# NOT HOW YOU THINK, IT'S WHAT YOU SEE: DECOUPLING PERCEPTION FROM REASONING

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## ABSTRACT

The ability of Vision-Language Models (VLMs) to reason depends on a complex interplay between visual perception and abstract cognition. While it is widely recognized that perception is a significant bottleneck, systematically diagnosing how it fails and developing methods to unlock latent reasoning capabilities remains a key challenge. To address this, we introduce a cognitively-inspired framework that decomposes VLM behavior through four distinct paradigms: 1) Direct Visual Rule Learning (holistic processing), 2) Deductive Rule Learning (explicit rule extraction), 3) Componential Analysis (CA), which decouples perception by reasoning over task-agnostic textual descriptions, and 4) Interactive Componential Analysis (ICA), which introduces a feedback loop for targeted visual probing. Our framework's emphasis on task-agnostic decomposition and cognitive parallels provides a unique lens for analysis compared to prior decoupling efforts. Applying this framework across an expanded suite of benchmarks, we conduct a comprehensive evaluation on both proprietary and open-source multi-image VLMs. Our results confirm that perception is a primary bottleneck and show that our CA and ICA paradigms yield substantial performance gains, unlocking the latent reasoning abilities of powerful LLMs. Crucially, ICA demonstrates that an interactive loop can resolve fine-grained visual ambiguities that static descriptions cannot, outperforming the non-interactive CA approach. Our work provides a robust diagnostic toolkit for the community and offers concrete architectural insights, demonstrating that interactive, decoupled systems are a promising path toward more general and capable visual intelligence.

## 1 INTRODUCTION

Human cognition adeptly integrates visual perception with abstract reasoning to navigate the world (Kunda, 2020; Lake et al., 2017). While Vision-Language Models (VLMs) have made remarkable progress (Zhao et al., 2023; Radford et al., 2021), their ability to perform complex visual reasoning remains brittle. It is widely recognized that a primary failure point is the model's visual perception, but we lack systematic tools to diagnose how these perceptual systems fail and frameworks to mitigate these failures to unlock latent reasoning.

To investigate these questions, we test models on two challenging task families that probe the limits of perception and reasoning. First, Bongard Problems (BPs) (Bongard, 1968), a classic test requiring few-shot discovery of an abstract visual rule. We use natural image variants, Bongard-OW (Wu et al., 2024) and Bongard-HOI (Jiang et al., 2022). Second, Winoground (Thrush et al., 2022), which tests visio-linguistic compositional reasoning through minimally contrastive image-caption pairs.

This paper introduces an evaluation framework designed to dissect the cognitive processes of VLMs on these tasks. Our core contribution is a framework grounded in cognitive science that, unlike prior work that inventories static capabilities, uses dynamic paradigms to model problem-solving strategies:

1. **Direct Visual Rule Learning (DVRL):** Simulates holistic processing (Biederman, 1987), where the model analyzes all images simultaneously.
2. **Deductive Rule Learning (DRL):** Mimics explicit, rule-based deduction (Rips, 1994), separating rule extraction from application.

3. **Componential Analysis (CA):** Parallels analytical decomposition (Gluck et al., 2008), reasoning over structured, task-agnostic textual descriptions.
4. **Interactive Componential Analysis (ICA):** Extends CA with a feedback loop, allowing the reasoning module to actively probe the perception module for targeted details.

This framework allows for systematic analysis of VLM behavior, identifying specific processing bottlenecks. By generating comprehensive, *task-agnostic* image descriptions, our componential paradigms allow us to *disentangle perception from reasoning*. ICA enhances this by enabling a dynamic perceptual process guided by reasoning needs. This approach facilitates multi-image reasoning on single-image architectures and even allows us to evaluate text-only LLMs by providing high-quality descriptions (Section 7.2).

Applying this framework across a broadened set of benchmarks and models, we find that our CA and ICA paradigms yield substantial performance gains. These methods achieve highly competitive results on Bongard-OW, Bongard-HOI, and Winoground, primarily by pairing high-fidelity descriptions with powerful reasoning models. This success across diverse tasks highlights the robustness of decoupling perception from reasoning. Concurrently, our analysis confirms a significant *perception bottleneck*, as models' performance drastically improves when their perceptual front-end is bypassed or guided.

Our contributions are:

1. A novel, cognitively-inspired framework with four distinct paradigms (including interactive reasoning) for the diagnostic evaluation of VLMs.
2. A componential method (CA and ICA) to disentangle perception from reasoning, enabling multi-image task evaluation for diverse architectures and unlocking latent reasoning in LLMs.
3. Comprehensive empirical results on multiple benchmarks and models, confirming the perception bottleneck and demonstrating that our interactive, decoupled methods can significantly mitigate it.
4. A demonstration of the effectiveness of this approach, achieving strong, competitive performance on challenging visual reasoning tasks.

## 2 Related Work

**VLM Benchmarks.** The evaluation of VLMs has rapidly evolved from foundational tasks like VQA (Antol et al., 2015) to benchmarks testing more complex reasoning. Recent efforts focus on multi-image understanding through interleaved corpora (Laurençon et al., 2024) and dedicated benchmarks such as MuirBench (Wang et al., 2024) or low-level perception tests like BLINK (Fu et al., 2024). Our work complements these by focusing on benchmarks specifically designed to probe core cognitive abilities that resist simple linguistic mediation: abstract few-shot rule discovery using natural image Bongard Problems (BPs) (Wu et al., 2024; Jiang et al., 2022) and fine-grained compositional reasoning via Winoground (Thrush et al., 2022).

**Cognitive Science Grounding.** Our framework is grounded in cognitive science perspectives on human problem-solving (Newell et al., 1972). Our paradigms model distinct cognitive strategies: *Direct Visual Rule Learning (DVRL)* mirrors rapid, holistic processing (Biederman, 1987); *Deductive Rule Learning (DRL)* reflects explicit, rule-based deduction (Rips, 1994); and our *Componential Analysis (CA)* paradigms parallel analytical decomposition, where problems are broken into constituent parts for systematic reasoning (Gluck et al., 2008).

**Decoupling Frameworks and Chain-of-Thought.** Our approach is related to a growing body of work on decoupling perception and reasoning in VLMs. This includes Multimodal Chain-of-Thought (CoT) prompting (Zhang et al., 2023; Zheng et al., 2023) and dedicated evaluation frameworks. For instance, Prism (Qiao et al., 2024) provides a valuable framework for assessing a static inventory of fine-grained VLM skills like object recognition and counting.

Our contribution is distinct in three key ways. First, our paradigms are grounded in cognitive processes (e.g., holistic vs. deductive), analyzing how a model solves a problem, not just what skills it possesses. Second, our CA paradigm deliberately uses task-agnostic descriptions, creating a

clean separation between raw perceptual capability and downstream reasoning, unlike many CoT methods that generate task-conditioned descriptions. Finally, our new Interactive CA (ICA) paradigm introduces a novel dynamic feedback loop, where the reasoning module actively probes the perception module. This moves beyond the static, one-pass evaluations common in prior work to model a more realistic, iterative reasoning process.

## 3 MODELS

We evaluated a diverse suite of VLMs, distinguishing between models based on their multi-image context capacity. State-of-the-art proprietary systems, including **GPT-4o** (OpenAI, 2024) and **Gemini 2.0** (Google, 2024), can natively process the large number of images (13) required for our DVRL and DRL paradigms on Bongard Problems. In contrast, while some contemporary open-source models like **Pixtral-12B** (Agrawal et al., 2024), **Llama-Vision-3.2** (Meta, 2024), and **LLaVA** variants (Liu et al., 2023; XTuner, 2025) accept multiple images, none currently support the large context required for a direct evaluation in these paradigms. This technical constraint underscores the necessity of our Componential Analysis (CA) paradigm as the primary method for assessing complex, multi-image reasoning on these powerful open-source architectures. For ablation studies, we also used text-only LLMs (**Llama3** (Grattafiori et al., 2024), **Phi-4** (Abdin et al., 2024), etc.). All evaluations used few-shot prompting at zero temperature. Further details are in Appendix A.4.

## 4 DATASET AND TASK

We test our framework on a diverse suite of benchmarks chosen to probe distinct cognitive abilities. Our primary testbed is Bongard-OW (Wu et al., 2024), a 500-case subset testing few-shot abstract rule discovery on natural images (see Figure 1 for an example). To assess generalization, we use Bongard-HOI (Jiang et al., 2022) (400 samples) to evaluate reasoning about human-object interactions, and Winoground (Thrush et al., 2022) (400 samples) for fine-grained compositional grounding. Together, these tasks provide a robust testbed for analyzing high-level visual reasoning, from abstraction to compositionality, across our different cognitive paradigms.


Figure 1: Example Bongard-OW task. *Left*: Positive examples. *Center*: Negative examples. *Right*: Query. Rule: *A group photo at a wedding reception*. Query is negative. (3 of 6 examples shown per set).

## 5 COGNITIVELY-INSPIRED EVALUATION PARADIGMS

We evaluate VLMs using four paradigms designed to probe different facets of visual reasoning and assess performance under systematically varied cognitive demands, inspired by human cognitive strategies. All paradigms require the model to output a structured response including analysis, the derived rule, query description, and classification (`positive/negative`). Figure 2 provides a schematic overview. Specific prompts are detailed in Appendix A.5.

### 5.1 DIRECT VISUAL RULE LEARNING (DVRL)

This paradigm assesses holistic reasoning by presenting all 13 images (6 positive, 6 negative, 1 query) simultaneously to the VLM. It demands the model integrate information across the entire set to identify the rule and classify the query in one step. This mirrors the human ability to quickly grasp the 'gist' of a visual scene or problem. Due to requiring simultaneous multi-image input, only models like Gemini 2.0 and GPT-4o were tested under this paradigm.

### 5.2 DEDUCTIVE RULE LEARNING (DRL)

Mimicking deliberative, rule-based deduction, DRL involves two stages:

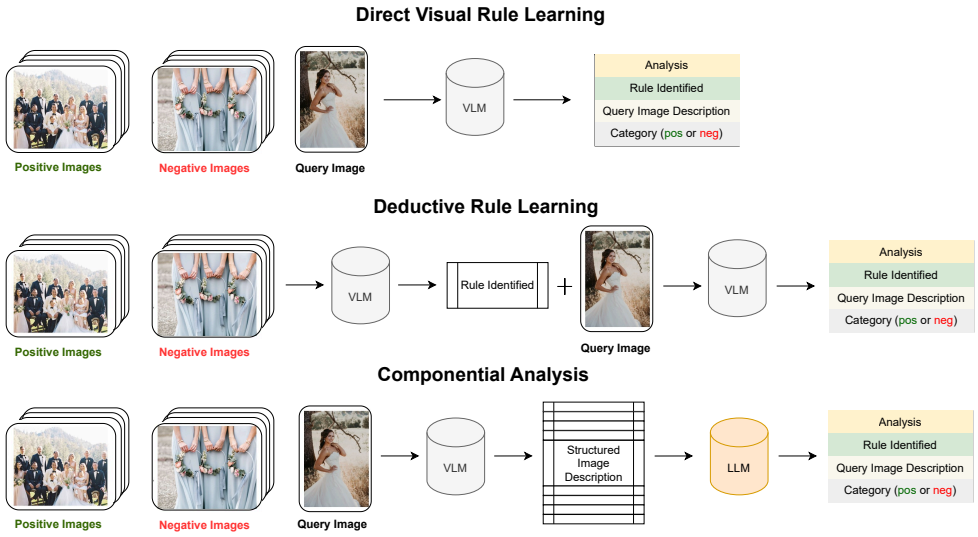


Figure 2: **Cognitively-Inspired Evaluation Paradigms. DVRL** (Direct Visual Rule Learning): Concurrent processing of all images, mimicking holistic perception. Requires multi-image input capability. **DRL** (Deductive Rule Learning): Two-stage process separating rule extraction from application, mimicking explicit deduction. **CA** (Componential Analysis): Multi-stage process involving individual image description followed by reasoning over text, mimicking analytical decomposition and enabling perception-reasoning separation.

1. **Rule Extraction:** The VLM analyzes the 12 context images (positive/negative sets) to identify and concisely summarize (max 20 words) the distinguishing rule.
2. **Rule Application:** The VLM receives the previously generated rule summary and the query image, classifying the query based solely on the provided rule.

This separation allows examining the fidelity of both rule formation and rule application processes.

### 5.3 Componential Analysis (CA)

Reflecting analytical problem decomposition, CA proceeds in stages based on textual representations:

1. **Image Description:** The VLM generates a detailed, structured, and ideally *task-agnostic* JSON description for each of the 13 images *individually*.
2. **Text-Based Reasoning:** A powerful LLM receives the collection of 13 JSON descriptions (labeled positive/negative/query) and performs rule extraction and query classification based *only* on this textual input.

This paradigm is crucial as it (a) allows evaluating models lacking direct multi-image input, (b) enables assessing reasoning largely independent of perceptual errors, and (c) facilitates evaluation of text-only LLMs on visual reasoning tasks.

### 5.4 Interactive Componential Analysis (ICA)

To mitigate the limitations of static perception revealed by CA, this paradigm extends it with a dynamic, multi-step feedback loop that emulates a "look again" strategy.

1. **Initial Description:** Same as in CA, the VLM generates initial, task-agnostic descriptions for each image.

2. **Ambiguity Identification & Question Formulation:** A reasoning LLM analyzes the initial descriptions and the task goal (e.g., the Winoground captions) to identify the most critical, ambiguous visual detail needed for a confident decision. It then formulates a specific, targeted question about this detail.
3. **Focused Re-Perception:** The VLM is shown the relevant image again, but this time is asked to answer only the targeted question from the previous step.
4. **Synthesized Reasoning:** The LLM integrates the initial descriptions with the new, high-precision information from the Q&A step to make its final classification.

This interactive process allows the model to actively resolve perceptual ambiguities, moving beyond a single static "glance" to perform more robust, human-like visual verification.

## 6 Results and Analysis

This section details the performance of the evaluated VLMs, beginning with the primary Bongard-OW benchmark and then examining generalizability.

### 6.1 Performance on Bongard-OW

Table 1 presents the core results on our 500-sample Bongard-OW subset. Under **Direct Visual Rule Learning (DVRL)**, applicable only to GPT-4o and Gemini 2.0, performance was strong but below optimal (Gemini 2.0: 82.2%, GPT-4o: 80.0%), suggesting limitations in purely holistic, simultaneous multi-image reasoning for this complex task.

| Model | DVRL | DRL | CA |
|---|---|---|---|
| GPT-4o | 80.0 | 88.0 | **92.8** |
| Gemini 2.0 | 82.2 | 86.8 | **93.6** |
| Pixtral-12B | - | - | 87.2 |
| Llama-Vision-11B | - | - | 53.4 |
| Llama-Vision-90B | - | - | 55.1 |
| Llava-7B | - | - | 66.2 |
| Llava-Llama3-8B | - | - | 53.2 |
| Prior SOTA | (GPT-4 + InstructBLIP) | | 63.8 |
| Human Average | (across samples) | | 91.0 |

Table 1: Classification accuracy (%) across evaluation paradigms on the Bongard-OW subset. Paradigms abbreviated: DVRL, DRL, CA. Dashes (-) indicate non-applicability due to model input limitations.

Performance improved markedly under **DRL** for both models (GPT-4o: 88.0%, Gemini 2.0: 86.8%). The explicit separation of rule extraction and application stages appears beneficial, aligning with the idea that breaking down complex cognitive tasks can improve performance.

**Componential Analysis (CA)**, reasoning over textual descriptions, yielded the highest accuracies for the top models (GPT-4o: 92.8%, Gemini 2.0: 93.6%). Notably, these results establish a **new state-of-the-art (SOTA)** on the Bongard-OW Text-score benchmark, surpassing the reported human average (91.0% Wu et al. (2024)). The previous best machine performance Wu et al. (2024) involved using GPT-4 to reason over captions generated by models such as InstructBLIP, achieving a maximum accuracy of 63.8%. Our significant improvement with the CA paradigm underscores the efficacy of its comprehensive, task-agnostic description generation (Stage 1) coupled with advanced reasoning engines (Stage 2). Pixtral-12B also achieved strong CA performance (87.2%). However, a significant gap emerged with other open-source models. Models like Llama-Vision and LLaVA variants exhibited much lower CA accuracy, often with dramatic imbalances between positive and negative sample performance (e.g., Llava-Llama3-8B: 53.2% overall, heavily biased towards negative samples). This pattern strongly suggests that the bottleneck for these models is not necessarily the abstract reasoning itself, but rather the fidelity of their internal *visual perception* and subsequent translation into usable representations. (here, text descriptions).

The consistent trend of accuracy increasing from DVRL through DRL to CA for GPT-4o and Gemini 2.0 further reinforces the value of structured reasoning and, particularly, the effectiveness of the component-based textual reasoning approach for this task when perception is adequate.

### 6.2 Performance on Bongard HOI

On Bongard-HOI, we evaluated GPT-4o and Gemini 2.0 across the four standard test splits (sosa, soua, uosa, uoua; N=100 each from balanced sampling). The results, shown in Table 2, largely replicated the trends observed on Bongard-OW. Performance systematically improved with increased paradigm structure (DVRL < DRL < CA) for both models. Our Componential Analysis (CA) paradigm, particularly with GPT-4o as the reasoning engine, achieved an average accuracy of 77.3% across the splits (with individual splits like sosa and soua reaching 83%), establishing a new state-of-the-art for VLM-based approaches on this benchmark. This surpasses prior SOTA Raghuraman et al. (2024) results from non-VLM specialized methods, such as the reported 76.4% average from a CLIP fine-tuned via PMF approach Raghuraman et al. (2024). Gemini 2.0 with CA also demonstrated strong competitive performance with an average of 74.5%. This consistency validates our framework's applicability and the benefit of structured evaluation across different complex natural image reasoning datasets. Notably, overall model performance on HOI is lower than on OpenWorld, and a significant gap remains to the high human average scores (avg. 91.4% Jiang et al. (2022)), suggesting HOI's unique challenges in discerning subtle interaction-based rules.

| Model | | Avg |
|---|---|---|
| Gemini 2.0 | **DVRL** | 50.8 |
| | **DRL** | 61.3 |
| | **CA** | 74.5 |
| GPT-4o | **DVRL** | 68.5 |
| | **DRL** | 71.8 |
| | **CA** | 77.3 |
| Prior SOTA | PMF | 76.4 |
| Human Avg. | – | 91.4 |

Table 2: Average performance (%) on Bongard-HOI four test-splits across three paradigms.

### 6.3 Performance on Winoground with Static CA

We applied our static CA paradigm to Winoground, generating task-agnostic descriptions and then using an LLM for matching. As shown in Table 3, this approach achieves new state-of-the-art results across all three metrics. Using GPT-4o as the reasoning engine yields Text: 75.5%, Image: 58.5%, and Group: 52.0%, significantly surpassing prior SOTA. This success demonstrates that our task-agnostic, decoupled strategy is highly effective not just for rule-discovery, but also for fine-grained compositional reasoning.

### 6.4 Interactive CA on Winoground: Mitigating Perceptual Gaps

While CA is powerful, we hypothesized its static, one-pass descriptions might miss the single, subtle visual detail that differentiates Winoground pairs. To address this, we applied our Interactive CA (ICA) paradigm, allowing the reasoner to "look again" by asking a targeted question to the perception module.

The results, presented in Table 3, show a significant and consistent performance uplift over the static CA approach for both models tested.

| Model | Text Score | Image Score | Group Score |
|---|---|---|---|
| **GPT-4o + CA** | **75.50** | **58.50** | **52.00** |
| Gemini 2.0 + **CA** | 71.00 | 48.75 | 42.00 |
| **GPT-4o + ICA** | **78.00** | **62.75** | **55.25** |
| Gemini 2.0 + **ICA** | 72.50 | 55.25 | 46.75 |
| Llama3.3-70B + **CA** | 68.25 | 49.25 | 41.75 |
| Qwen2.5-32B + **CA** | 67.00 | 46.25 | 40.00 |
| Phi-4-14B + **CA** | 65.25 | 46.00 | 37.75 |
| Qwen2.5-14B + **CA** | 59.25 | 34.50 | 27.25 |
| MMICL + CoCoT (Zhang et al., 2024) | 64.25 | 52.5 | 50.75 |

Table 3: State-of-the-art performance on the **Winoground benchmark** achieved using our **Componential Analysis (CA)** paradigm. Scores reported are the standard Winoground metrics: *Text Score* (correct caption selection per image description), *Image Score* (correct image selection per caption), and *Group Score* (all selections correct per sample), averaged over 400 samples.

Critically, the largest gains are on the Image and Group scores, which are most sensitive to fine-grained visual details. For instance, Gemini's Image Score improved by a remarkable 6.5 points. This demonstrates that the interactive feedback loop is highly effective at resolving the exact visual ambiguities that Winoground is designed to test. This finding confirms that the perception bottleneck is not immutable; it can be actively mitigated by a dynamic, multi-pass reasoning process that guides perception.

In summary, across diverse reasoning tasks, our Componential Analysis paradigms consistently achieve high and often state-of-the-art performance. The success of the interactive ICA variant further highlights that dynamic, decoupled approaches—where reasoning can actively probe perception—are a powerful and promising direction for building more robust and accurate VLMs.

## 7 Ablation Studies: Isolating Perception and Reasoning

To further investigate the interplay between visual perception, rule representation, and reasoning, we conducted targeted ablation studies. Both studies presented below serve to underscore the critical role of the initial representation derived from visual input – whether it's applying a rule *to* a perceived query image (Section 7.1) or reasoning *from* perceived context images (Section 7.2).

### 7.1 Rule Application Fidelity

How well can models apply an abstract rule once it's formulated? To isolate rule application from rule extraction, we provided models with high-quality rule summaries (generated by GPT-4o) and the query image, tasking them solely with classification based on the given rule. This tests the model's ability to ground the symbolic rule in the visual input of the query image.

Table 4 shows performance for several open-source models under this condition. Models like Pixtral-12B demonstrate relatively strong and balanced rule application. Comparing this to Table 1, the generally higher scores here than in CA (where models generate their own descriptions) support the idea that rule application itself is less challenging for these models than the initial perception/description phase.

| Model | Acc |
|---|---|
| LLaVA-7B + **DRL** | 72.0 |
| Llama-vision-11B + **DRL** | 68.2 |
| Pixtral-12B + **DRL** | 83.8 |
| LLaVA-13B + **DRL** | 70.0 |
| LLaVA-34B + **DRL** | 74.8 |
| Llama-vision-90B + **DRL** | 74.2 |

Table 4: **Rule Application Accuracy:** Accuracy (Acc) in % when classifying query images based on externally provided rules in DRL paradigm.

### 7.2 Impact of Description Quality on Reasoning

Complementing the previous ablation, we investigated how reasoning performance changes when the initial perceptual stage (description generation) is standardized using a high-fidelity source. We generated descriptions for all context and query images using GPT-4o and then used these descriptions as input to the reasoning stage (Stage 2) of the Componential Analysis paradigm for various target models, including weaker VLMs and even text-only LLMs.

The results in Table 5 were revealing. Providing high-quality descriptions dramatically improved the reasoning accuracy of VLMs that struggled when using their own descriptions. Llama-Vision-11B, for example, improved from 53.4% (Table 1) to 84.17%, and Llama-Vision-90B from 55.1% to 90.98%. This provides strong evidence that the reasoning capabilities of these models are significantly underestimated

| Model | Acc |
|---|---|
| Llava:7b + **CA** | 80.56 |
| Llava:34b + **CA** | 81.56 |
| Llama-vision:11b + **CA** | 84.17 |
| Llama-vision:90b + **CA** | 90.98 |
| Deepseek-r1:14b + **CA** | 87.98 |
| Gemma2:27b + **CA** | 88.98 |
| Qwen2.5:7b + **CA** | 90.38 |
| Phi4:14b + **CA** | 91.98 |
| Qwen2.5:32b + **CA** | 92.79 |
| Qwen2.5:14b + **CA** | 92.99 |

Table 5: **Impact of High-Quality Descriptions**: Accuracy (Acc) in % using Componential Analysis (Stage 2 reasoning) with image descriptions generated externally by GPT-4o. Includes VLMs and LLMs models respectively separated by line.

by end-to-end evaluations; their primary limitation lies in generating accurate perceptual representations. Further illustrating this sensitivity to description source quality, Table A.6 in the Appendix details a comparison using components generated by Pixtral-12B.

Remarkably, this approach also enabled text-only LLMs to perform the visual reasoning task effectively. Models such as Phi-4 (14B) achieved 91.98% accuracy, while several Qwen models also exceeded 90%. This demonstrates that: (1) High-quality textual descriptions can serve as effective surrogates for visual input, enabling modality transfer for reasoning tasks. (2) The CA paradigm, particularly when coupled with controlled descriptive input, serves as a powerful tool for isolating and evaluating the core symbolic reasoning abilities of both VLMs and LLMs, independent of their integrated perceptual systems. These findings strongly reinforce the conclusion that improving visual perception is paramount for enhancing end-to-end visual reasoning in many current models.

### 7.3 Additional Analysis

**Semantic Similarity Analysis** during DRL (Table A.3) confirmed that derived rules generally aligned well with query descriptions, particularly for positive samples. The relatively high similarity for negative samples highlights the challenge of the dataset's near-miss counterexamples.

**Qualitative Error Analysis** Examining samples misclassified by both top models (GPT-4o, Gemini 2.0) under CA revealed recurring error patterns (details in Appendix A.7.7, Table A.9). Frequent issues involved over-generalizing rules, missing critical objects/properties present in positive examples, focusing on spurious correlations, or failing to consistently apply derived rules. These qualitative examples underscore that even highly capable models exhibit fragility in nuanced visual detail processing and robust symbolic rule manipulation.

## 8 Discussion

This research leveraged a cognitively-inspired framework to dissect the mechanisms of visual reasoning in VLMs. By evaluating performance across paradigms mirroring human cognitive strategies (holistic-*DVRL*, deductive-*DRL*, analytical-*CA*), we moved beyond aggregate scores to probe how these models process complex information. A central finding emerges: a critical perception bottleneck limits many contemporary VLMs, masking strong downstream reasoning capabilities. While advanced models (GPT-4o, Gemini 2.0) excel when reasoning over high-fidelity textual descriptions, many open-source models falter, pointing to failures in reliably extracting relevant visual information.

The success of the CA paradigm is particularly insightful. Its strength lies in effectively decoupling perception from reasoning via task-agnostic descriptions. Unlike context-dependent CoT approaches, CA first builds a comprehensive, independent textual "world model" of each image. This allows powerful LLMs to apply their sophisticated reasoning abilities on a clean, symbolic representation. The resulting robust performance across different reasoning types (abstraction in BPs, compositionality in Winoground) suggests that modular architectures—featuring specialized perception modules that output rich symbolic data for general reasoning engines—are a highly promising direction.

The success of our Interactive CA (ICA) paradigm takes this insight a crucial step further. While static CA bypasses the bottleneck, ICA demonstrates how to actively mitigate it. On a fine-grained task like Winoground, where a single detail is critical, the ability for the reasoner to formulate a targeted question and prompt a "second look" from the perception module led to significant performance gains (Table 3). This result is pivotal: it suggests the perception bottleneck is not an immutable property but often a failure of one-pass processing. By modeling a more realistic, iterative process of verification—akin to human visual scanning—ICA shows that the connection between perception and reasoning modules should not be a one-way street, but a dynamic, bidirectional dialogue.

Our ablation studies provide strong converging evidence. Isolating reasoning by providing high-quality external descriptions (Section 7.2) resulted in dramatic performance improvements for bottlenecked models and enabled high performance even from text-only LLMs. This clearly demonstrates that a model's latent reasoning capability often far exceeds what its end-to-end performance suggests.

In conclusion, our cognitively-inspired framework serves a dual purpose. It is both a valuable diagnostic tool for pinpointing the prevalent perception bottleneck and a proof-of-concept for a more powerful architectural class. The success of our componential, and especially our interactive, paradigms reveals the significant latent reasoning potential within today's models. More importantly, it offers a clear path forward: building modular, interactive systems where reasoning can dynamically guide perception is a key step towards more robust and general visual intelligence.

**Limitations** Our work has several important limitations that define avenues for future research.

The primary limitation of our componential paradigms (CA and ICA) is their reliance on language as an intermediate representation. Their effectiveness is likely highest on tasks where critical visual properties are readily verbalizable. For challenges that hinge on non-verbalizable or geometric reasoning—such as the fine-grained correspondence tasks in benchmarks like BLINK (Fu et al., 2024)—the utility of a purely text-mediated approach may be reduced. While our interactive ICA shows that a dynamic dialogue can resolve ambiguities missed by static descriptions, its scope is still bounded by what can be effectively queried and described in text.

Second, while our study covers abstract, compositional, and interactive reasoning, the framework's applicability to other complex visual domains, such as scientific chart interpretation or mathematical reasoning, requires further investigation.

Finally, we acknowledge several practical scope limitations. This work did not conduct a systematic analysis of prompt sensitivity, a known factor in VLM performance. A deeper investigation into the computational costs and latency trade-offs of our multi-stage paradigms, especially the interactive ICA, is also warranted for practical application.

## 9 Conclusion

This paper introduced a cognitively-inspired framework to dissect the perception-reasoning interface in VLMs. Through four distinct paradigms—including our novel Interactive Componential Analysis (ICA)—we systematically analyzed VLM problem-solving strategies, revealing two key insights. First, our diagnostic approach confirms that a critical perception bottleneck limits many contemporary VLMs, masking significant latent reasoning abilities.

Second, and more importantly, we demonstrate a powerful architectural solution. Our componential paradigms, which decouple perception from reasoning via task-agnostic textual descriptions, achieve highly competitive performance across diverse benchmarks testing abstraction (Bongard-OW), interaction (Bongard-HOI), and compositionality (Winoground). The success of the interactive ICA paradigm, which allows the reasoning module to actively probe and guide perception, is particularly significant. It shows that the perception bottleneck is not an immutable barrier but can be dynamically mitigated.

Ultimately, our work suggests that the path toward more robust visual intelligence lies not just in scaling monolithic models, but in developing modular, interactive architectures. By providing both a diagnostic toolkit and a proof-of-concept for this interactive approach, we offer a blueprint for a new class of systems capable of more deliberate, verifiable, and human-like visual reasoning.

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# APPENDIX

## A.1 BROADER RELEVANCE

This study offers insights with broader implications for developing more robust and human-like AI systems. Our cognitively-inspired evaluation paradigms provide valuable tools for assessing and understanding the strengths and limitations of Vision-Language Models (VLMs) on complex visual reasoning tasks. The insights gained extend beyond Bongard problems, contributing to the development of VLMs capable of advanced reasoning in real-world applications. Our key finding regarding the visual processing bottleneck in many models has significant implications for future research aimed at bridging the performance gap and unlocking the full potential of accessible models. The demonstration of high performance by advanced VLMs underscores the potential for sophisticated visual understanding, reinforcing the importance of architectures integrating robust perception and reasoning. Finally, our comparative evaluation contributes to discussions about AI accessibility and transparency, identifying specific areas for improvement and paving the way for more reliable AI.

## A.2 ATTENTION AND MEMORY IN VISUAL REASONING

While our study primarily focuses on the interplay between perception and reasoning, the roles of attention and memory are also implicitly present in our paradigms. The DVRL paradigm likely engages VLM "visual attention" mechanisms (Bahdanau et al., 2016) to identify salient features across the image set, akin to human holistic processing (Biederman, 1987; Li et al., 2002). DRL relies on the model's ability to "memorize" the extracted rule, involving processes related to working memory (Baddeley, 2012) and internal representation storage (Squire, 1992). Although not directly measured, their involvement is inherent. Future work could explore these aspects more explicitly, perhaps via attention map analysis (Vaswani et al., 2017) or probing memory representations (Vaishnav and Serre, 2023).

## A.3 DATASET DETAILS

### A.3.1 BONGARD OPENWORLD DATASET

We utilize a subset of 500 test cases from the Bongard OpenWorld dataset (Wu et al., 2024). The full dataset contains 1001 samples, each with 7 positive and 7 negative real-world images distinguished by a "commonsense" rule. Our evaluation set was created by taking the first 250 samples and generating two test cases from each (one positive query, one negative query), resulting in 500 balanced test cases. Specific sample IDs used will be released.

#### A.3.1.1 COMMONSENSE VALUE CATEGORIES

Table A.1 summarizes the rule categories.

| ID | Concept Category | Example |
|---|---|---|
| 0 | Anything else | Animals are running. |
| 1 | Human-Object Interaction (HOI) | A person playing the guitar. |
| 2 | Taste / Nutrition / Food | A plate of high-calorie food. |
| 3 | Color / Material / Shape | A wooden floor in the living room. |
| 4 | Functionality / Status / Affordance | An animal capable of flying in the tree. |
| 5 | And / Or / Not | A man without beard. |
| 6 | Factual Knowledge | A building in US capital. |
| 7 | Meta Class | Felidae animals. |
| 8 | Relationship | A bench near trees. |
| 9 | Unusual Observations | Refraction of light on a glass cup. |

Table A.1: Commonsense ID Categories and Examples in Bongard OpenWorld dataset (Wu et al., 2024).

#### A.3.1.2 COMMONSENSE VALUE DISTRIBUTION IN OUR SUBSET

Table A.2 shows the distribution in our subset. Category '0' is predominant.

| ID | Count | Percentage (%) |
|---|---|---|
| 0 | 365 | 73.0 |
| 3 | 36 | 7.2 |
| 9 | 26 | 5.2 |
| 1 | 15 | 3.0 |
| 2 | 14 | 2.8 |
| 4 | 12 | 2.4 |
| 5 | 10 | 2.0 |
| 6 | 10 | 2.0 |
| 8 | 8 | 1.6 |
| 7 | 4 | 0.8 |
| **Total** | **500** | **100.0** |

Table A.2: Distribution of Commonsense ID Categories in the 500 Bongard-OW test cases used in our evaluation subset.

### A.3.2 BONGARD-HOI DATASET

To assess generalizability on natural images with a different reasoning focus (human-object interactions), we used the Bongard-HOI dataset (Jiang et al., 2022). We evaluated performance on its four standard test splits, defined by object/action novelty:

- `sosa`: seen object, seen action
- `soua`: seen object, unseen action
- `uosa`: unseen object, seen action
- `uoua`: unseen object, unseen action

The original splits vary significantly in size and balance (e.g., `sosa`: 200 pos/200 neg queries; `soua`: 2236 pos/1348 neg; `uosa`: 660 pos/660 neg; `uoua`: 695 pos/695 neg). For consistent cross-split evaluation in this work, we created balanced subsets by sampling 100 test cases from each of the four splits, ensuring an equal distribution of 50 positive and 50 negative query images per split. This resulted in a total evaluation set of 400 samples for Bongard-HOI (100 per split), used for the results reported in Table 2.

### A.3.3 WINOGROUND DATASET

To test performance on fine-grained visio-linguistic compositional reasoning, we utilized the Winoground dataset (Thrush et al., 2022). This dataset comprises 400 samples specifically designed to challenge compositional understanding. Each sample contains a pair of minimally contrastive images $(I_0, I_1)$ and a corresponding pair of minimally contrastive captions $(C_0, C_1)$, requiring models to correctly match image $I_0$ to caption $C_0$ and image $I_1$ to caption $C_1$. We used all 400 samples provided in the standard dataset release for our Winoground evaluations reported in Section 6.3 and Table 3.

### A.3.4 DATASET AVAILABILITY

Bongard OpenWorld: `https://rujiewu.github.io/Bongard-OW.github.io/`.
Bongard-HOI: `https://github.com/NVlabs/Bongard-HOI/blob/master/assets/dataset.md`.
Winoground: `https://huggingface.co/datasets/facebook/winoground`

Details on the specific subsets and samples used in our evaluations will be released upon publication.

## A.4 Model and Experiment Details

### A.4.1 Model Details

**VLMs:** GPT-4o; Gemini 2.0; Pixtral-12B; Llama-Vision-3.2 (11B, 90B); LLaVA (Llama-2 based; 7B, 13B, 34B); LLaVA-Llama3-8B. **Text-Only LLMs (for Ablation 7.2):** Phi-4 (14B) (Abdin et al., 2024); Qwen2.5 (7B, 14B, 32B) (Yang et al., 2024); Deepseek-r1 (32B, 70B) (Guo et al., 2025); Gemma2 (27B) (Team et al., 2024).

### A.4.2 Experiment Configuration

- **Access:** APIs for closed models; Ollama for open models.
- **Input:** Base64 images in prompts (see Appendix A.5).
- **Image Handling:** API defaults or max 1024px (Ollama). Multi-image calls for DVRL where supported.
- **Decoding:** Temperature 0.
- **Fine-tuning:** None.
- **Hardware:** NVIDIA GPUs (2080Ti, 3090, 6000 Ada).

### A.4.3 Evaluation Metrics

- **Classification Accuracy:** Primary metric (% correct).
- **Semantic Similarity:** Cosine similarity of OpenAI embeddings ('text-embedding-3-large') between descriptions/rules. Inspired by (Risch et al., 2021).

### A.4.4 Winoground Score Calculation using Componential Analysis

This section defines the calculation of Winoground (Thrush et al., 2022) scores (`text_score`, `image_score`, `group_score`) within our Componential Analysis (CA) paradigm (Section 6.2).

In the standard Winoground task, a sample $i$ consists of two images $I_{0,i}, I_{1,i}$ and two captions $C_{0,i}, C_{1,i}$, where $(C_{0,i}, I_{0,i})$ and $(C_{1,i}, I_{1,i})$ are the ground truth correct pairs. Models are typically evaluated based on a scoring function $s(C, I)$ indicating the match between a caption and an image.

In our CA paradigm, the reasoning model (Stage 2) does not access images $I_{0,i}, I_{1,i}$ directly. Instead, it operates on textual image descriptions $D_{0,i}, D_{1,i}$ generated in Stage 1. The model is prompted to make explicit choices about the best match between descriptions and captions. Let $Choice_C(D_k, \{C_0, C_1\})$ denote the caption ($C_0$ or $C_1$) chosen by the model as the best match for description $D_k$. Similarly, let $Choice_D(C_k, \{D_0, D_1\})$ denote the description ($D_0$ or $D_1$) chosen for caption $C_k$.

The scores for each sample $i$ in the dataset $W$ (where $N = |W| = 400$) are calculated as follows:

**1. Text Score ($f_{CA}$):** This measures if the correct caption is selected for each image description. We use an indicator function $\mathbb{I}[\cdot]$ which is 1 if the condition inside is true, and 0 otherwise.

$$f_{CA}(i) = \mathbb{I}\Big[\begin{array}{c} Choice_C(D_{0,i}, \{C_{0,i}, C_{1,i}\}) = C_{0,i} \\ and \\ Choice_C(D_{1,i}, \{C_{0,i}, C_{1,i}\}) = C_{1,i} \end{array}\Big] \tag{1}$$

This score is 1 only if the model correctly identifies the caption for *both* description $D_{0,i}$ and description $D_{1,i}$.

**2. Image Score ($g_{CA}$):** This measures if the correct image description is selected for each caption.

$$g_{CA}(i) = \mathbb{I}\Big[\begin{array}{c} Choice_D(C_{0,i}, \{D_{0,i}, D_{1,i}\}) = D_{0,i} \\ and \\ Choice_D(C_{1,i}, \{D_{0,i}, D_{1,i}\}) = D_{1,i} \end{array}\Big] \tag{2}$$

This score is 1 only if the model correctly identifies the description for *both* caption $C_{0,i}$ and caption $C_{1,i}$.

**3. Group Score ($h_{CA}$):** This requires all associations within the sample to be correct.

$$h_{CA}(i) = f_{CA}(i) \wedge g_{CA}(i) \tag{3}$$

Equivalently, $h_{CA}(i) = 1$ if and only if $f_{CA}(i) = 1$ and $g_{CA}(i) = 1$.

## A.5 Model Prompts

### A.5.1 Direct Visual Rule Learning

The prompt used for the Direct Visual Rule Learning paradigm is designed to elicit a holistic analysis of the provided images, encouraging the model to identify a distinguishing rule and apply it to the query image. The prompt emphasizes the distinction between positive ($cat\_2$) and negative ($cat\_1$) examples and guides the model to provide a structured output containing its analysis, the identified rule, details about the query image, and the final classification.

```
def visual_concept_test_prompt(m, n):
    """
    Generates a visual analysis prompt.

    Args:
        m (int): Number of positive samples.
        n (int): Number of negative samples.

    Returns:
        str: The formatted prompt string.
    """
    return f"""
    You are provided with {m + n + 1} images: the first {m} samples are
        `cat_2`, the next {n} samples are `cat_1`, and the last image is
        the `query image`.
    Analyze the common characteristics or patterns found in the `cat_2`
        samples (positive samples: following 1 common rule) that
        distinctly separate them from the `cat_1` samples (negative
        samples: it might not follow any possible rule).
    Your task is to:

    1. Determine the rule or criterion that distinguishes the `cat_2`
        samples from the `cat_1` ones.
    2. Analyse the `query image` (last image).
    3. Provide your conclusion for the `query image` if it can be
        categorized as either `cat_1` or `cat_2` based on the analysis
        and the rule.

    Ensure that the output is clear, well-formatted, and free of
        unnecessary explanations.
    Omit the ``` tags at the beginning and end of the page. The format
        of your output should be as follows:

    - **Analysis**: (Your analysis here)
    - **Rule**: (The distinguishing rule here)
    - **Query Image**: (Query image details)
    - **Conclusion**: (cat_1 or cat_2)
    """
```

### A.5.2 Deductive Rule Learning

The Deductive Rule Learning paradigm employs a two-stage prompting strategy. The first stage focuses on rule extraction from positive and negative examples, while the second stage applies the extracted rule to classify a query image. The prompts for each stage are detailed below.

#### A.5.2.1 First-Stage Prompt (Rule Extraction)

This prompt guides the model to identify and summarize a distinguishing rule based on provided positive and negative examples. It emphasizes conciseness in the rule summary.

```
    def visual_concept_prompt(m, n):
    try:
        if m < 0 or n < 0:
            raise ValueError(f"Invalid input: m and n must be
                non-negative. Received m={m}, n={n}.")

        if m > 0 and n > 0:
            prompt = f"""
                You are provided with {m + n} images: the first {m}
                    samples are cat_2, the next {n} samples are cat_1.
                    Analyze the common characteristics or patterns found
                    in the cat_2 samples (positive samples: following 1
                    common rule) that distinctly separate them from the
                    cat_1 samples (negative samples: it might not follow
                    any possible rule).
                Your task is to provide the rules that defines cat_2
                    samples. At the end, write "summary" of the rule
                    identified in less than 20 words.
                Ensure that the output is clear, well-formatted, and
                    free of unnecessary explanations. Omit the ``` tags
                    at the beginning and end of the page.
                """
        if n == 0:
            prompt = f"""
                You are provided with {m} images: {m} samples are cat_2.
                    Analyze the common characteristics or patterns found
                    in the cat_2 samples (positive samples: following 1
                    common rule) that distinctly separate them from
                    negative samples which might not follow any possible
                    rule.
                Your task is to provide the rules that defines cat_2
                    samples. At the end, write "summary" of the rule
                    identified in less than 20 words.
                Ensure that the output is clear, well-formatted, and
                    free of unnecessary explanations. Omit the ``` tags
                    at the beginning and end of the page.
                """
        return prompt

    except ValueError as e:
        print(f"Error: {e}")
        raise
```

#### A.5.2.2 Second-Stage Prompt (Rule Application)

This prompt presents the previously extracted rule summary and a query image, prompting the model to classify the image based on the rule. It reinforces the Bongard problem context and requests a structured output.

```
# Define the visual analysis prompt
def visual_concept_test_prompt(m, n, summary):
    return f"""
    We are working with Bongard dataset where there are {m} image in the
        cat_2 and {n} images in the cat_1. Summary of the common
        characteristics or patterns found in the cat_2 samples (positive
        samples: following 1 common rule) that distinctly separate them
        from the cat_1 samples (negative samples: it might not follow
        any possible rule) is as follows: \n {summary}.
```

```
    Your task is to ponder over the rule and provide your conclusion for
        the ‘query image‘ if it can be categorized as either "cat_1" or
        "cat_2".

    Ensure that the output is clear, well-formatted, and free of
        unnecessary explanations.
    Omit the ‘‘‘ tags at the beginning and end of the page. The format
        of your output should be as follows:

    - **Analysis**: (Your analysis here)
    - **Rule**: (The distinguishing rule here)
    - **Query Image**: (Query image details)
    - **Conclusion**: (cat_1 or cat_2)
    """
```

### A.5.3 Componential Analysis

The Componential Analysis paradigm also uses a two-stage prompting strategy. The first stage generates detailed image descriptions, while the second stage derives a rule from these descriptions and applies it to a query image. The specific prompts for each stage are presented below.

#### A.5.3.1 First-Stage Prompt (Image Description Generation)

This prompt instructs the model to generate a comprehensive, hierarchical description of a given image in JSON format. It guides the model to cover various aspects of the image, from scene and objects to activities and contextual elements, facilitating detailed comparative analysis in the subsequent stage.

```
# Define the visual analysis prompt
def visual_concept_prompt():
    """
    Generates a visual analysis prompt.

    Args:

    Returns:
        str: The formatted prompt string.
    """
    return """
            Carefully examine the provided image and identify all
                possible visual elements, organizing them into a
                detailed hierarchical structure. Start with broad
                categories and progress to more specific subcategories.
                This should cover everything visible in the image,
                ensuring no detail is overlooked. Structure your
                findings in a JSON format to enable easy comparison and
                synthesis of data from other images. This will help
                discern patterns, contexts, and rules valuable for
                identifying or understanding query images.

            Your hierarchy might encompass the following elements:

            1. **Scene/Environment**: Description of the overall setting
                depicted, such as urban, natural, indoor, or outdoor
                scenes.
            2. **Objects**: Define distinct items or entities present in
                the scene.
            - **Living Beings**: Animals, humans, or other biological
                entities.
                - Species or classification (e.g., dog, bird, human).
                - Characteristics (e.g., color, posture, movement).
            - **Inanimate Objects**: Both synthetic and natural elements.
                - Categories (e.g., vehicle, building, trees).
```

```
            - Properties (e.g., color, size, material, shape).
        3. **Activities**: Observable actions or interactions
            involving any objects or beings.
        - Specific descriptions of actions (e.g., walking, flying).
        - Participants involved in these actions.
        4. **Contextual Elements**: Environmental conditions and
            time markers, such as time of day or weather.
        - Detailed characteristics (e.g., cloudy, night, winter).
        5. **Visual Patterns**: Prominent colors, textures, and
            patterns that are visually significant.
        6. **Emotional Undertones**: Any emotional presence or
            expressions evident in the image.
        7. **Textual Information**: Any visible text within the
            image, including what it says and its visual style.
        8. **Summary**: A concise narrative summarizing the overall
            content and context of the image.

        Ensure that every aspect from the image is represented under
            these categories. The information should be presented in
            the following JSON format:

        {
        "Scene": {
            "Description": "..."
        },
        "Objects": {
            "Living Beings": [...],
            "Inanimate Objects": [...]
        },
        "Activities": [...],
        "Contextual Elements": {
            "Time of Day": "...",
            "Weather": "..."
        },
        "Visual Patterns": {
            "Dominant Colors": [...],
            "Textures": [...]
        },
        "Emotional Undertones": "..."
        "Textual Information": "..."
        "Summary": "..."
        }
        Ensure that the JSON output is clear, well-formatted, and
            free of unnecessary explanations. Omit the ```json tags
            at the beginning and end of the page.
        """
```

#### A.5.3.2 Second-Stage Prompt (Rule Derivation Instruction)

This prompt guides the model to analyze the JSON descriptions generated in the first stage, derive a distinguishing rule, and apply it to classify a query image. It emphasizes the use of the provided JSON format and requests a structured output.

```
def user_eval_prompt(all_image_specs, m, n):
    return f"""
        We are working with the Bongard dataset, which contains {m}
            images in cat_2 (positive samples) and {n} images in cat_1
            (negative samples). These categories are defined as follows:
        - Cat_2: Positive samples that follow a single common rule.
        - Cat_1: Negative samples that may not follow any specific rule.

        The image descriptions for the positive samples, negative
            samples, and the test image are provided in JSON format.
```

```
            Analyze the common patterns or characteristics in the cat_2
            samples that distinguish them from cat_1 samples.

        Your task is to:
        1. Derive the rule that defines the cat_2 samples.
        2. Apply this rule to categorize the test image.

        Here are the image descriptions:

        ### Positive Samples (cat_2):
        {all_image_specs[:m]}

        ### Negative Samples (cat_1):
        {all_image_specs[m:m+n]}

        ### Test Image:
        {all_image_specs[-1]}

        Provide your output in the following format:

        - **Analysis**: (Your analysis here)
        - **Rule**: (The distinguishing rule here)
        - **Test Image**: (Test image details)
        - **Conclusion**: (cat_1 or cat_2)
        """
```

## A.6 Prompts for Winoground Componential Analysis (Stage 2 Reasoning)

For the Winoground benchmark (Thrush et al., 2022), Stage 2 of our Componential Analysis (CA) paradigm requires a reasoning model to evaluate matches between image descriptions (JSON strings generated in CA Stage 1 from the Winoground images) and the provided captions. The following prompts were used to guide the reasoning LLM in selecting the best match, forming the basis for calculating the Text Score and Image Score components as detailed in Appendix A.4.4. Both prompts instruct the model to perform a systematic, step-by-step comparison and to return its analysis and final categorization in a structured JSON format.

### A.6.1 Prompt for Text Score Component Decision

The following Python function defines the prompt presented to the reasoning LLM. Given one image's detailed JSON description and two candidate captions (Caption 0 and Caption 1), the model is tasked to determine which caption has a higher possibility of matching the image description. This process is repeated for the second image description in the Winoground pair to gather the necessary data points for the Text Score.

```
def text_score_prompt(image_description, caption_0, caption_1):
    '''
    Generates a prompt for an LLM to determine if an image description
        has a higher possibility
    of matching caption_0 or caption_1 by evaluating each match
        individually and comparing them,
    using a detailed JSON description and commonsense reasoning.

    Args:
        image_description (str): A JSON string description of an image.
        caption_0 (str): The first candidate caption.
        caption_1 (str): The second candidate caption.

    Returns:
        str: The formatted prompt string.
    '''
```

```
    prompt = f"""You are provided with a detailed JSON description of a
        single image and two different captions (Caption 0 and Caption
        1). Your task is to evaluate how well the image description
        matches *each* caption individually, determine which caption
        provides a stronger match (higher possibility), and explain why.
        Apply commonsense reasoning where needed.

    **Image Description (JSON):**
    ```json
    {image_description}```

    **Caption 0:** "{caption_0}"
    **Caption 1:** "{caption_1}"

    **Instructions:**
    1.  **Deconstruct Image Description:** Identify the main entities
        (using 'id's), actions ('Activities'), attributes
        ('characteristics', 'properties'), and relationships ('Spatial
        Relationships') detailed in the JSON description. Use
        commonsense to understand the full context implied by the
        description.
    2.  **Evaluate Match with Caption 0:** Systematically check how well
        the key elements identified in Caption 0 (entities, actions,
        attributes, relationships) are supported by the details in the
        'Image Description' JSON.
        * Look for specific 'id's, 'characteristics', 'actor_ids',
            'target_ids', 'action' descriptions, 'relationship' types,
            etc., in the JSON that align with Caption 0's elements.
        * Use commonsense reasoning to map JSON details to caption terms
            (e.g., 'characteristics' like "elderly" might correspond to
            "old person").
        * Assess the overall strength of the match (e.g., "strong
            support", "partial support", "weak support",
            "contradiction"). Note any discrepancies.
    3.  **Evaluate Match with Caption 1:** Perform the same systematic
        check and assessment against Caption 1.
        * Look for specific JSON details supporting or contradicting
            Caption 1's elements.
        * Use commonsense reasoning.
        * Assess the overall strength of the match for Caption 1. Note
            any discrepancies.
    4.  **Compare Matches and Conclude:** Compare the strength of the
        match assessed for Caption 0 versus Caption 1. Explain *why* the
        image description represents one caption with a higher
        possibility or accuracy than the other. Highlight the specific
        JSON details (or lack thereof) that lead to this conclusion.
        Explicitly mention where commonsense was applied during the
        evaluation or comparison.
    5.  **Categorize:** Assign 'cat_0' if the image description has a
        higher possibility of matching Caption 0, or 'cat_1' if it has a
        higher possibility of matching Caption 1.

    Return your response strictly in the following JSON format:
    {{
        "analysis": (Your detailed analysis comparing the match strength
            for each caption against the image description, explaining
            why one is a better fit, and noting the use of commonsense),
        "category": ('cat_0' or 'cat_1')
    }}

    Do not include any text outside of the JSON structure. Your decision
        must be based on evaluating the match between the image
        description and each caption, then comparing those evaluations.
    """
    return prompt
```
```

### A.6.2 Prompt for Image Score Component Decision

Similarly, the following Python function defines the prompt used for the Image Score component. Given one caption and two candidate image descriptions (Image 0 Description and Image 1 Description, both JSON strings), the model is tasked to determine which image description has a higher possibility of matching the caption. This is repeated for the second caption in the Winoground pair.

```
def image_score_prompt(caption, image_0_description,
    image_1_description):
    '''
    Generates a prompt for an LLM to determine if a caption has a higher
        possibility
    of matching image_0_description or image_1_description by evaluating
        each match
    individually and comparing them, using detailed JSON descriptions
        and commonsense reasoning.

    Args:
        caption (str): The caption to evaluate.
        image_0_description (str): The JSON string description of the
            first image.
        image_1_description (str): The JSON string description of the
            second image.

    Returns:
        str: The formatted prompt string.
    '''
    prompt = f"""You are provided with a single caption and detailed
        JSON descriptions of two different images (Image 0 and Image 1).
        Your task is to evaluate how well the caption matches *each*
        image description individually, determine which description
        provides a stronger match (higher possibility), and explain why.
        Apply commonsense reasoning where needed.

    **Caption**: "{caption}"

    **Image 0 Description (JSON):**
    ```json
    {image_0_description}```

    **Image 1 Description (JSON):**
    ```json
    {image_1_description}```

    **Instructions:**
    1.  **Deconstruct Caption:** Identify the main entities, actions,
        attributes, and relationships mentioned in the caption (e.g.,
        "old person", "kisses", "young person"). Use commonsense to
        understand the full context implied by the caption.
    2.  **Evaluate Match with Image 0:** Systematically check how well
        the key elements identified in the caption are supported by the
        details in `Image 0 Description`.
        * Look for specific `id`s, `characteristics`, `actor_ids`,
            `target_ids`, `action` descriptions, `relationship` types,
            etc., in the JSON that align with the caption's elements.
        * Use commonsense reasoning to map caption terms to JSON details
            (e.g., "old person" might correspond to `characteristics`
            like "elderly").
        * Assess the overall strength of the match (e.g., "strong
            support", "partial support", "weak support",
            "contradiction"). Note any discrepancies.
    3.  **Evaluate Match with Image 1:** Perform the same systematic
        check and assessment against `Image 1 Description`.
        * Look for specific JSON details supporting or contradicting the
            caption's elements.
```

```
        * Use commonsense reasoning.
        * Assess the overall strength of the match for Image 1. Note any
            discrepancies.
    4.  **Compare Matches and Conclude:** Compare the strength of the
        match assessed for Image 0 versus Image 1. Explain *why* one
        description represents the caption with a higher possibility or
        accuracy than the other. Highlight the specific JSON details (or
        lack thereof) from *both* descriptions that lead to this
        conclusion. Explicitly mention where commonsense was applied
        during the evaluation or comparison.
    5.  **Categorize:** Assign 'cat_0' if the caption has a higher
        possibility of matching Image 0 Description, or 'cat_1' if it
        has a higher possibility of matching Image 1 Description.

    Return your response strictly in the following JSON format:
    {{
        "analysis": (Your detailed analysis comparing the match strength
            for each description against the caption, explaining why one
            is a better fit, and noting the use of commonsense),
        "category": ('cat_0' or 'cat_1')
    }}

    Do not include any text outside of the JSON structure. Your decision
        must be based on evaluating the match between the caption and
        each description, then comparing those evaluations.
    """
    return prompt
```

## A.7 Results and Extended Analysis

### A.7.1 Performance on Bongard Openworld

| | Gemini 2.0 | | GPT-4o | |
|---|---|---|---|---|
| **Category** | **Mean** | **Std Dev** | **Mean** | **Std Dev** |
| Positive | 0.915 | 0.02 | 0.902 | 0.02 |
| Negative | 0.868 | 0.02 | 0.866 | 0.02 |

Table A.3: Semantic Similarity (Cosine) between query descriptions and rules derived during Deductive Rule Learning.

### A.7.2 Performance on Bongard-HOI

(Refer to Table A.4 in main text)

### A.7.3 Winoground Performance Context

To contextualize the performance of our Componential Analysis (CA) paradigm applied to Gemini 2.0 on Winoground (reported in Section 6.2), we also ran evaluations using Gemini Pro Vision with several prompting strategies. Table A.5 shows these comparative results on the 400-sample Winoground set used. While advanced CoT methods like DDCoT and CoCoT improve over the baseline for Gemini Pro Vision, the CA paradigm applied to Gemini 2.0 achieves competitive scores, particularly on the text metric, demonstrating its effectiveness.

### A.7.4 Comparison of Description Sources (Pixtral-12B vs. GPT-4o)

The results, detailed in Table A.6, consistently show that using image components described by GPT-4o yielded higher downstream reasoning accuracy compared to using components described

| Model | Paradigm | sosa | soua | uosa | uoua | Avg |
|---|---|---|---|---|---|---|
| Gemini 2.0 | DVRL | 50 | 54 | 49 | 50 | 50.8 |
| | DRL | 63 | 62 | 55 | 65 | 61.3 |
| | CA | 77 | 74 | 70 | 77 | 74.5 |
| GPT-4o | DVRL | 68 | 75 | 61 | 70 | 68.5 |
| | DRL | 73 | 77 | 64 | 73 | 71.8 |
| | CA | 83 | 83 | 66 | 77 | 77.3 |
| Human Avg. | – | 87.2 | 90.0 | 93.6 | 94.9 | 91.4 |

Table A.4: Performance (%) on Bongard-HOI splits across paradigms. Human average taken from (Jiang et al., 2022) **Splits:** sosa: seen_obj_seen_act, soua: seen_obj_unseen_act, uosa: unseen_obj_seen_act, uoua: unseen_obj_unseen_act. Human average from cited source.

| Model / Strategy | Text | Image | Group |
|---|---|---|---|
| Gemini (Baseline) | 30.75 | 26.00 | 25.00 |
| Gemini + DDCoT | 45.00 | 25.00 | 23.75 |
| Gemini + CCoT | 22.50 | 33.00 | 20.75 |
| Gemini + CoCoT | 40.00 | 32.50 | 27.75 |
| **Gemini 2.0 + CA (Ours)** | **71.91** | **48.71** | **42.01** |

Table A.5: Performance comparison on Winoground (400 samples). CA refers to our Componential Analysis paradigm. Other results use Gemini Pro Vision with different prompting strategies.

by Pixtral-12B across all tested reasoning models. While both description sources enabled strong performance, the advantage conferred by GPT-4o's descriptions (ranging from approximately 2% to over 11% improvement depending on the reasoning model) further underscores the critical dependence of reasoning outcomes on the fidelity, richness, and potentially the alignment of the initial perceptual descriptions with the concepts required by the reasoning task. This reinforces the significance of the VLM's front-end visual processing and description capabilities as a key factor influencing overall visual reasoning performance.

| | Components (%) | |
|---|---|---|
| **Model** | **Pixtral-12B** | **GPT-4o** |
| Deepseek-R1-14B | 83.21 | 87.98 |
| Llama3.2-vision-90B | 89.05 | 90.98 |
| Phi-4-14B | 86.86 | 91.98 |
| Qwen2.5-14B | 90.51 | 92.99 |
| LLaVA-7B | 68.61 | 80.56 |
| Llama3.2-vision-11B | 80.29 | 84.17 |
| LLaVA-34B | 79.56 | 81.56 |
| Phi-3-14B | 84.67 | 86.97 |

Table A.6: Performance comparison using Componential Analysis (Stage 2) with image descriptions generated by either Pixtral-12B or GPT-4o. Evaluated across various reasoning models.

### A.7.5 Componential Analysis Results by Commonsense Category

Analysis of GPT-4o and Gemini 2.0 performance in CA across commonsense categories (Appendix Table A.7) showed generally strong performance, indicating robustness to varied conceptual rules. Minor variations suggested potential differences in handling specific types of context or attributes, possibly reflecting training data nuances.

| ID | Concept Category | GPT-4o (%) | Gemini 2.0 (%) |
|---|---|---|---|
| 0 | Anything else | 92.88 | 94.23 |
| 1 | Human-Object Interaction (HOI) | 86.67 | 92.86 |
| 2 | Taste / Nutrition / Food | 100.00 | 85.71 |
| 3 | Color / Material / Shape | 88.89 | 91.67 |
| 4 | Functionality / Status / Affordance | 100.00 | 100.00 |
| 5 | And / Or / Not | 90.00 | 80.00 |
| 6 | Factual Knowledge | 90.00 | 90.00 |
| 7 | Meta Class | 100.00 | 100.00 |
| 8 | Relationship | 100.00 | 100.00 |
| 9 | Unusual Observations | 92.31 | 92.31 |

Table A.7: Overall accuracy (%) of GPT-4o and Gemini 2.0 on the Bongard-OW test set using Componential Analysis, broken down by Commonsense ID category. Performance variations highlight differing model strengths on specific concept types.

### A.7.6 Impact of CoT-like Structure

(Refer to Table A.8 below)

| Prompt Type | Accuracy (%) | | |
|---|---|---|---|
| | Overall | neg | pos |
| Minimal (No CoT) | 61.6 | 39.2 | 84.0 |
| Structured (CoT-like) | 80.0 | 66.4 | 93.6 |

Table A.8: Impact of Structured Prompting on DVRL accuracy (GPT-4o).

### A.7.7 Detailed Error Analysis Examples

(Refer to Table A.9 below)

| No. | Test ID | Caption (Rule) | Reason for Error (Based on GPT-4o o/p) |
|---|---|---|---|
| 1 | 0021_neg_0 | Cars on the city streets at night | Weak reasoning (similarity): Rule requires vehicles, test image (painting) lacks them explicitly, though context implies city. |
| 2 | 0014_neg_0 | A person playing a guitar. | Rule extraction error: Rule too general (e.g., "person with instrument"), misses specific object (guitar) mentioned in analysis. |
| 3 | 0033_neg_0 | A bicycle is placed in the corner | Rule extraction error: Misses key property (in a corner / specific placement context). Test image (collage) lacks this context. |
| 4 | 0037_neg_0 | The girl has long and thin braids on her head. | Rule extraction error: Rule too general (e.g., "girl with braids"), misses specific property (long and thin). |
| 5 | 0076_pos_0 | Various kinds of rings | Rule extraction error: Rule misses specific object (ring), focuses on property (intricate design) absent in query. |
| 6 | 0076_neg_0 | Various kinds of rings | Rule extraction error: Rule misses specific object (ring), too general. |

Continued on next page

| No. | Test ID | Caption (Rule) | Reason for Error (Based on GPT-4o Output) |
|---|---|---|---|
| 7 | 0082_neg_0 | Live coral on the sea floor. | Weak reasoning (similarity): Rule identifies 'coral', but test image description fails to mention it. Perceptual description error. |
| 8 | 0084_neg_0 | A wooden fence surrounding a grassy field. | Rule extraction error: Rule misses specific object (grass), uses broader term (greenery). Test image has greenery but not clearly grass. |
| 9 | 0112_neg_0 | A wooden floor in the living room. | Rule extraction error: Misses key objects (living room, floor), focuses only on 'wooden' and general 'indoor'. |
| 10 | 0117_neg_0 | Colorful ribbons. | Rule extraction error: Rule too general, misses specific object (ribbons). |
| 11 | 0122_neg_0 | A satellite view of Earth. | Rule extraction error: Misses specific viewpoint (top-down satellite), uses more general 'aerial'. |
| 12 | 0136_pos_0 | Spectator seats view in the stadium. | Weak reasoning/Rule Application error: Rule mentions "sports or spectators", query image description lacks both, leading to incorrect negative classification despite being stadium seats. |
| 13 | 0213_neg_0 | Checkerboard pattern fabrics | Rule extraction error: Misses specific object context (fabric), although pattern is identified. |
| 14 | 0234_neg_0 | A beautiful stone sculpture | Rule extraction error: Focuses on wrong property ('prominent' obelisk) instead of the intended rule property ('tall' obelisk). |
| 15 | 0247_pos_0 | Small river filled with reeds | Rule extraction error: Misses key object (reeds), while focusing on negative constraints (no industrial presence) which are weakly present. |

Table A.9: Error Analysis: Examples of Bongard-OW cases misclassified by both GPT-4o and Gemini 2.0 in Componential Analysis. Captions indicate the ground truth rule (Wu et al., 2024). Reasoning based on analyzing GPT-4o's generated analysis, rule, and query description.