

# Tackling Vision Language Tasks through Learning Inner Monologues

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## Abstract

Visual language tasks such as Visual Question Answering (VQA) or Visual Entailment (VE) require AI models to comprehend and reason with both visual and textual content. Driven by the power of Large Language Models (LLMs), two prominent methods have emerged: (1) the hybrid integration between LLMs and Vision-Language Models (VLMs), where visual inputs are firstly converted into language descriptions by VLMs, serving as inputs for LLMs to generate final answer(s); (2) visual feature alignment in language space, where visual inputs are encoded as embeddings and projected to LLMs' language space via further supervised fine-tuning. The first approach provides light training costs and interpretability but is hard to be optimized in an end-to-end fashion. The second approach presents decent performance, but feature alignment usually requires large amounts of training data and lacks interpretability.

To tackle this dilemma, we propose a novel approach, Inner Monologue Multi-Modal Optimization (IMMO), to solve complex vision language problems by simulating Inner Monologue, a cognitive process in which an individual engages in silent verbal communication with themselves. More specifically, we enable LLMs and VLMs to interact through natural language conversation (i.e., Inner Monologue) and propose to use a two-stage training process to learn how to do Inner Monologue (self-asking questions and answering questions). IMMO is evaluated on two popular tasks and achieves competitive performance with less training data when compared with state-of-the-art models while concurrently keeping the interpretability. The results suggest that by emulating the cognitive phenomenon of internal dialogue, our approach can enhance reasoning and explanation abilities, contributing to the more effective fusion of vision and language models. More importantly, instead of using predefined human-crafted monologues, IMMO learns this process within the deep learning models, broadening its potential applications across various AI challenges beyond vision and language tasks.

## 1 Introduction

Evidence shows that explicitly using natural language as the intermediate representation of reasoning is effective and essential for human cognition (Goldin-Meadow and Gentner 2003; Forbus, Liang, and Rabkina 2017; Crouse, McFate, and Forbus 2018; Chen et al. 2020; Lee et al. 2019;

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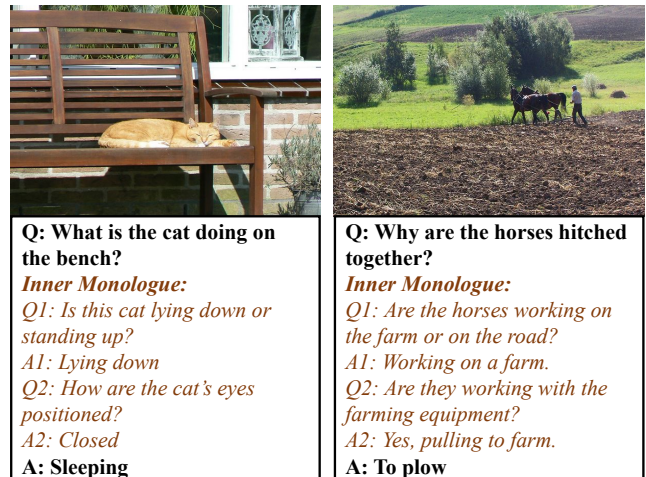


Figure 1: Examples of multi-modal Inner Monologue. Q, A, and Image are from a visual question-answer sample. The Inner Monologue part in brown consists of questions (Q1, Q2) from the Reasoner module and answers (A1, A2) from the Observer module.

Zhang et al. 2023). Recently, large language models (LLMs) have achieved substantial advancements. Notable models like PaLM (Chowdhery et al. 2022), InstructGPT (Ouyang et al. 2022), and LLaMA (Touvron et al. 2023) showcase their immense potential in the field of natural language processing and commonsense reasoning. Many researchers explore using natural language as the intermediate representation to bridge multiple modalities. For instance, various modalities, including the vision modality, can be first projected to the natural language space, and then LLMs are utilized to perform multi-modality understanding via language processing. Two research directions to add visual inputs into language space have been actively studied recently. The first direction is the hybrid integration between vision-language models (VLMs) and LLMs (Yang et al. 2022; Salaberria et al. 2023; Zhu et al. 2023a). Hybrid integration approaches aim to enable LLMs to utilize VLMs in a zero-shot or few-shot manner, i.e., LLMs act as central reasoners or planners and VLMs serve as tools or sensors. These models do not require heavy training costs and provide interpretability as

the model outputs from LLMs and VLMs are transparent. However, as LLMs do not access the visual inputs directly, they may miss some visual details in the images. Also, most hybrid integration approaches merge LLMs and VLMs in a discrete space, which are hard to optimize in an end-to-end fashion. The second direction is embedding alignment (Dai et al. 2023; Chen et al. 2023; Li et al. 2023a; Liu et al. 2023). Visual information is transformed into visual embeddings, which are then mapped onto the language embedding space and employed as input embeddings for LLMs. Then, the LLMs are tuned via supervised fine-tuning to fuse vision and language information together to achieve decent performance. However, learning the cross-modality embedding alignment heavily relies on the training data. To get decent performance, users need to prepare a large number of high-quality data containing accurate domain knowledge and complex reasoning, which requires heavy engineering efforts and high data curation costs. Furthermore, during the inference time, the entire model remains a black box, making interpretation difficult (Gao et al. 2022). The heavy costs associated with collecting cross-modality data, combined with low interpretability, limit the applicability of this approach in many domains in practice.

To address the challenges, we introduce a novel approach, **Inner Monologue Multi-Modal Optimization (IMMO)**, to solve complex vision language problems by simulating the Inner Monologue process, a cognitive process in which an individual engages in silent verbal communication with themselves. When people solve complicated reasoning problems, they tend to use “Inner Monologue” by performing reasoning via multi-turn self-conversations in their minds. Inner Monologue helps people organize their thoughts and work through the optimal answers as a form of problem-solving (Cherney 2023; Huang et al. 2022). Inspired by this process, we enable LLMs and VLMs to interact through natural language conversation and propose to use supervised learning and reinforcement learning to learn how to perform the Inner Monologue. We choose one LLM as the *Reasoner* and one VLM as the *Observer*. Given a visual input and a visual reasoning problem, the Observer perceives the visual information and abstracts it to a natural-language description. The Reasoner decides whether the description has sufficient information to solve the problem or generates an advanced question for the Observer to acquire more visual information. With multiple turns, the Reasoner organizes the information and works through an answer. Figure 1 shows two examples of solving visual questions with the Inner Monologue. To automatically learn the process of the Inner Monologue, the entire system is optimized by a policy gradient method named Proximal Policy Optimization (PPO) (Schulman et al. 2017).

In summary, our contributions are as follows:

- Inspired by human cognition, we propose a novel approach IMMO for vision-and-language reasoning. IMMO includes a Reasoner model and one or more Observer model(s) to communicate with each other in natural language, significantly improving their ability to solve complex problems together. IMMO can be trained efficiently and has interpretability. This Inner Monologue-

based approach is flexible and can be adapted to other modalities or models.

- We propose a two-stage training process to let Observer(s) and Reasoner learn how to work together: first using annotated multi-turn reasoning data to train the initial model to imitate human Inner Monologue format, then adopting reinforcement learning to improve the model on the downstream task. To support training, we created a new human-like multi-turn Inner Monologue reasoning training corpus by augmenting existing VQA data with GPT-3.5. We find this low-cost training corpus effective.<sup>1</sup>
- We evaluate IMMO on two vision-language reasoning tasks. Experiments show that IMMO can achieve competitive results compared with GPT-4-based hybrid integration approaches, while it uses significantly less training data and provides greater interpretability compared with embedding alignment approaches.

## 2 Related Works

The success of large pre-trained language models has led to significant advancements in solving vision-language problems by fusing visual representations into the language space. The essence of these works is to allow LLMs to understand information from other modalities, using their rich pre-trained language knowledge and the emerging ability (Wei et al. 2022a). Several recent works have explored two research directions: embedding alignment and hybrid integration. Approaches with embedding alignment focus on projecting visual embeddings to the language space and fusing vision and language information via supervised fine-tuning in the language space (Dai et al. 2023; Liu et al. 2023). These models learn the embedding projection from perception models to LLMs with a large amount of high-quality vision-language instruction-tuning data. Despite the impressive performance, these models demand extensive training costs (resources, electric energy, high-quality annotated data) and struggle with interpretability, given the difficulty for humans to understand latent embeddings and comprehend the reasoning process of deep models. While maintaining good performance, our approach focuses on converting visual inputs into language descriptions, thus providing better interpretability. Approaches involving hybrid integration convert visual inputs to language descriptions, such as image captions, via VLMs and solve problems with LLMs (Yang et al. 2022; Salaberria et al. 2023). However, this approach may lead to captions that are irrelevant to the question. To address this problem, several works adapt interactive multi-turn conversations to promote VLMs and LLMs interacting with each other and acquiring more information (You et al. 2023; Zhu et al. 2023a). Despite these works providing more interpretability and accessibility, they are usually in zero-shot or few-shot settings and perform significantly less than the embedding-alignment-based approaches. Our approach introduces a novel framework to

<sup>1</sup>The code and data are released at <https://github.com/ucscirkm/immo>.

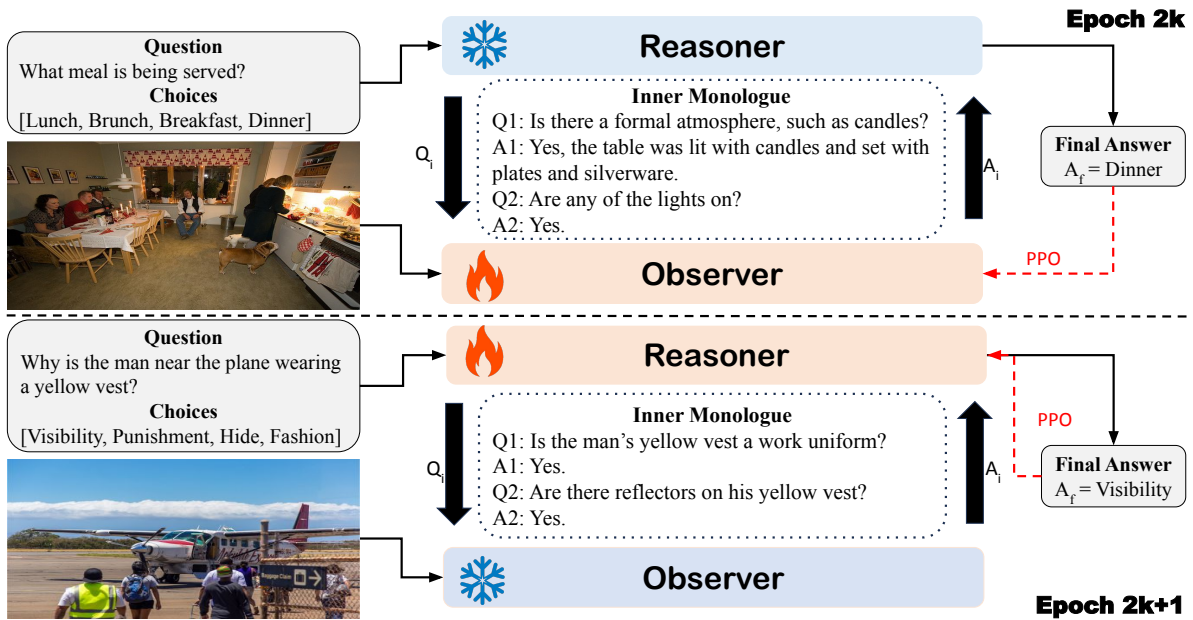


Figure 2: The IMMO framework automatically acquires Inner Monologue capabilities through reinforcement learning. In each training epoch, the Reasener (LLM) and Observer (VLM) are alternately designated as the actively trainable model, highlighted with a pink hue and a fire icon, while the other model assumes the role of a static environmental representation, distinguished by a light blue shade and a snow icon. During the  $(2k)$ -th epoch, the Reasener functions as the fixed environmental model, while the Observer becomes the focus of updates. Subsequently, in the  $(2k + 1)$ -th epoch, the roles shift, with the Reasener now undergoing updates as the active model and the Observer assuming the position of the static environmental representation. PPO policy gradients are used for iterative updates of the model parameters.

optimize hybrid integration systems end-to-end, which improves performance while preserving interpretability.

Another branch of research related to our work is multi-agent learning. Researchers in multi-agent collaborations have studied communication and dialog between models (Foerster et al. 2016). Such interactions enable models to exchange information, clarify doubts, negotiate strategies, and collaborate towards a common goal. They can share experiences, strategies, and insights gained from different perspectives. Multi-Agent Reinforcement Learning has been studied in various applications such as the games of Go, robotics, and autonomous driving. Depending on whether the agents are fully collaborative, fully competitive, or a mix of the two, one of the two approaches, Markov/stochastic games and extensive-form games, are usually used (Zhang, Yang, and Başar 2021). The RL method we proposed is motivated by these earlier works, while our study focuses on agents that can output natural language and facilitate model-to-model communication using **natural language** with the help of the recent advance in large-scale language models.

### 3 Approach

An overview of the IMMO framework for solving complex vision and language problems is shown in Figure 2. Our framework contains two components: the Reasener and the Observer. The “Inner Monologue” process in the IMMO is described as: The observer takes images as the inputs and generates textual descriptions to describe the key informa-

tion it observes; the Reasener takes the generated textual descriptions and performs reasoning by either generating a new query for the Observer or generating the final results of the task. We choose an LLM as our Reasener model and a VLM as our Observer model. The objective of the Reasener is to generate effective queries to obtain targeted information, and the objective of the Observer is to provide correct information based on the queries from the Reasener. With multi-turn querying-answering conversations between the Reasener and the Observer, the Reasener gathers information to address the vision and language problems, and the Observer receives the queries and perceives more visual details from the image.

#### 3.1 Inner Monologue Multi-Modal Optimization

In the IMMO framework, the Reasener and the Observer work together to solve a problem. Initially, the Observer receives the Image  $I$  and generates a caption  $C$  to describe the basic visual information in the image. A text container  $IM$  is used here to track the Inner Monologue, including the initial caption  $C$ :

$$IM_0 = C = Observer(I) \tag{1}$$

At the intermediate  $i$ -th turn ( $i \in [1, t]$  where  $t$  is the pre-defined maximum conversation turn), the Reasener and the Observer interact for conversations. Firstly, the Reasener receives the original textual description of the problem/task  $P$  combined with  $IM_{i-1}$  and generates a query  $Q_i$ . Then,

given  $Q_i$ , the Observer provides the answer  $A_i$  based on the image. This process is shown as the equations 2, and 3.

$$Q_i = \text{Reasoner}(P, IM_{i-1}) \quad (2)$$

$$A_i = \text{Observer}(I, Q_i) \quad (3)$$

At the end of each turn, both the question and answer that are generated within the current turn are added to the Inner Monologue history. The  $IM_i$  is defined as:

$$IM_i = C + \sum_{j=0}^i (Q_j + A_j) \quad (4)$$

After the final conversation turn  $t$ , the Reasoner provides its prediction  $A_f$  for the original problem  $P$  based on all the collected Inner Monologue:

$$A_f = \text{Reasoner}(P + IM_t) \quad (5)$$

During the multi-turn iteration, the Observer only accesses the input image and the most recent information query generated by the Reasoner, while the Reasoner can access the complete QA history at any given timestamp through the input prompt. Once the interaction reaches a pre-defined number of turns, the system prompts LLM for the final prediction. Next, we describe how IMMO optimizes the Reasoner and the Observer jointly.

### 3.2 Two-Stage Training

Although this multi-turn conversational framework can be used in a zero-shot manner through prompting, the collaboration between the Reasoner and the Observer is sub-optimal. The collaboration between the Reasoner and Observer should be further improved. For example, the Reasoner needs to be familiar with the Observer’s capability to generate appropriate queries that the Observer can answer. The Observer, on the other hand, should be optimized to extract correct visual information based on the queries from the Reasoner.

To alleviate the aforementioned underperformed collaboration problem, IMMO uses a two-stage training process. First, high-quality Inner Monologue conversational data is used for supervised fine-tuning (SL) of the Reasoner. Second, reinforcement learning (RL) is used to optimize downstream tasks. Figure 2 illustrates the overview of the RL stage of the IMMO framework.

**Supervised Human-Prior Fine-Tuning** To provide the Reasoner and the Observer a better starting point for reinforcement learning in the next stage, we employ supervised fine-tuning, similar to the approach used in Instruct-GPT (Ouyang et al. 2022; Cruz Jr, Du, and Taylor 2017). Our training process focuses on imparting effective Inner Monologue to the model, going beyond simple chit-chat or prompt-based zero-shot learning. To achieve this, we enhance our pre-trained language model by introducing human prior knowledge and reasoning patterns with supervised fine-tuning. We utilize high-quality multi-turn conversational question-answering pairs annotated by humans as

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#### Algorithm 1: IMMO Reinforcement Learning

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**Dataset:** (Problem  $P$ , Image  $I$ , Ground Truth  $G$ ) tuples

**Reasoner:** a pre-trained large language model

**Observer:** a pre-trained vision-language model

**N:** training epoch

**t:** pre-defined max turns

**k:** any none-negative integer

```

1: for epoch = 1 to N do
2:   Set Reasoner as the active model  $\mathcal{M}$ 
3:   Set Observer as the environment model  $\mathcal{E}$ 
4:   if epoch = 2k then
5:     Set Observer as the active model  $\mathcal{M}$ 
6:     Set Reasoner as the environment model  $\mathcal{E}$ 
7:   end if
8:   Sample  $(P, I, G)$  from the dataset
9:    $C \leftarrow \text{Observer}(I)$ 
10:  Set  $IM_0 = C$ 
11:  for  $i = 1$  to  $t$  do
12:     $Q_i \leftarrow \text{Reasoner}(P, IM_{i-1})$ 
13:     $A_i \leftarrow \text{Observer}(I, Q_i)$ 
14:     $IM_i = IM_{i-1} + Q_i + A_i$ 
15:  end for
16:   $A_f = \text{Reasoner}(P, IM_t)$ 
17:  Reward  $\leftarrow \mathcal{R}$  {Eq. 7}
18:  Update  $\mathcal{M}$  using PPO
19: end for

```

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our training data. Both the Reasoner and the Observer are trained on the human-annotated data as a warm-up process.

To impart human reasoning patterns to the language model, we employ the instruction fine-tuning method (Chung et al. 2022) in this training step. Inspired by Chains-of-Thought prompting (Wei et al. 2022b) in the reasoning task, this stage trains the model to mimic the correct thinking path. Instead of directly answering the basic question, the correct pattern involves reasoning through multiple turns of QA pairs and then arriving at the final answer. Utilizing the concept of transfer learning (Brown et al. 2020; Zhuang et al. 2020), this process does not have to be repeated when applied to different downstream datasets.

**Reinforcement Learning** IMMO uses a special alternative training process for system-level reinforcement learning to jointly optimize multiple models while considering the dynamic interactions between models. Since the system involves two models, we use the alternating training strategy to prevent issues arising from updating two models simultaneously, such as the imbalance of capabilities of the Reasoner and the Observer (Goodfellow et al. 2014). Specifically, at the  $2k$ -th epoch where  $k$  is a non-negative integer, we set the Observer as the active model (policy network) and the Reasoner as the environment model to provide feedback; at the  $2k + 1$ -th epoch, we switch the Reasoner to be active and change the Observer as the environment model. During training, we only update the active model. Following the common approaches used in previous works (Stienon et al. 2020; Ouyang et al. 2022) for fine-tuning autoregressive decoder-only generative model, we treat the ac-

tive model as the policy networks. The active model is updated by PPO and the environment model remains frozen. Notably, the active model and the environment model only affect which model is updated, and the input/output of each model strictly follows the multi-turn framework as shown in Figure 2. The algorithm uses the exact matching between the predicted answer  $A_f$  and the ground-truth answer  $G$  as the major reward factor:

$$r(A_f, G) = \begin{cases} 1 & \text{if } A_f = G \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

The final reward  $R$  shown in equation 7 also includes a KL penalty (Jaques et al. 2017) weighted by  $\beta$  to ensure that the updated model  $\mathcal{M}$  does not deviate too far from the well-trained starting point  $\mathcal{M}_0$  (Ziegler et al. 2019).

$$R = r(A_f, G) + \beta KL(\mathcal{M}, \mathcal{M}_0) \quad (7)$$

The training goal is to optimize the policy that maximizes the expected reward. The overall training procedure is shown in Algorithm 1.

## 4 Experiment

To evaluate the effectiveness of IMMO for complex vision-language reasoning, we conduct experiments on two popular tasks: Commonsense Visual Question Answering (VQA) and Visual Entailment (VE). We expect the ideal dataset for method validation to focus on multi-hop commonsense knowledge reasoning over visual information understanding. This section first describes our implementation of the IMMO framework and then presents the details of these two tasks.

### 4.1 Data and Implementation

We construct a new training corpus for supervised human-prior fine-tuning by utilizing the A-OKVQA (Schwenk et al. 2022) dataset, which includes human-annotated reasoning paths labeled as rationale. We derive Inner Monologue from rationale. By prompting GPT-3.5 in a zero-shot manner, we transform rationale into two-turn question-answering pairs and augment 17k data from the A-OKVQA training set. Each sample in the training corpus contains a question, a choice list, two rounds of QA conversations, and a final answer. At the supervised fine-tuning stage, we optimize the autoregressive LLM by performing the next token prediction task over this augmented corpus. At the reinforcement learning stage, the training is mainly based on the Transformers-Reinforcement-Learning (TRL) solution (Von Werra et al. 2020) to wrap up the Hugging Face trainer (Wolf et al. 2020). For different tasks (VQA or VE), RL is performed on task-specific training sets.

Our proposed system uses the Vicuna-7b (Chiang et al. 2023) language model and BLIP-2 (Li et al. 2023b) vision-language model. To ensure computational efficiency, we employed the Low-rank adaptation (LoRA) (Hu et al. 2021) to train only 0.06% of the Vicuna-7b model, which corresponds to 5 million parameters. Our experiments primarily focus on validating the methodology. For broader applicability, we chose a model that can be trained on a single NVIDIA

Method <sup>2</sup>	Training	Reasoning Aids	Accuracy(%)
PICa	Zero-shot	None	54.3
Vicuna	16-shots	Chain-of-Thought	68.6
IMMO	16-shots	Inner-Monologue	74.0
Vicuna	SL	Chain-of-Thought	78.3
IMMO	SL+RL	Inner-Monologue	<b>84.8</b>

Table 1: Results on ScienceQA.

A100-40G GPU or equivalent instead of a more powerful but larger model. For simplicity, we used a fixed set of hyper-parameters. Task-specific prompts for both LLM and VLM were designed manually, inspired by prompt templates used by You et al. (2023); Liu et al. (2023).

### 4.2 Commonsense Visual Question Answering

We conduct experiments on the ScienceQA (SQA) (Lu et al. 2022) dataset, a standard benchmark for commonsense visual question answering. It consists of 21k QA pairs collected from elementary and high school courses, with 48.7% of the questions including images, making it a VQA task. Success on this dataset requires appropriate commonsense knowledge as well as reasoning skills. We follow the official train/validation/test split for all our experiments.

**Baselines** To study the impact of RL optimization and Inner Monologue on model performance, we conduct experiments with three baselines. As demonstrated in Table 1, different training methods and reasoning aids were examined, while we used Vicuna-7B as LLM and BLIP-2 as the captioning model in all cases. The first baseline is PICa (Yang et al. 2022), which first proposed LLM plus image captions for Knowledge Base VQA. For a fair comparison, instead of using the default GPT-3 as LLM in PICa, we let PICa use Vicuna as its LLM. The second baseline is Vicuna-16-shots, which incorporates the Chain-of-Thoughts (CoT) prompting (Wei et al. 2022b) with the Vicuna model. The third baseline is Vicuna-SL, which is LLM fined-tuned on both warmup (A-OKVQA) and downstream (SQA) training data following instruction fine-tuning (Chung et al. 2022; Taori et al. 2023). We also compare two training methods for IMMO: few-shot learning (IMMO 16-shots) vs. two-stage training described in Section 3.2 (IMMO SL+RL).

**Results** Following the baseline setting, table 1 presents our results on the SQA test set. PICa, as a zero-shot baseline, achieves a modest accuracy of 54.3%. By using 16 in-context examples and CoT, Vicuna-16-shots attain an accuracy of 68.6%. With the same LLM model and in-context examples, enabling Inner Monologue with only few-shot learning (IMMO-16-shots) improves the performance by 5.4% (from 68.6% to 74%). With the two-stage training, IMMO further improves and achieves 84.8% accuracy, surpassing the Vicuna-SL, which had only a single round of visual information access, by 6.5%. Our experiment results

<sup>2</sup>All the experiments in the table are named after the methods, and the language models involved are all Vicuna-7B.

Method		Accuracy(%)
Emb	MiniGPT4 (Zhu et al. 2023b)	35.1
	LLaVA (ZS) (Liu et al. 2023)	40.3
	OFA (Wang et al. 2022)	91.0
IdealGPT (You et al. 2023)		55.3
NL	Vicuna-16-shots	49.8
	Vicuna-SL	59.8
	IMMO	65.7

Table 2: Results on SNLI-VE. The *Emb* group includes embedding alignment approaches, while the *NL* group includes methods using text to represent visual information.

highlight the role of Inner Monologue in facilitating reasoning while also demonstrating how RL training can enhance the overall system’s capabilities.

### 4.3 Visual Entailment

SNLI-VE (Xie et al. 2018) is a widely-used VE task built on top of SNLI (Bowman et al. 2015) and Flickr30k (Plummer et al. 2015) image datasets. This task is designed as a classification problem for vision-language reasoning: identify whether the relationship between the given image premise and text hypothesis is entailment, neural, or contradiction.

**Result** Table 2 shows the results on the SNLI-VE dev set. We add another baseline: IdealGPT, a recent hybrid integration approach that utilizes the rich reasoning knowledge of GPT-3.5-175B. Among approaches that use text to represent visual information, IMMO achieves the best performance. With a much smaller LLM, our best-performing checkpoints trained from Vicuna-7B achieved a 10.4% improvement over IdealGPT (65.7% vs 55.3%).

The results of embedding-based methods (MiniGPT4, LLaVA, and OFA) are also reported as a reference. Well-tuned embedding-based methods such as OFA work extremely well on this dataset, illustrating the power of using a single model for end-to-end optimization. The results suggest that for tasks like SNLI-VE where natural language is not enough to describe necessary visual information, approaches that convert images into text for LLM reasoning are sub-optimal. However, in real-world practice, many companies choose not to perform single-model-based end-to-end (embedding) optimization because interpretability is required and/or the training cost is too high. In such situations, hybrid integration like IMMO could be a good choice.

## 5 Ablation Studies and Analysis

### 5.1 Representative Cases

Figure 3 displays instances of successful outcomes (a, b, and c) as well as an unsuccessful case (d) depicting the interpretable Inner Monologues generated by IMMO. Example (b) shows LLM’s ability to compensate for VLM inaccuracies (incorrect A2) through reasoning and available information. Moreover, the questioning path in (b) and (c) demonstrate LLM’s vigilance in monitoring VLM responses, per-

	LLaVA	Chamaleon	UnifiedQA	IMMO
Interpretable	✗	✓	✓	✓
Trainable	✓	✗	✓	✓
Model size	13B	GPT-4	223M	9B
Tuned param	13B	0	223M	5M
Data usage	770K	-	17K	25K
SQA	90.9	86.5	74.1	84.8

Table 3: Comparison with other ScienceQA approaches.

sisting in using subsequent questions Q2 to validate information after Q1, even when the information is enough to answer the main question. On the other side, (d) exposes how the VLM’s limited geographical background knowledge hinders LLM from arriving at an accurate answer. The erroneous visual information from VLM misleads the LLM into an incorrect final prediction. These examples illustrate the interpretability of IMMO.

### 5.2 Comparison With Additional VQA Methods

We did some further analysis to compare representative solutions on the SQA task (Table 3). The embedding alignment approach, LLaVA, performs well; however, it requires extensive training data and lacks interpretability. Hybrid integration such as IMMO, Chamaleon (Lu et al. 2023) and UnifiedQA (Khashabi et al. 2020; Lu et al. 2022) employ modular architecture, enabling model-wise interpretability by access to individual outputs from sub-modules. Chameleon is based on GPT-4, which is not publicly available and poses constraints on its adoption and further fine-tuning. Compared with Chamaleon, IMMO achieved comparable performance with a significantly smaller model. UnifiedQA uses supervised training akin to our Vicuna-SL baseline, however, it falls short due to the lack of system-wide optimization and information loss when converting images to captions. Compared with UnifiedQA, IMMO addresses these problems via Inner Monologue and two-stage training, which significantly improves the performance of the hybrid integration method. Furthermore, compared to Chamaleon and UnifiedQA, which offer simple model-level interpretability, IMMO’s complex multi-round reasoning procedure is also transparent and human-readable.

Notably, we can not rule out the possibility that black-box models like GPT-4 might have inadvertently or intentionally undergone training using publicly accessible test data. Thus, we list the performance of those black-box models here for reference instead of as a baseline for a fair comparison. We expect the proposed approach could be applied to other LLMs and VLMs, such as GPT-4 or LLaVA, and further improve their performance.

### 5.3 The Impact of Conversation Turns

To examine the impact of Inner Monologue turns on performance, we conduct ablation tests on ScienceQA using both few-shot and trained approaches. Using the same set of hyperparameters, we evaluate turns ranging from 0 to 5, where 0 means VLM only provides an initial caption. As shown in Figure 4, accuracy notably rises on the SQA test set from 0

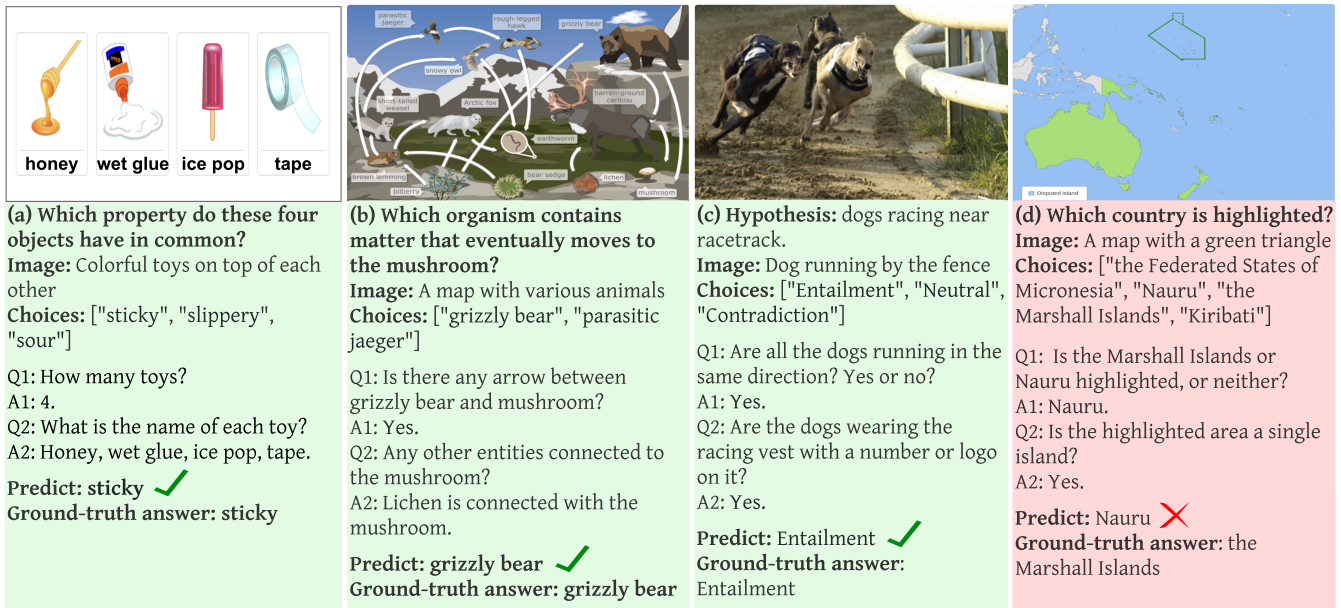


Figure 3: Success and failure examples of IMMO.

to 2 turns, plateauing thereafter. Our analysis identifies SQA questions as demanding less multi-hop reasoning than background knowledge. Thus, LLM’s primary learned strategy involves querying key facts initially, followed by confirmation or asking for side information. Also, more conversations bring uncertainty to the interaction as LLM may ask less relevant questions after 3 turns or VLM brings incorrect visual information. This trend is accentuated under the few-shot setting. Without training, LLM appears to be less robust to noise conversation, so the performance rapidly decreases after 2 turns. It’s important to note that these findings are specific to ScienceQA question patterns, underscoring the best Inner Monologue turns are highly based on the dataset’s characteristics.

## 6 Conclusion and Future Work

Inspired by cognitive modeling, we apply Inner Monologue, a commonly seen human reasoning process, in the interaction between LLM and VLM. We proposed to learn which questions to ask and how to answer questions during the multi-round monologue using a two-stage training framework together with a newly constructed training corpus from existing VQA datasets. Our experiments demonstrated the ability to learn how to do Inner Monologues, as well as the effectiveness of acquiring information and reasoning through Inner Monologues.

This paper is a first step towards this research direction, and there is much room for future improvement. Our current implementation promotes the Reasoner querying certain turns, while an ideal reasoner should autonomously determine whether to continue querying or end the Inner Monologue with direct answers (for example, when adequate information has been gathered or due to time/resource constraints). Our implementation only includes one Observer,

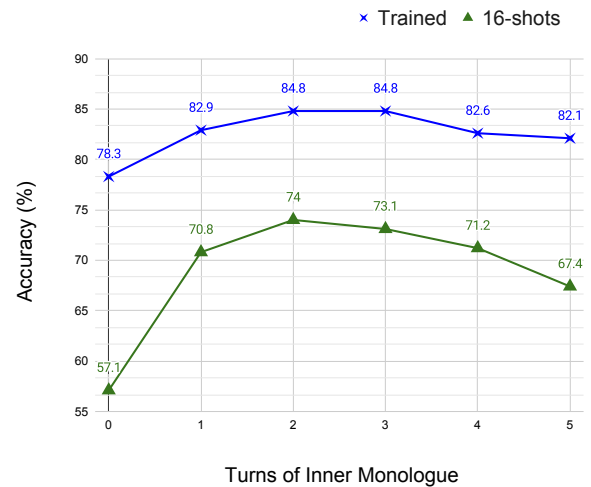


Figure 4: Ablation study on different Inner Monologue turns using on ScienceQA test set under few-shot and trained manner.

while it’s possible to include more Observers with different modalities or functionalities. Due to the resource limits, we used a synthetic way to generate supervised training data, while organizations with ample resources could hire human annotators to provide more labeled data with higher quality. The reward function could also be further studied. More importantly, our proposed approach is an automated way of generating intermediate steps Chain-of-Thought, and we expect the concept of Inner Monologue can be widely applied to a variety of use cases.

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