLEU-1 score on VCR and VQA-X respectively. Furthermore, self-training using our method’s pseudo-ground truth explanations shows consistent progress compared with traditional generation-based self-training.

Further in-depth ablation studies elucidate the impact of ReVisE and the insights behind it, indicating that sentences can effectively guide visual attention, and that sentence structure and phrasing style are pivotal for few-shot self-training.

Our contribution are summarized as follows:

- We demonstrate that recent pre-trained models require only a fraction of the annotations used by previous explanation generation approaches to reach the same quality.
- We proposed and implemented the Recursive Recursive Visual Explanation (ReVisE), a method that iteratively refines explanations by re-computing visual features.
- We show that self-training using ReVisE to produce pseudo-ground truth annotations further improves the quality of explanations.

## 2 Related Work

**Vision-Language Models (VLM)** Large Vision-Language models have showcased significant potential in vision-language tasks, including VQA, image captioning, and image-text retrieval (Li et al., 2023; Alayrac et al., 2022; Bao et al., 2021; Chen et al., 2022; Li et al., 2021, 2020; Wang et al., 2021; Kim et al., 2021; Bao et al., 2022). Recently, BLIPv2 (Li et al., 2023) was proposed. This model aligns vision with language through a light-weighted transformer architecture (QFormer), rendering it computationally efficient for training on

downstream tasks.

**Vision-Language Natural Language Explanation (VL-NLE)** VL-NLE tasks demand a comprehensive understanding and reasoning across both vision and language modalities (Kim et al., 2021). There are two prevailing strategies: the first is a modular approach integrating two separate modules—one for predicting an answer, and another for generating an explanation—represented by works such as e-UG (Kayser et al., 2021), PJ-X (Park et al., 2018), FME (Wu and Mooney, 2018), RTV (Marasovic et al., 2022), and QA-only (Kayser et al., 2021). The second approach is a unified one that uses a single model to generate an answer and explanation simultaneously; relevant works include NLX-GPT (Sammami et al., 2022) and OFA-X<sub>MT</sub> (Plüster et al., 2022). Our work utilizes the more efficient and training-effective unified approach. However, these methods fall short in effectively integrating the reasoning alignment between vision and language, a gap we address with ReVisE.

**Vision-Language Reasoning** Vision-language reasoning is a cornerstone of vision-language explanation generation. (Hendricks et al., 2016) spearheaded the field by deriving visual explanations from deep networks. (Anderson et al., 2022) focused on visually-grounded navigation instructions, while (Park et al., 2019) applied temporal reasoning to visual tasks. Recently, chain-of-thought (Wei et al., 2021, 2022b,a) has been harnessed to approach tasks using a step-by-step reasoning methodology, effectively enhancing the coherence and logical flow of language reasoning (Wei et al., 2022b; Wang et al., 2022a), self-consistency (Wang et al., 2022b; Lyu et al., 2023) and multimodal reasoning. (Lu et al., 2022; Zhang et al., 2023; Ge et al., 2023)

**Few-Shot Self Training** Self-training, a technique which uses a trained model to generate pseudo-labels for unlabeled data for further model training, improves the model’s robustness (Chen et al., 2020; Hendrycks et al., 2019) and benefits vision-language tasks (Baevski et al., 2022; Zhu et al., 2020; Wu and Mooney, 2019). Few-shot self-training, which trains on a small number of samples with pseudo-labels, is used to enhance model performance when data resources are scarce or training costs are high (Li et al., 2019; Mukherjee and Awadallah, 2020; Chen et al., 2021). However, the quality of self-generated pseudo labels greatly influences the effectiveness of few-shot self-training (Zou et al., 2019; Xie et al., 2020; Li and Zhou, 2005). In this work, we demonstrate that ReVisE can generate robust pseudo-explanations beneficial for few-shot vision-language self-training.

**Iterative computation of visual features** The iterative computation of visual features based on text have been applied in previous works to refine visual grounding of an image (Yang et al., 2020), which showed that re-computing visual feature can benefit the visual attention. However, how re-computing benefits text generation remains unexplored. Our work focuses on the text-generation task and shows that the iterative approach can simultaneously benefit the grounding of an image and the quality of the generated text.

### 3 Method

In this section, we first provide an overview of the architecture of BLIPv2 (Li et al., 2023) and how we trained BLIPv2 for VL-NLE tasks. Then, we provide a detailed introduction and pseudo code for ReVisE. Finally, we discuss how ReVisE is employed for self training.

#### 3.1 Finetuning BLIPv2 on VL-NLE

BLIPv2 is a generative vision-language model that provides a powerful tool for bridging the divide between vision and language. Its architecture features a lightweight, multi-layer transformer, the QFormer, which computes cross-attention between  $K = 32$  pretrained query tokens and encoded image features. Instead of jointly training a text encoder and a vision encoder as in traditional models, BLIPv2 takes a novel approach by freezing the language model parameters and only train the vision encoder and QFormer to convert image features into tokens interpretable by the language model.

This strategy enhances the integration between visual and language components, leading to better task comprehension.

Given an image denoted as  $I$ . We use the image encoder  $E_{image}$  to encode the image to get the image features  $F_I$ . We denote  $K$  BLIPv2 pretrained tokens as  $T$ . These tokens, together with  $F_I$ , are passed to the QFormer  $QF$ , which processes  $F_I$  and  $T$  to produce the image queries  $Q_I$ :

$$Q_I = QF(E_{image}(I), T) \quad (1)$$

We denote the tokenized prompt as  $P$ , with the format "Answer the question by reasoning step by step. Question: {} Answer:". We concatenate  $Q_I$  and  $P$  to form the full input  $F$  to the language model  $L$ , then we feed it into the language model and obtain the output generated by language model  $O$ :

$$O = L(concat(Q_I, P)) \quad (2)$$

We calculate a cross-entropy loss  $L_{CE}$  between the generated output  $O$  and the ground truth sentence  $G$ , which is constructed in the format "[answer] because [explanation]" . :

$$L_{CE} = -sum(G * log(O)) \quad (3)$$

The model parameters are updated to minimize this loss. Only the parameters of the QFormer and the vision encoder are updated while the parameters of the language model are kept frozen.

#### 3.2 Recursive Visual Explanation (ReVisE)

---

##### Algorithm 1 Pseudo Code for ReVisE

---

```

1: Input: Image  $I$ , Question  $Q$ 
2: Output: Final Answer  $A_n$ , Explanation  $E_n$ 
3:  $F_I = E_{image}(I)$ 
4:  $n = 0$ 
5: while  $A_n \neq A_{n-1}$  do
6:    $E_n = Tokenize(A_n)$ 
7:    $E_{n, embedded} = Embed(E_n)$ 
8:    $Concat_n = concat(E_{n, embedded}, T)$ 
9:    $Q_{I,n} = QF(Concat_n, F_I)$ 
10:   $A_{n+1}, E_{n+1} = L(Q_{I,n})$ 
11:   $n = n + 1$ 
12: end while
13: return  $A_n, E_n$ 
```

---

Given an image  $I$  and question  $Q$ , we first encode the image into a feature set  $F_I$  through the image encoder  $F_I = E_{image}(I)$  and obtain initial image queries using the pretrained  $K$  queries through the QFormer  $Q_I = QF(F_I, T)$ . We then initialize our iterative steps indexed by  $n = 0$ . At

the very first step  $n = 0$ , we feed the image queries  $Q_I$  and question  $Q$  into the model to generate an initial answer  $A_0$  and explanation  $E_0$ ,

$$A_0, E_0 = L(concat(Q, F_I)) \quad (4)$$

For each following iteration  $n > 0$ , the output  $O_n$  is of the form “[answer] because [explanation]”. We tokenize the explanation part of  $O_n$ , denoted as  $E_n$ . The tokenized explanation  $E_n$  is then fed through an embedding layer.

$$E_{n, \text{embedded}} = Embed(E_n). \quad (5)$$

We then concatenate  $E_{n, \text{embedded}}$  with the  $K$  BLIPv2 pretrained tokens  $T$  to create  $Concat_n = concat(T, E_{n, \text{embedded}})$ . This concatenated structure  $Concat_n$  is then passed into the QFormer to calculate a cross attention with the image feature set  $F_I$ , which then generates a new image query  $Q_{I,n}$  based on the explanation  $E_n$ ,  $T$ , and  $F_I$

$$Q_{I,n} = QF(Concat_n, F_I) \quad (6)$$

This new image query  $Q_{I,n}$  is then used as input to the language model  $L$ , which regenerates an explanation and an answer for the next step  $n + 1$ , denoted as  $A_{n+1}$  and  $E_{n+1}$

$$A_{n+1}, E_{n+1} = L(Q_{I,n}) \quad (7)$$

This process is repeated recursively until the model converges in its answer. In practice, we limit the maximum iteration number to 5 to prevent potential non-convergence. We provide a pseudo code in Algorithm 1 and a method pipeline in Figure 1.

### 3.3 ReVisE for Self Training

ReVisE’s recursive querying process allows the model to correct its own answers, which could lead to further performance improvement. Leveraging this, we propose a few-shot self-training mechanism using the explanations generated by ReVisE. Suppose we have a set of samples  $\mathcal{S}$  for which we have the ground-truth answers but lack annotated explanations. Initially, we randomly select a few-shot subset  $\mathcal{S}' \subseteq \mathcal{S}$  such that the model originally incorrectly answers these instances, but corrects its answers through ReVisE. Let  $A_i^{\text{corr}}$  denote the correct answer and  $E_i^{\text{ReVisE}}$  the explanation generated by ReVisE for the  $i$ th sample in  $\mathcal{S}'$ . We then use these pairs,  $(A_i^{\text{corr}}, E_i^{\text{ReVisE}})$ , to further finetune the model. During this phase, we freeze both

the language model and the vision encoder, leaving only the QFormer for further finetuning.

$$\theta_{QF}^{\text{new}} = \arg \min_{\theta_{QF}} \sum_{i \in \mathcal{S}'} \mathcal{L}(A_i^{\text{corr}}, E_i^{\text{ReVisE}}; \theta_{QF}) \quad (8)$$

where  $\mathcal{L}$  denotes the loss function,  $\theta_{QF}$  represents the parameters of the QFormer, and  $\theta_{QF}^{\text{new}}$  are the updated parameters. This finetuning procedure is designed to bolster the model’s ability to generate accurate and explanatory responses.

We contrast this self-training strategy with a traditional approach. In the traditional approach, the model is given the correct answer directly to generate an explanation  $E_i^{\text{gen}}$  whereas in our approach  $E_i$  is generated through recursive querying. In the traditional self-training approach, the model parameters are updated as follows:

$$\theta_{QF}^{\text{new}} = \operatorname{argmin}_{\theta_{QF}} \sum_{i \in \mathcal{S}'} \mathcal{L}(A_i^{\text{corr}}, E_i^{\text{gen}}; \theta_{QF}), \quad (9)$$

By juxtaposing these two self-training strategies, we aim to assess the potential benefits of our proposed method, where explanations generated by ReVisE serve as a corrective mechanism, over the conventional approach that relies solely on the model’s ability to self-generate explanations from provided answers. A pseudo code is in Appendix C.

## 4 Experiments

In this section, we first introduce the basic settings including the task formulation, training details, baselines, and metrics. Then, we provide detailed experiment results and in-depth analysis for the results.

### 4.1 Settings

**Task Formulation** Our focus is on Vision-Language Natural Language Explanation (VL-NLE) tasks which demand generating an answer and a high-quality explanation given an image-question pair. We test our method on three established VL-NLE datasets (VQA-X (Park et al., 2018), e-SNLI-VE (Do et al., 2020), and VCR (Zellers et al., 2019)), and provide additional results for AOK-VQA (Schwenk et al., 2022). Appendix E provides detailed dataset descriptions.

**Implementation Details** For finetuning BLIPv2 on VL-NLE tasks, we maintain language model frozen and concurrently fine-tune the vision encoder with the QFormer, adopting a learning rate of  $1e - 5$ . We use the entirety of VQA-X while only selecting

Table 1: Filtered Scores comparison for VCR, e-SNLI-VE, and VQA-X against state-of-the-art models. Our BLIPv2 model is fine-tuned on 5% of the VCR and e-SNLI-VE datasets and on the complete dataset for VQA-X while others are all finetuned on the full dataset.

	<b>B1</b>	<b>B2</b>	<b>B3</b>	<b>B4</b>	<b>M</b>	<b>R-L</b>	<b>C</b>	<b>S</b>	<b>BS</b>
VCR									
PJ-X	21.8	11.0	5.9	3.4	16.4	20.5	19.0	4.5	78.4
FME	23.0	12.5	7.2	4.4	17.3	22.7	27.7	24.2	79.4
e-UG	20.7	11.6	6.9	4.3	11.8	22.5	32.7	12.6	79.0
QA-Only	18.0	10.2	6.0	3.8	11.2	22.0	30.6	11.6	78.9
RTV	18.0	10.2	6.0	3.8	11.2	21.9	30.1	11.7	78.9
OFA-X <sub>MT</sub>	22.3	13.0	8.0	5.2	11.3	24.3	44.6	17.8	79.3
NLX-GPT	24.7	15.0	9.6	6.6	12.2	26.4	<b>46.9</b>	18.8	80.3
<b>ReVisE (Ours)</b>	<b>28.9</b>	<b>21.7</b>	<b>17.6</b>	<b>14.4</b>	<b>15.5</b>	<b>29.5</b>	40.2	<b>27.9</b>	<b>82.2</b>
e-SNLI-VE									
PJ-X	29.4	18.0	11.3	7.3	14.7	28.6	72.5	24.3	79.1
FME	30.6	19.2	12.4	8.2	15.6	29.9	83.6	26.8	79.7
RVT	29.9	19.8	13.6	9.6	18.8	27.3	81.7	32.5	81.1
QA-only	29.8	19.7	13.5	9.5	18.7	27.0	80.4	32.1	81.1
e-UG	30.1	19.9	13.7	9.6	19.6	27.8	85.9	<b>34.5</b>	<b>81.7</b>
OFA-X <sub>MT</sub>	32.4	21.8	15.2	10.8	17.9	31.4	108.2	32.8	80.4
NLX-GPT	37.0	25.3	17.9	12.9	18.8	34.2	117.4	33.6	80.8
<b>ReVisE (Ours)</b>	<b>38.3</b>	<b>26.5</b>	<b>19.0</b>	<b>13.8</b>	<b>19.7</b>	<b>34.7</b>	<b>126.7</b>	34.2	81.5
VQA-X									
PJ-X	57.4	42.4	30.9	22.7	19.7	46.0	82.7	17.1	84.6
FME	59.1	43.4	31.7	23.1	20.4	47.1	87.0	18.4	85.2
e-UG	57.3	42.7	31.4	23.2	22.1	45.7	74.1	20.1	87.0
QA-Only	51.0	36.4	25.3	17.3	18.6	41.9	49.9	14.9	85.3
RTV	51.9	37.0	25.6	17.4	19.2	42.1	52.5	15.8	85.7
OFA-X <sub>MT</sub>	64.0	49.4	37.6	28.6	23.1	51.0	110.2	22.6	86.8
NLX-GPT	64.2	49.5	37.6	<b>28.5</b>	23.1	51.5	<b>110.6</b>	22.1	86.9
<b>ReVisE (Ours)</b>	<b>64.6</b>	<b>50.0</b>	<b>37.7</b>	28.2	<b>23.2</b>	<b>51.8</b>	108.9	<b>22.6</b>	<b>88.1</b>

a random 5% subset from e-SNLI-VE and VCR and AOK-VQA. Under the few-shot self-training scenario, we use 32 examples and exclusively finetune the QFormer, applying a learning rate of  $1e-6$ . More implementation details are provided in Appendix B.

**Baselines** For finetuned BLIPv2, we compare it with previous state of the art models that uses either unified approach or modular approach on the three VL-NLE datasets, including e-UG (Kayser et al., 2021), PJ-X (Park et al., 2018), FME (Wu and Mooney, 2018), RTV (Marasovic et al., 2022), QA-only (Kayser et al., 2021), NLX-GPT (Sammani et al., 2022), OFA-X<sub>MT</sub> (Plüster et al., 2022). We provide backbone information in Appendix A. **Evaluation Metrics** In keeping with established practices, we employ N-gram scores, including BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), ROUGE (Lin, 2004), CIDEr (Vedantam et al., 2015), SPICE (Anderson et al., 2016), and BERTScore (Zhang et al., 2019). We also use a more recent metric, G-Eval (Liu et al., 2023), which uses GPT4 (Bubeck et al., 2023) and Auto-Chain-Of-Thought (Zhang et al., 2022) for evaluation that has been shown to align better with

human evaluations. Details of these metrics are available in Appendix D. In accordance with established methods, we present filtered scores that represent results for explanations accompanied by correct answers. Additionally, we also report scores for instances where incorrect answers were given, providing a comprehensive view of the model’s performance.

## 4.2 Finetuned BLIPv2

In Table 1, we present our method’s performance against other state-of-the-art models using filtered scores for consistency. Leveraging only 5% of the VCR and e-SNLI-VE datasets and the entire VQA-X dataset, we managed to match or exceed benchmark scores with substantially less data. This highlights that advanced pre-trained models like BLIPv2 can achieve comparable performance using fewer annotations. The unique design of BLIPv2, which preserves the language model while transforming visual features into language model-interpretable tokens, offers a promising avenue for future vision-language model architecture research.

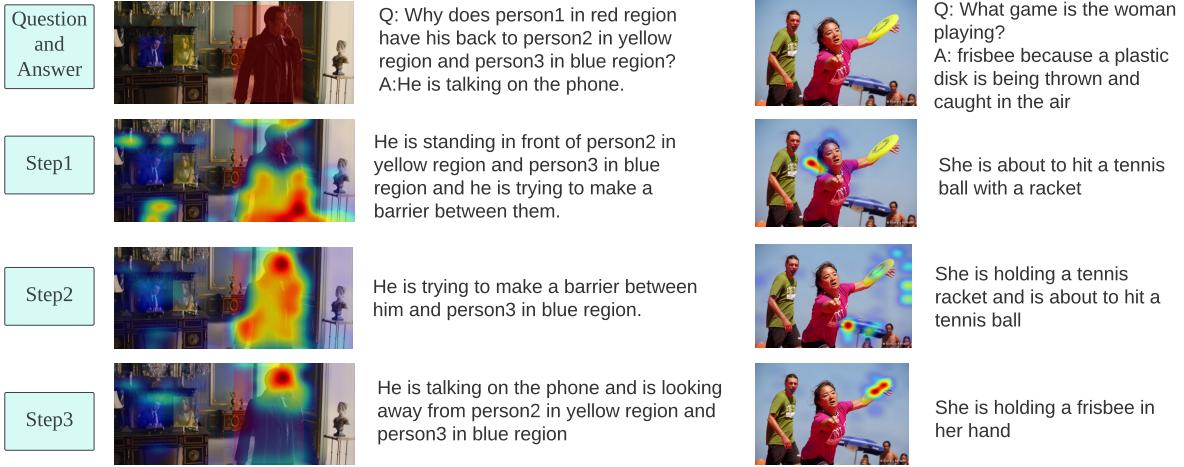


Figure 2: We provide case study of the ReVisE process. We use grad-cam to visualize how the visual attention changes along with how language explanation changes over steps.

Table 2: ReVisE Improvement Scores for VQA-X, eSNLI-VE, AOKVQA, and VCR. Our approach was evaluated on samples initially misinterpreted by the BLIPv2 model. The score of state of the art model NLX-GPT on the same metric is also provided for reference.

	B1	B2	B3	B4	M	R-L	C	S	BS	G-Eval
e-SNLI-VE										
NLX-GPT	31.9	20.3	13.3	9.0	16.4	27.8	85.1	31.2	79.52	5.42
Ours (w/o ReVisE)	35.0	22.7	15.2	10.3	17.9	29.9	101.0	30.6	79.30	6.21
Ours(w/ ReVisE)	<b>36.7</b>	<b>23.7</b>	<b>15.8</b>	<b>10.8</b>	<b>18.2</b>	<b>31.1</b>	<b>104.0</b>	<b>31.4</b>	<b>79.90</b>	<b>6.64</b>
VQA-X										
NLX-GPT	51.7	35.3	23.6	16.1	16.9	40.3	59.1	14.5	<b>83.77</b>	2.62
Ours(w/o ReVisE)	51.1	34.3	22.6	14.6	15.8	39.6	51.7	12.6	83.28	2.98
Ours(w/ ReVisE)	<b>54.8</b>	<b>37.3</b>	<b>25.0</b>	<b>16.2</b>	<b>17.6</b>	<b>41.3</b>	<b>62.6</b>	<b>15.0</b>	83.52	<b>4.24</b>
AOK-VQA										
NLX-GPT	55.1	38.3	27.1	18.1	16.2	44.0	57.4	14.3	85.43	4.12
Ours(w/o ReVisE)	57.5	39.9	28.1	19.0	16.5	44.4	59.1	15.3	<b>86.36</b>	4.46
Ours(w/ ReVisE)	<b>59.7</b>	<b>41.5</b>	<b>28.9</b>	<b>19.7</b>	<b>17.7</b>	<b>44.6</b>	<b>60.4</b>	<b>16.8</b>	85.86	<b>4.82</b>
VCR										
NLX-GPT	18.5	9.7	5.4	3.2	9.0	20.1	24.5	12.6	73.64	2.01
Ours(w/o ReVisE)	26.7	19.4	15.6	12.7	13.1	24.6	19.6	21.7	79.25	3.65
Ours(w/ ReVisE)	<b>27.2</b>	<b>20.3</b>	<b>16.4</b>	<b>13.4</b>	<b>14.1</b>	<b>26.2</b>	<b>28.7</b>	<b>23.7</b>	<b>79.35</b>	<b>3.97</b>

### 4.3 Recursive Visual Explanation (ReVisE)

In Table 2, we showcase ReVisE’s impact on augmenting model performance. As our approach aims at self-correcting and refining initially poor-quality explanations, we evaluate ReVisE on samples initially misinterpreted by the BLIPv2 model. The process involves using recursive language querying to extract pertinent image features, progressively refining the model’s output. We find that ReVisE persistently enhances the quality of the generated explanations, underscoring the critical role of language as a guide for image feature extraction.

Figure 2 exhibits representative examples from the VL-NLE datasets, clearly demonstrating the self-correcting mechanism of ReVisE. Employing grad-CAM visualizations (Selvaraju et al., 2017), we

elucidate how ReVisE guides the model’s attention allocation over steps. While initially, the attention maps are broad or focus on areas irrelevant to the question, ReVisE’s language-guided procedure redirects the model’s attention towards areas pertinent to the question at hand, suggesting an improvement in the model’s interpretability.

By taking the explanation from one iteration and using it as input for the next, the model refines its interpretation and visual attention. Conceptually, it’s analogous to a person rephrasing a statement repeatedly to enhance clarity.

### 4.4 Few-Shot Self-Training

In Table 3, we show results for few-shot self-training. We use explanations generated by Re-

Table 3: Performance comparison of ReVisE in a few-shot self-training context for e-SNLI-VE, VQA-X, AOKVQA, and VCR. The table depicts results without self-training, with traditional self-training, and with ReVisE self-training. We use 32-shot in all these experiments.

	B1	B2	B3	B4	M	R-L	C	S	BS	G-Eval
e-SNLI-VE										
No Self-train	35.0	22.7	15.2	10.3	17.9	29.9	101.0	30.6	79.30	6.21
w/o ReVisE	34.9	22.7	15.3	10.4	17.9	29.8	100.7	30.5	79.21	6.49
w/ReVisE	<b>36.2</b>	<b>23.5</b>	<b>15.8</b>	<b>10.9</b>	<b>18.2</b>	<b>30.5</b>	<b>103.2</b>	<b>30.7</b>	<b>79.61</b>	<b>6.75</b>
VQA-X										
No Self-train	51.1	34.3	22.6	14.6	15.8	39.6	51.7	12.6	83.28	2.98
w/o ReVisE	51.2	34.1	22.4	14.3	15.9	39.6	50.6	12.6	83.00	3.21
w/ReVisE	<b>53.5</b>	<b>36.6</b>	<b>24.8</b>	<b>16.2</b>	<b>16.9</b>	<b>40.7</b>	<b>58.9</b>	<b>13.8</b>	<b>83.65</b>	<b>4.41</b>
AOK-VQA										
No Self-train	57.5	39.9	28.1	19.0	16.5	44.4	59.1	15.3	86.36	4.46
w/o ReVisE	57.3	40.2	28.4	19.2	16.6	44.8	61.1	15.7	<b>86.44</b>	4.44
w/ReVisE	<b>60.0</b>	<b>41.1</b>	<b>28.7</b>	<b>19.6</b>	<b>18.6</b>	<b>45.1</b>	<b>62.4</b>	<b>18.1</b>	85.28	<b>4.71</b>
VCR										
No Self-train	26.7	19.4	15.6	12.7	13.1	24.6	19.6	21.7	79.25	3.65
w/o ReVisE	26.9	19.6	15.7	12.7	13.3	25.2	21.1	21.9	79.35	3.99
w/ReVisE	<b>27.1</b>	<b>20.1</b>	<b>16.2</b>	<b>13.3</b>	<b>13.7</b>	<b>25.4</b>	<b>21.6</b>	<b>23.1</b>	<b>79.55</b>	<b>4.14</b>

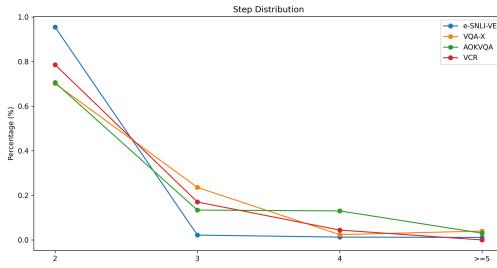


Figure 3: We display the distribution of convergence steps, indicating the percentage of samples that reach convergence at each respective step. We show results of e-SNLI-VE, VQA-X, AOKVQA and VCR and found that most samples converge by step2 and at least 90% samples converge by step3.

VisE to self-train on samples that are initially incorrect but self-corrected during the ReVisE process. When compared to providing the model with the correct answers directly to let it generate an explanation on the same samples, self-training with ReVisE explanations led to better performance, indicating the model benefits more from its own reasoning process than simply digesting the correct answers.

Qualitative results in Figure 4 reveal minor semantic differences between ReVisE-generated pseudo-explanations and explanations crafted with provided ground-truth answers. The variations typically lie in phrasing style or sentence structures, suggesting that attention to sentence structure or phrasing pattern could prove crucial for high-quality pseudo-explanations in few-shot self-training.

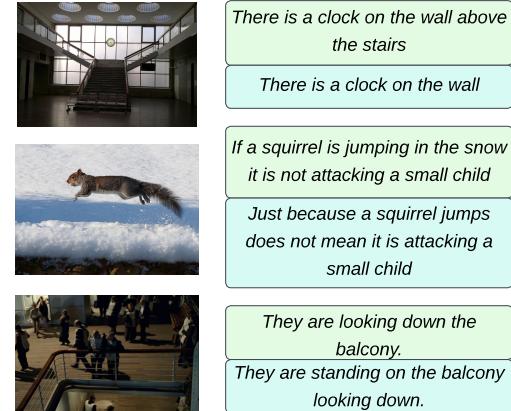


Figure 4: Comparison between pseudo-explanations generated by ReVisE(in the box above) and pseudo-explanations generated directly providing groundtruth answers(in the box below).

Additionally, we explored the impact of varying the number of self-training samples. As shown in Table 5, while any addition of few-shot samples enhances self-training, even as few as 8-shot samples can improve the model’s performance.

#### 4.5 Ablation Study

**Implicit VS Explicit Language** In our approach, we forward both the integrated  $K$  queries and the language queries after cross-attention. We compare this procedure with forwarding only  $K$  queries after cross-attention, as illustrated in Figure 6. The  $K$  queries integrate language information implicitly through the cross-attention process but do not forward the encoded text directly.

Table 4: Ablation study examining the impact of limiting ReVisE iterations to 2 and 3. Since up to 90% of samples converge by the third step, constraining iteration steps to 3 yields strong results.

	B1	B4	M	R-L	C	S
e-SNLI-VE						
2Steps	36.6	10.6	18.1	31.0	103.0	31.0
3Steps	36.7	10.8	18.2	31.1	103.2	31.4
VQA-X						
2Steps	54.6	15.7	17.5	41.0	59.6	14.9
3Steps	54.8	16.2	17.6	41.3	60.6	15.0
VCR						
2Steps	27.0	13.4	14.0	26.0	28.3	23.6
3Steps	27.2	13.4	14.1	26.2	28.7	23.7

Table 5: Ablation study investigating the effect of varying sample sizes for few-shot self-training. We present results for 8-shot, 16-shot, and 32-shot self-training approaches, using pseudo-explanations generated by ReVisE.

	B1	B4	M	R-L	C	S
e-SNLI-VE						
8-shot	35.5	10.5	17.9	30.1	101.5	30.6
16-shot	35.7	10.6	18.0	30.2	101.8	30.5
32-shot	36.2	10.9	18.2	30.5	103.2	30.7
VQA-X						
8-shot	53.3	15.8	16.7	40.6	57.4	13.2
16-shot	53.3	15.7	16.7	40.3	56.9	13.6
32-shot	53.5	16.2	16.9	40.7	58.9	13.8
VCR						
8-shot	26.9	12.9	13.3	25.2	20.7	22.3
16-shot	27.1	13.1	13.5	25.3	21.4	22.6
32-shot	27.1	13.3	13.7	25.4	21.6	23.1

The ablation study results in Table 6 indicate that implicit language integration through the  $K$  queries alone does not significantly enhance performance. Explicitly combining language queries offer crucial semantically-grounded context which cannot be captured by the  $K$  learned queries alone, thus providing a more substantial advantage in refining the model’s image comprehension.

**Limit Iteration Steps** Recursive querying may be time-consuming, so we limit the maximum number of steps to 2 and 3 to investigate its impact. As shown in Table 4, limiting the steps to 3 achieved performance nearly on par with that of unrestricted steps. Furthermore, Figure 3 presents the percentage of samples that reach convergence at each respective step, indicating that most samples converge by the second step and 90% of the samples converge by step3. The e-SNLI-VE samples exhibit the fastest convergence, potentially due to the simplicity of their answer options.

Table 6: Ablation Study for three VL-NLE datasets. ‘I’ refers to incorporating language signal implicitly and ‘E’ refers to incorporating language signal explicitly. Generally, ‘E’ outperforms ‘I’.

	B1	B4	M	R-L	C	S
e-SNLI-VE						
I	35.0	10.4	17.9	29.9	100.8	30.6
E	<b>36.7</b>	<b>10.8</b>	<b>18.2</b>	<b>31.1</b>	<b>104.0</b>	<b>31.4</b>
VQA-X						
I	51.0	14.8	16.0	39.9	52.4	12.5
E	<b>54.8</b>	<b>16.2</b>	<b>17.6</b>	<b>41.3</b>	<b>62.6</b>	<b>15.0</b>
VCR						
I	24.1	11.1	12.0	24.3	18.7	19.4
E	<b>25.5</b>	<b>11.6</b>	<b>12.4</b>	<b>24.5</b>	<b>20.0</b>	<b>19.8</b>



Figure 5: Failure cases when iterations doesn’t converge or adding more iterations worsens the performance.

**Failure Cases** We notice certain instances ( 2%) where additional iterations negatively affect the quality of the generates explanations, as illustrated in Figure 5. For most failure cases, the model enters into a recursive loop. In some others, the model initially generates explanations closely aligning with the ground truth but diverged with subsequent iterations. This reveals the importance for a balance between the depth of reasoning and model certainty in recursive reasoning.

**Data Efficiency** We provide further ablation on the amount of training data used. On the e-SNLI-VE dataset, we tried 1%, 3%, and 5% of the dataset and report the filtered score. The results are shown in Table 7. This illustrates that our model, leverag-

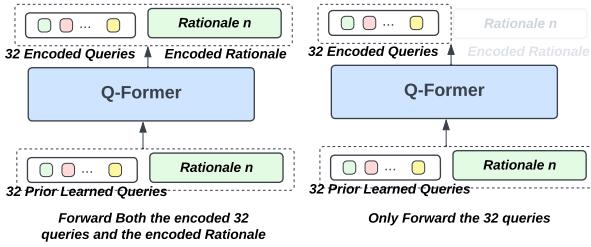


Figure 6: Comparison between forwarding all the encoded queries with forwarding only the  $K$  queries after cross-attention.

ing recent advancements in pre-trained models, can deliver high-quality explanations even with substantially fewer annotations than traditional methods.

Table 7: Ablation Study for the amount of data used on e-SNLI-VE dataset. We tried using 1%, 3% and 5% of the training data and reported the filtered scores.

	<b>B1</b>	<b>B4</b>	<b>M</b>	<b>R-L</b>	<b>C</b>	<b>S</b>
1%	37.0	13.4	19.4	33.9	122.3	33.5
3%	38.0	13.6	19.7	34.5	126.7	34.0
5%	38.3	13.8	19.7	34.7	126.7	34.2

## 5 Conclusion

In this paper, we introduce ReVisE, a method for generating natural language explanations for visual reasoning tasks with a small number of annotations. We demonstrate its high performance in generating language explanations using significantly less data compared to existing models, enabling the model’s self-correction mechanism, and effectively facilitating few-shot self-training by generating robust pseudo-explanations. Our work raises the question of whether recursive procedures like ReVisE can be used to improve performance in other multimodal domains as well.

## Limitations

Although BLIPv2 has a large potential for vision-language explanation, it might encode social bias. As (Chuang et al., 2023) illustrated, vision-language models have been shown to inherit biases from their training datasets. Conducting a thorough investigation of the potential bias of BLIPv2 and addressing it would be an important future work. Also, further enhancing the method to identify and address the failure cases is also a future work to improve this method.

## Ethics Statement

The proposed methods, rooted in the principles of transparency and interpretability, promote the ethical goal of developing AI systems that are easily comprehensible and verifiable. By enabling AI to generate more coherent explanations, we contribute to the objective of trustworthy AI.

## References

- Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, et al. 2022. Flamingo: a visual language model for few-shot learning. *Advances in Neural Information Processing Systems*, 35:23716–23736.
- Nathan Anderson, Caleb Wilson, and Stephen D. Richardson. 2022. Lingua: Addressing scenarios for live interpretation and automatic dubbing. In *Proceedings of the 15th Biennial Conference of the Association for Machine Translation in the Americas (Volume 2: Users and Providers Track and Government Track)*, pages 202–209, Orlando, USA. Association for Machine Translation in the Americas.
- Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. 2016. Spice: Semantic propositional image caption evaluation. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part V 14*, pages 382–398. Springer.
- Peter Anderson, Qi Wu, Damien Teney, Jake Bruce, Mark Johnson, Niko Sünderhauf, Ian Reid, Stephen Gould, and Anton Van Den Hengel. 2018. Vision-and-language navigation: Interpreting visually-grounded navigation instructions in real environments. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3674–3683.
- Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. 2015. Vqa: Visual question answering. In *Proceedings of the IEEE international conference on computer vision*, pages 2425–2433.
- Alexei Baevski, Wei-Ning Hsu, Qiantong Xu, Arun Babu, Jiatao Gu, and Michael Auli. 2022. Data2vec: A general framework for self-supervised learning in speech, vision and language. In *International Conference on Machine Learning*, pages 1298–1312. PMLR.
- Satanjeev Banerjee and Alon Lavie. 2005. Meteor: An automatic metric for mt evaluation with improved correlation with human judgments. In *Proceedings of the acl workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization*, pages 65–72.

- Hangbo Bao, Li Dong, Songhao Piao, and Furu Wei. 2021. Beit: Bert pre-training of image transformers. *arXiv preprint arXiv:2106.08254*.
- Hangbo Bao, Wenhui Wang, Li Dong, Qiang Liu, Owais Khan Mohammed, Kriti Aggarwal, Subhajit Som, Songhao Piao, and Furu Wei. 2022. Vlmo: Unified vision-language pre-training with mixture-of-modality-experts. *Advances in Neural Information Processing Systems*, 35:32897–32912.
- Khaled Bayoudh, Raja Knani, Fayçal Hamdaoui, and Abdellatif Mtibaa. 2021. A survey on deep multi-modal learning for computer vision: advances, trends, applications, and datasets. *The Visual Computer*, pages 1–32.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901.
- Sébastien Bubeck, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrke, Eric Horvitz, Ece Kamar, Peter Lee, Yin Tat Lee, Yuanzhi Li, Scott Lundberg, et al. 2023. Sparks of artificial general intelligence: Early experiments with gpt-4. *arXiv preprint arXiv:2303.12712*.
- Ting Chen, Simon Kornblith, Kevin Swersky, Mohammad Norouzi, and Geoffrey E Hinton. 2020. Big self-supervised models are strong semi-supervised learners. *Advances in neural information processing systems*, 33:22243–22255.
- Xi Chen, Xiao Wang, Soravit Changpinyo, AJ Piergiovanni, Piotr Padlewski, Daniel Salz, Sebastian Goodman, Adam Grycner, Basil Mustafa, Lucas Beyer, et al. 2022. Pali: A jointly-scaled multilingual language-image model. *arXiv preprint arXiv:2209.06794*.
- Yiming Chen, Yan Zhang, Chen Zhang, Grandee Lee, Ran Cheng, and Haizhou Li. 2021. Revisiting self-training for few-shot learning of language model. *arXiv preprint arXiv:2110.01256*.
- Ching-Yao Chuang, Varun Jampani, Yuanzhen Li, Antonio Torralba, and Stefanie Jegelka. 2023. Debiasing vision-language models via biased prompts. *arXiv preprint arXiv:2302.00070*.
- Virginie Do, Oana-Maria Camburu, Zeynep Akata, and Thomas Lukasiewicz. 2020. e-snli-ve: Corrected visual-textual entailment with natural language explanations. *arXiv preprint arXiv:2004.03744*.
- Pierre Dognin, Igor Melnyk, Youssef Mroueh, Inkit Padhi, Mattia Rigotti, Jarret Ross, Yair Schiff, Richard A Young, and Brian Belgodere. 2020. Image captioning as an assistive technology: Lessons learned from vizwiz 2020 challenge. *arXiv preprint arXiv:2012.11696*.
- Jiaxin Ge, Hongyin Luo, Siyuan Qian, Yulu Gan, Jie Fu, and Shanghang Zhan. 2023. Chain of thought prompt tuning in vision language models. *arXiv preprint arXiv:2304.07919*.
- Lisa Anne Hendricks, Zeynep Akata, Marcus Rohrbach, Jeff Donahue, Bernt Schiele, and Trevor Darrell. 2016. Generating visual explanations. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part IV 14*, pages 3–19. Springer.
- Dan Hendrycks, Mantas Mazeika, Saurav Kadavath, and Dawn Song. 2019. Using self-supervised learning can improve model robustness and uncertainty. *Advances in neural information processing systems*, 32.
- Maxime Kayser, Oana-Maria Camburu, Leonard Salewski, Cornelius Emde, Virginie Do, Zeynep Akata, and Thomas Lukasiewicz. 2021. e-vil: A dataset and benchmark for natural language explanations in vision-language tasks. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 1244–1254.
- Wonjae Kim, Bokyung Son, and Ildoo Kim. 2021. Vilt: Vision-and-language transformer without convolution or region supervision. In *International Conference on Machine Learning*, pages 5583–5594. PMLR.
- Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. 2023. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. *arXiv preprint arXiv:2301.12597*.
- Junnan Li, Ramprasaath Selvaraju, Akhilesh Gotmare, Shafiq Joty, Caiming Xiong, and Steven Chu Hong Hoi. 2021. Align before fuse: Vision and language representation learning with momentum distillation. *Advances in neural information processing systems*, 34:9694–9705.
- Ming Li and Zhi-Hua Zhou. 2005. Setred: Self-training with editing. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 611–621. Springer.
- Wei Li, Can Gao, Guocheng Niu, Xinyan Xiao, Hao Liu, Jiachen Liu, Hua Wu, and Haifeng Wang. 2020. Unimo: Towards unified-modal understanding and generation via cross-modal contrastive learning. *arXiv preprint arXiv:2012.15409*.
- Xinzhe Li, Qianru Sun, Yaoyao Liu, Qin Zhou, Shibao Zheng, Tat-Seng Chua, and Bernt Schiele. 2019. Learning to self-train for semi-supervised few-shot classification. *Advances in neural information processing systems*, 32.
- Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

- Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. 2014. Microsoft coco: Common objects in context. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6–12, 2014, Proceedings, Part V 13*, pages 740–755. Springer.
- Yang Liu, Dan Iter, Yichong Xu, Shuohang Wang, Ruochen Xu, and Chenguang Zhu. 2023. Gpteval: Nlg evaluation using gpt-4 with better human alignment. *arXiv preprint arXiv:2303.16634*.
- Pan Lu, Swaroop Mishra, Tanglin Xia, Liang Qiu, Kai-Wei Chang, Song-Chun Zhu, Oyvind Tafjord, Peter Clark, and Ashwin Kalyan. 2022. Learn to explain: Multimodal reasoning via thought chains for science question answering. *Advances in Neural Information Processing Systems*, 35:2507–2521.
- Qing Lyu, Shreya Havaldar, Adam Stein, Li Zhang, Delip Rao, Eric Wong, Marianna Apidianaki, and Chris Callison-Burch. 2023. Faithful chain-of-thought reasoning. *arXiv preprint arXiv:2301.13379*.
- Ana Marasovic, Iz Beltagy, Doug Downey, and Matthew Peters. 2022. Few-shot self-rationalization with natural language prompts. In *Findings of the Association for Computational Linguistics: NAACL 2022*, pages 410–424, Seattle, United States. Association for Computational Linguistics.
- Ishan Misra, Ross Girshick, Rob Fergus, Martial Hebert, Abhinav Gupta, and Laurens Van Der Maaten. 2018. Learning by asking questions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 11–20.
- Subhabrata Mukherjee and Ahmed Awadallah. 2020. Uncertainty-aware self-training for few-shot text classification. *Advances in Neural Information Processing Systems*, 33:21199–21212.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics*, pages 311–318.
- Dong Huk Park, Trevor Darrell, and Anna Rohrbach. 2019. Robust change captioning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4624–4633.
- Dong Huk Park, Lisa Anne Hendricks, Zeynep Akata, Anna Rohrbach, Bernt Schiele, Trevor Darrell, and Marcus Rohrbach. 2018. Multimodal explanations: Justifying decisions and pointing to the evidence. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 8779–8788.
- Bryan A Plummer, Liwei Wang, Chris M Cervantes, Juan C Caicedo, Julia Hockenmaier, and Svetlana Lazebnik. 2015. Flickr30k entities: Collecting region-to-phrase correspondences for richer image-to-sentence models. In *Proceedings of the IEEE international conference on computer vision*, pages 2641–2649.
- Björn Plüster, Jakob Ambsdorf, Lukas Braach, Jae Hee Lee, and Stefan Wermter. 2022. Harnessing the power of multi-task pretraining for ground-truth level natural language explanations. *arXiv preprint arXiv:2212.04231*.
- Fawaz Sammani, Tanmoy Mukherjee, and Nikos Deligiannis. 2022. Nlx-gpt: A model for natural language explanations in vision and vision-language tasks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8322–8332.
- Dustin Schwenk, Apoorv Khandelwal, Christopher Clark, Kenneth Marino, and Roozbeh Mottaghi. 2022. A-okvqa: A benchmark for visual question answering using world knowledge. In *Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part VIII*, pages 146–162. Springer.
- Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. 2017. Grad-cam: Visual explanations from deep networks via gradient-based localization. In *Proceedings of the IEEE international conference on computer vision*, pages 618–626.
- Masahiro Suzuki and Yutaka Matsuo. 2022. A survey of multimodal deep generative models. *Advanced Robotics*, 36(5-6):261–278.
- Ramakrishna Vedantam, C Lawrence Zitnick, and Devi Parikh. 2015. Cider: Consensus-based image description evaluation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4566–4575.
- Boshi Wang, Xiang Deng, and Huan Sun. 2022a. Iteratively prompt pre-trained language models for chain of thought. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 2714–2730.
- Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc Le, Ed Chi, and Denny Zhou. 2022b. Self-consistency improves chain of thought reasoning in language models. *arXiv preprint arXiv:2203.11171*.
- Zirui Wang, Jiahui Yu, Adams Wei Yu, Zihang Dai, Yulia Tsvetkov, and Yuan Cao. 2021. Simvlm: Simple visual language model pretraining with weak supervision. *arXiv preprint arXiv:2108.10904*.
- Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. 2021. Finetuned language models are zero-shot learners. *arXiv preprint arXiv:2109.01652*.
- Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. 2022. Chain-of-thought reasoning with large language models. *arXiv preprint arXiv:2205.04041*.

- 2022a. Emergent abilities of large language models. *arXiv preprint arXiv:2206.07682*.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Ed Chi, Quoc Le, and Denny Zhou. 2022b. Chain of thought prompting elicits reasoning in large language models. *arXiv preprint arXiv:2201.11903*.
- Jialin Wu and Raymond Mooney. 2019. Self-critical reasoning for robust visual question answering. *Advances in Neural Information Processing Systems*, 32.
- Jialin Wu and Raymond J Mooney. 2018. Faithful multimodal explanation for visual question answering. *arXiv preprint arXiv:1809.02805*.
- Qizhe Xie, Minh-Thang Luong, Eduard Hovy, and Quoc V Le. 2020. Self-training with noisy student improves imagenet classification. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10687–10698.
- Zhengyuan Yang, Tianlang Chen, Liwei Wang, and Jiebo Luo. 2020. Improving one-stage visual grounding by recursive sub-query construction. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XIV 16*, pages 387–404. Springer.
- Rowan Zellers, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. From recognition to cognition: Visual commonsense reasoning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 6720–6731.
- Rowan Zellers, Ximing Lu, Jack Hessel, Youngjae Yu, Jae Sung Park, Jize Cao, Ali Farhadi, and Yejin Choi. 2021. Merlot: Multimodal neural script knowledge models. *Advances in Neural Information Processing Systems*, 34:23634–23651.
- Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q Weinberger, and Yoav Artzi. 2019. Bertscore: Evaluating text generation with bert. *arXiv preprint arXiv:1904.09675*.
- Zhuosheng Zhang, Aston Zhang, Mu Li, and Alex Smola. 2022. Automatic chain of thought prompting in large language models. *arXiv preprint arXiv:2210.03493*.
- Zhuosheng Zhang, Aston Zhang, Mu Li, Hai Zhao, George Karypis, and Alex Smola. 2023. Multi-modal chain-of-thought reasoning in language models. *arXiv preprint arXiv:2302.00923*.
- Fengda Zhu, Yi Zhu, Xiaojun Chang, and Xiaodan Liang. 2020. Vision-language navigation with self-supervised auxiliary reasoning tasks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10012–10022.
- Yang Zou, Zhiding Yu, Xiaofeng Liu, BVK Kumar, and Jinsong Wang. 2019. Confidence regularized self-training. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 5982–5991.

## A Model Backbone

We present model parameters and vision transformer backbone for the different models in Table 8

Models	Backbone	Trainable Params
FME	ResNet-101	142M
RVT	ResNet-101	277M
e-UG	ResNet 101	277M
OFA-X	ResNet152	472M
NLX-GPT	ViT	182M
Ours	ViT	108M

Table 8: The vision backbone for FME, RVT, e-UG, OFA, NLX-GPT and Ours.

## B Additional Implementation Details

We provide additional implementation details. When training on BLIPv2 we use beam search with num beam = 5 during decoding. For AOK-VQA, we also set length penalty to -1, consistent with the original BLIPv2. During training, we use cosine annealing scheduler and AdamW optimizer and train for 6 epochs. Since BLIPv2 does not have any regional proposals, we followed (Zellers et al., 2021) and add colored bounding boxes around the people/objects referred to and refer to them as "person1 in red region" or "person2 in yellow region". As (Zellers et al., 2021) demonstrates, through fine-tuning, the model learns a matching between the color referred to in language and the color denoted in the image.

## C Pseudo Algorithm For ReVisE self-training

We also provide a pseudo code for self-training in algorithm 2, which is a pseudo code description of the self-training process in the Method section.

## D Detailed Metrics

We provide details of the recent new metric G-Eval (Liu et al., 2023). This metric commences by formulating a task and employs GPT3.5 (Brown et al., 2020) and GPT4 (Bubeck et al., 2023) to autonomously generate evaluation steps using the Auto Chain-of-Thought (AutoCoT) (Zhang et al., 2022). Subsequently, the task instruction along with the AutoCoT evaluation steps and the sample under consideration are fed to the GPT model together to obtain a comprehensive score from 1-10.

---

**Algorithm 2** ReVisE for Self Training

---

```
1: Input: Model  $M$ , Samples  $S$ , Few-shot size  $k$ 
2: Output: Finetuned Model  $M'$ 
3: Initialize:  $TrainingSet \leftarrow \{\}$ 
4: for each  $sample \in S$  do
5:    $(A_{old}, E_{old}) \leftarrow M.\text{generateAnswerWithoutReVisE}(sample)$ 
6:    $(A_{new}, E_{new}) \leftarrow M.\text{generateAnswerWithReVisE}(sample)$ 
7:   if  $M.\text{checkAnswer}(A_{old})$  is False and
       $M.\text{checkAnswer}(A_{new})$  is True then
8:      $TrainingSet.add((sample, E_{generated}))$ 
9:   end if
10: end for
11: Randomly select  $k$  samples from  $TrainingSet$  to form
     $FewShotSet$  for few-shot self training
12:  $M' = M.\text{finetuneQFormer}(FewShotSet)$ 
13: return  $M'$ 
```

---

This metric has been shown to align better with human evaluations than previous metrics.

## E Data Details

VQA-X and A-OKVQA both augments the VQAv2 dataset (Antol et al., 2015) with explanations for each answer. The images in VQA-X are sourced from the COCO dataset (Lin et al., 2014), and it comprises 33K QA pairs drawn from 28K images. e-SNLI-VE provides explanations for the Visual Entailment Prediction task, which involves answering whether a given image and hypothesis are in entailment, contradiction, or neutral relationship. The images for this dataset are drawn from Flickr30k (Plummer et al., 2015), and it contains over 430K examples. VCR is a dataset that presents a model with an image, a question, and a list of objects that are annotated with bounding boxes, and requires the model to first select an answer and then explain it. VCR includes 290K samples of questions, answers, and rationales. For each of the dataset, we use the original train set of each dataset and their own test set.