
Understanding Space Is Rocket Science - Only Top Reasoning Models Can Solve Spatial Understanding Tasks

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Abstract

We propose RocketScience, an open-source contrastive VLM benchmark that tests for spatial relation understanding. It is comprised of entirely new real-world image-text pairs covering mostly relative spatial understanding and the order of objects. The benchmark is designed to be very easy for humans and hard for the current generation of VLMs, and this is empirically verified. Our results show a striking lack of spatial relation understanding in open source and frontier commercial VLMs and a surprisingly high performance of reasoning models. Additionally, we perform a disentanglement analysis to separate the contributions of object localization and spatial reasoning in chain-of-thought-based models and find that the performance on the benchmark is bottlenecked by spatial reasoning and not object localization capabilities. We release the dataset with a CC-BY-4.0 license and make the evaluation code available at: <https://github.com/nilshoehing/rocketscience>.

1 Introduction

Language models with vision capabilities have enabled powerful applications [35], from turning sketches into website prototypes to recommending recipes based on a photo of fridge contents. At the same time, these models still struggle with fundamental tasks that are often trivial to humans, particularly those that centre around understanding spatial relationships between objects in an image.

Several benchmarks have attempted to measure these shortcomings. However, many suffer from significant limitations: they often recycle existing datasets [17, 26, 38, 39, 44, 55, 62, 68], lack contrastive structure [10, 16, 19, 27, 56], or rely on synthetic or schematic images [3, 30, 31] (see



Figure 1: Left: A contrastive pair from our RocketScience benchmark, showing two images and captions differing only in object positions. Right: Examples of problematic data in other benchmarks, such as reused or synthetic data, from [3] (cc-by-sa-4.0), [17] (originally from [37] cc-by-4.0), [53] (MIT) and [56] (apache-2.0)

Figure 1). As a result, these benchmarks tend to overestimate model performance, sometimes even allowing pure language models to score highly on supposedly vision-language tasks [24, 48, 61].

The reuse of older datasets raises concerns about data contamination, as their contents may already be present in the training corpora of contemporary language models. Non-contrastive benchmarks often permit the use of unintended shortcuts, thereby failing to evaluate the specific capabilities they are designed to test. Furthermore, the inclusion of synthetic images in evaluation datasets poses challenges, as performance on such data does not reliably transfer to real-world scenarios. A notable example is the CLEVR dataset [30], where models have achieved near-saturating performance for years, despite continuing to struggle with real-image counterparts.

To address these issues, we introduce *RocketScience*, a benchmark specifically designed to rigorously evaluate spatial understanding in VLMs. The dataset is comprised of 482 manually curated, contrastive image-text pairs representing diverse, real-world scenes (indoors, outdoors, across varying lighting conditions - see Appendix C). Each example forms a question-answer pair that is trivially solvable by humans within seconds, yet proves difficult for current vision-language models.

We evaluate three major categories of models: (1) dual-encoder models such as those in the CLIP family, (2) vanilla multimodal large language models (MLLMs), both open- and closed-source, and (3) advanced reasoning-based MLLMs like o4-mini and Gemini 2.5 Pro. Our results show that all models, except those explicitly designed for multimodal reasoning, perform at chance levels. In contrast, models utilizing chain-of-thought (CoT) prompting or reinforcement learning-based reasoning approaches approach near-perfect performance on this benchmark. We further disentangle model performance along two key axes: entity localization and spatial reasoning. Our analysis reveals that poor performance on spatial understanding tasks stems primarily from limitations in reasoning capabilities, rather than failures in localizing objects.

Our contributions are summarized as follows:

- A new open-source, contrastive benchmark, RocketScience, built entirely from scratch using diverse, real-world (non-synthetic) data, specifically designed to evaluate spatial reasoning capabilities in VLMs.
- An evaluation of three classes of models on the benchmark: CLIP-like models, VLMs and reasoning VLMs
- A disentangled analysis of reasoning-based model performance along two axes: object localization and spatial reasoning. We demonstrate that chain-of-thought reasoning is the primary bottleneck for solving spatial reasoning tasks.

2 Related Work

2.1 VLM Benchmarks and VLMs

Several benchmarks have been proposed to evaluate vision language models in recent years. They span commonsense reasoning [8, 9], understanding multiple images at the same time [67], noticing small differences between images [22], counting objects [47], abductive reasoning [66], visual analogies [71] and diagram understanding [76]. Larger benchmarks like OmniBench [34], MMEvalPro [29], MMStar [12] and WildVision [40] evaluate a wide range of VLM phenomena at the same time. Recently, particularly challenging benchmarks such as ZeroBench [53] and Humanity’s last exam [49] have been released although it remains debatable whether a benchmark which is also hard for humans is even desirable, since the difficulty might be the result of poorly designed questions.

At the same time, vision-language models have also substantially improved in recent years. While traditional VLMs answer questions immediately, recently models have been trained to produce a chain-of-thought (CoT) [70], which is step-by-step reasoning, to improve their performance.

2.2 Contrastive VLM Benchmarks

A common problem with VLM benchmarks is that they can largely be solved using language models alone. [12, 25, 26, 48, 64] This is because certain compositions of objects are more likely to appear in the world and questions about them can therefore be solved with common linguistic co-occurrences instead of visual understanding. To avoid this, contrastive benchmarks [3, 23, 31, 42, 50, 61] are composed of so-called contrastive pairs, which are tuples of two images and two matching texts, that ideally only differ in the exact concept that we want to test for. This means that if the one caption within a contrastive pair contains a particularly likely scenario, like "a person on a horse" the other caption will have to be the unlikely opposite, "a person under a horse". Due to this contrastive design, a surface level statistical linguistic understanding is not enough to solve them and models need to have an integrated visio-linguistic understanding of the world to be able to solve them.

2.3 Spatial Understanding

Spatial understanding concerns reasoning about object positions and is evaluated across different modalities. For VLMs, benchmarks such as [15, 28, 52, 57, 77] test abstract spatial reasoning with simple shapes. Language-only datasets like SpartQA [43] and WorldSense [6] use question answering, while CVR [74] provides a visual outlier-detection task. Text-to-image benchmarks, including DrawBench [54], DALL-Eval [14], and VISOR [20], assess spatial understanding through compositional prompts. Others, such as SpatialRGBT-Bench [13] and Q-Spatial Bench [36], target distance reasoning. Among these diverse notions of spatial understanding, we focus specifically on spatial relations (e.g., on, under), as they form the foundation for more complex reasoning.

2.4 Spatial Relation Benchmarks

To measure progress on the understanding of spatial relations, a range of benchmarks have been developed over the past few years. We provide an extensive overview of them in Table 2 in Appendix A that also includes benchmarks with only a subset dedicated to spatial relations. A large portion of them is non-contrastive, making them potentially sensitive to shortcut solutions. Recycling data from other datasets instead of sourcing new data is common as well, which can lead to unrepresentative scores when this old data leaks into model training, inflating the scores. We will also show empirical evidence for those benchmarks being easier than RocketScience in a later section in Figure 3a. Additionally a few test sets like VisMin [3] are synthetically generated, which means we cannot directly infer models’ competence on real data from their results, especially if the synthetic samples are very schematic. We know that slight changes applied to images can already change predictive models’ outputs [18] [1], so it is prudent not to assume that this domain transfer works automatically. Additionally, we can also still observe many artifacts and unrealistic appearing objects in synthetic data, although this is likely to improve with better image generation models in the future. Some of the older benchmarks are of significant size, which was common at the time, but can actually be expensive to evaluate on today, where most top models are not open source.

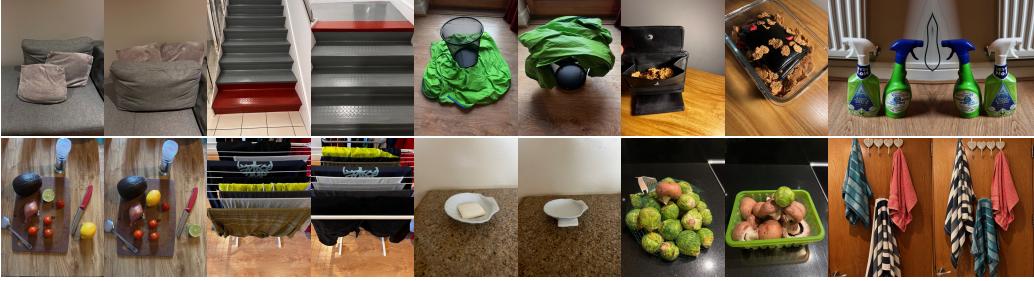


Figure 2: Overview of the contrastive RocketScience dataset.

Winoground [61], Naturalbench [32] and MMVP [63] only contain a small number of spatial understanding questions and no identifiable subset evaluating this property specifically. Therefore they are not included in Table 2. CLEVR [30] is the oldest of the benchmarks. It contains synthetic images of abstract shapes and is very schematic. VALSE [48], Visual Genome Relation [73] and SpatialEval [68] are known to be solvable to a high degree by a blind language model without any image inputs. [48, 64, 68] This likely also applies to many of the other non-contrastive benchmarks. Some of the non-contrastive benchmarks like SugarCrepe [26], ConMe [27] and SugarCrepe++ [17] put a great deal of effort into creating text foils (also known as *hard negatives*) to choose from. NuScenes-SpatialQA [62] is a huge benchmark with automatically generated captions that only covers the self driving car domain. Among the contrastive benchmarks, Rel3D [23] is impressively diverse for a synthetic dataset. FOREST [50] and VSR [38] add perspective change from the perspective of objects, introducing additional complexity.

3 RocketScience Benchmark

3.1 Benchmark Design

Based on the shortcomings outlined in Section 2, we have developed a carefully curated, real-world spatial understanding benchmark that includes a variety of different testing scenarios which avoid predefined schemas and that also follows a contrastive design to avoid shortcut solutions. (see Figure 2) In contrast to other recent benchmarks like Zerobench [53], we create image-text pairs that are understandable to humans while being challenging for machines. We prove that examples are not challenging merely due to them being inherently ambiguous with extremely high human performance. (See Section 4.4)

The main focus of this benchmark is to systematically evaluate relative spatial understanding and the order of objects, as several works have suggested that these properties are not effectively learned by many vision-language models [25, 26, 31, 38, 69]. We design the benchmark with contrastive pairs of new images and texts (each contrastive pair consists of two images and two matching captions with minimal differences). The benchmark requires two levels of understanding: object localization within the image and inference of their spatial relation. The questions are designed to require both steps, without shortcuts, by including the same objects in both parts of each contrastive pair.

3.2 Data Collection

We approximately balance the five main categories which all test for relative spatial understanding: horizontal position, vertical position, depth, proximity and order. The distribution of categories can be seen in Figure 8.

All images were collected in Europe and the USA with an iPhone 13 Mini. We intentionally exclude people and personally identifiable information for the purposes of data privacy. After collection, one author labeled the images and two additional authors checked their agreement with the labels, suggesting changes if necessary. We iterated this process until all authors agreed on the labels.

We add *Label* and *Category* tags to each contrastive pair, where the label specifies the spatial relation necessary to distinguish the two samples in the pair (e.g. "left of") and the category indicates the spatial category (e.g. horizontal position). A contrastive pair can have two categories when the

spatial relations are not polar opposites (e.g. "shoe in front of box" vs. "shoe to the right of box" would be assigned the categories horizontal position and depth).

3.2.1 Images

As some objects are impossible or extremely challenging to move in the real world, many of the pairs contrasting left and right positions consist of an original photo and its mirrored version as its opposite. Mirroring was only applied when no relevant text would be distorted through of mirroring.

To account for variation in lighting, images were captured in different lighting scenarios. These included: natural light outside, natural light inside, nighttime outside and artificial light inside. We note, however, that the lighting conditions are always consistent within a single contrastive pair.

3.2.2 Captions

Captions were designed such that the two captions for a pair of images could only differ in the position of the objects. For example:

- **Word order:** This represents the largest share of the dataset, e.g. "A chair to the left of a table" vs. "A table to the left of a chair"
- **Swapped Preposition:** This is necessary for some relations that cannot be inverted by simply changing the word order, e.g. "The scissors are close to the door" vs. "The scissors are far from the door".

In both cases, the semantics of the two captions are opposites (also termed *hard negatives*) with respect to the objects' positions. These hard negatives are required to assess whether a spatial relation has been successfully learned rather than simply the likelihood of a relation being associated with certain nouns (i.e. people on chairs, not chairs on people). With the exception of the "left" vs. "right" distinction, in many cases, hard negatives control for unlikely noun-relation cases, while a benchmark without hard negatives simply checks whether models have memorized the most likely case.

3.3 Scope and Variety

The benchmark is designed for spatial understanding, but the localization of the objects still requires additional understanding such as: counting, negation, quantifiers ("most of"), materials, size and colour. In comparison to What's Up [31], RocketScience is significantly more diverse and less schematic. We include a wide variety of scene characteristics such as indoor and outdoor environments, daytime and nighttime settings, objects at varying distances (both near and far), a range of object sizes (small and large), as well as natural and rural environments. (See Appendix C) This broad coverage makes our dataset substantially more representative of real-world conditions.

The physical objects found in the images are sourced from a wide range of objects from daily life within Europe and the US. The distribution of objects can be seen in Figure 9 in Appendix D. The most frequent adjectives are colors, but materials like "*wooden*" or "*metal*", in addition to counts and other object properties can be found in the dataset, see Figure 10 which is also in Appendix D.

3.4 Ambiguity

By design, most of the questions compare direct opposites, making ambiguity rare, however samples involving relations that are not direct opposites leave more room for interpretation. To prove solvability and to ensure unambiguous design we measure human performance. The humans obtain extremely high scores with low variance, from which we conclude that it is not ambiguous. (See Section 4.4 for details)

To ensure clarity in spatial references, we adopt the camera view as the default perspective for all annotations. Since the dataset excludes humans, we eliminate potential ambiguity arising from subjective references such as "on a person's left/right side". The camera-based viewpoint provides a consistent and semantically grounded interface between visual and linguistic modalities, reducing interpretational variability. Although most prompts contrast clearly defined opposites minimizing ambiguity, certain spatial relations, such as "near" vs. "far", or comparative attributes like "big" vs. "small", can be inherently subjective. To mitigate this subjectivity, each instance presents

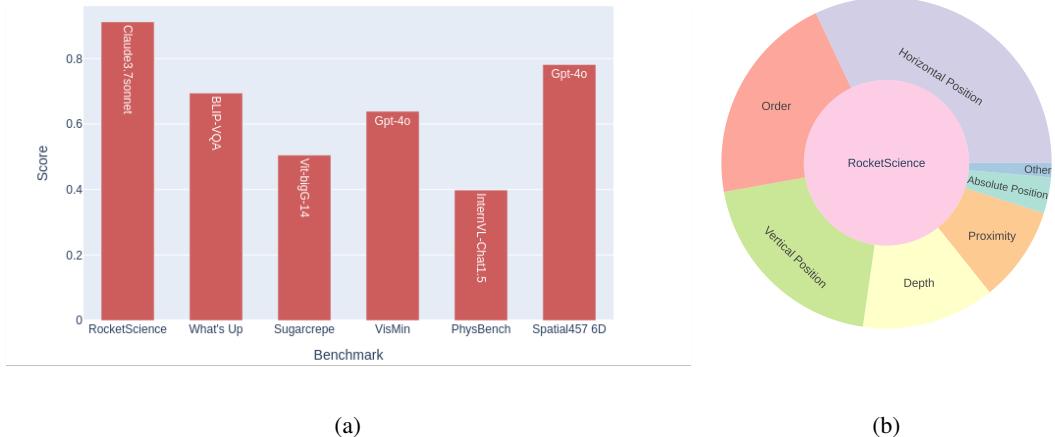


Figure 3: Overview of the RocketScience benchmark. **(a)** Benchmark quality score for popular benchmarks where higher values indicate greater challenge and headroom. **(b)** Categories contained in the RocketScience dataset. (Full breakdown in Figure 8 in Appendix D)

the model with two alternatives (e.g. a pair of captions or images), ensuring that the comparative context disambiguates the intended meaning. For instance, given two images and the caption “scissors close to the door”, the correct answer becomes the one where the scissors are closer to the door relative to the alternative. As discussed in Section 3.2.1, a subset of examples in the **horizontal position** category includes horizontally mirrored images. In some cases, mirrored text may be visible, but never in a way that would simplify the task.

3.5 Difficulty

Even in contrastive benchmarks, considerable care must be taken to prevent models from exploiting unintended correlations or shortcut signals (i.e. solving tasks via surface-level cues rather than the intended reasoning). In our benchmark, samples are designed to control for this by ensuring that both target entities are present in each image. For example, in the contrastive pair “beetroot in a bin” vs. “no beetroot in a bin”, both the beetroot and the bin appear in both images. The latter image still contains the beetroot, but located outside the bin. This ensures that solving the task requires understanding the spatial relation, rather than simply detecting object presence. This construction prevents the task from being reduced to simple object detection and enforces a requirement for spatial comprehension.

Additionally, a subset of image-text pairs is constructed to require fine-grained attribute localization, rather than reliance on nouns alone. For instance, in a caption such as “a crushed milk carton to the left of an intact milk carton”, both objects belong to the same category, but differ in visual attributes. Tasks of this nature increase linguistic complexity and demand comprehension of adjectives in context, further discouraging reliance on shallow pattern matching.

To account for the fact that benchmark datasets often leak into model training over time, we argue that benchmark difficulty and informativeness are best evaluated at the time of their release. To quantify this, we introduce a normalized scoring metric:

$$\text{Score} = \frac{1 - \text{SOTA}_{\text{AtRelease}}}{1 - \text{Random}} \quad (1)$$

where $\text{SOTA}_{\text{AtRelease}}$ is the best-performing *non-CoT* model at the time of dataset release, and Random represents the expected score from uniform guessing. This metric captures the benchmark’s potential to differentiate between random and competent models at release time, rather than its current saturation level. It also allows for fairer comparisons across datasets of varying ages. Under this metric, our benchmark RocketScience outperforms several contemporaneous datasets as can be observed in figure 3a, even though the metric favors older benchmarks as they do not have to compare to current SOTA models.

4 Experimental Setup & Evaluation

4.1 Models

We evaluate three main types of models: CLIP-like (contrastive) embedding models, language models with vision capabilities (VLMs) and reasoning VLMs with a hidden chain-of-thought (reflective models). The most interesting models in our context are those that have been trained for more fine-grained visual understanding like NegCLIP [73], Paligemma [7], SpaceOm [11] and GLM4.1 [60]. We also select a range of VLMs from top frontier VLMs like GPT-4o [46] and Llama4 [41]. Additionally, we also evaluate Gemini 2.5 [21] and o4-mini [45] as examples of reflective models. We only include commercial models that can be run for less than ten US Dollars on the benchmark and only run them once due to their cost.

4.2 Evaluation

Preprocessing: We resize all images to 1024×1024 . Most of the CLIP models and Paligemma include custom preprocessing that downsizes images further. Closed VLMs like GPT-4o and Claude Sonnet allow for large image inputs. For all API models we use .png to maintain image quality.

Inputs: Each contrastive pair is split into four questions:

- Q1: First image + both captions → Which is the correct caption?
- Q2: Second image + both captions → Which is the correct caption?
- Q3: First text + both images → Which is the correct image?
- Q4: Second text + both images → Which is the correct image?

The correct answer for Q1 and Q3 is always 1 and for Q2 and Q4 it's always 2. This automatic alternation means it is not necessary to shuffle the answers as is necessary for non-contrastive benchmarks to avoid models simply always choosing the first answer.

CLIP-like models receive the images and captions individually and compute the similarity between them. The exact inputs and outputs can be seen in Appendix B.

Decoding: For API models we set temperature = 0 where possible, to minimize variance. Please note that this still does not lead to fully deterministic according to their documentation [21, 41, 46]. CLIP models are deterministic during evaluation. For local VLMs, we use greedy decoding in order to ensure results are reproducible.

Hardware and Runtime: The local models were evaluated on a T4-GPU. Most CLIP models evaluate within a few minutes. The API models take between 1 and 2.5 hours to run, with the reflective models taking the most time.

4.3 Metrics

We use text score, image score and group score, as introduced by Winoground [61], for the CLIP-like models and modify the scores to be suitable for VLMs as follows: for text score, one image and two captions are used as input with the model then choosing the matching caption. For image score, two images and one caption act as the input and the model must select the correct image. This approach is not perfectly comparable to the original scores, as they are based on individually encoded texts and images, making them slightly harder than our newly defined VLM scores. The adapted image score, text score and group score are defined in Equations 2, 3 and 4 as follows:

$$f(I_0, I_1, T_0, T_1) = \begin{cases} 1, & \text{if } \hat{y}(I_0, I_1, T_0) = \text{"choose } I_0\text{" and } \hat{y}(I_0, I_1, T_1) = \text{"choose } I_1\text{"} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$g(I_0, I_1, T_0, T_1) = \begin{cases} 1, & \text{if } \hat{y}(I_0, T_0, T_1) = \text{"choose } T_0\text{" and } \hat{y}(I_1, T_0, T_1) = \text{"choose } T_1\text{"} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

$$h(I_0, I_1, T_0, T_1) = \begin{cases} 1, & \text{if } f(I_0, I_1, T_0, T_1) = 1 \text{ and } g(I_0, I_1, T_0, T_1) = 1 \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

where f, g, h are the equivalents of image score, text score and group score and I_0, I_1, T_0, T_1 are the images and texts from a contrastive pair.

4.4 Human Evaluation

To assess the solvability of the benchmark we present the questions to humans with no formal linguistics education. ($n=4$) The evaluation scheme is the same as for VLMs, so they either get a caption and have to choose between two images or get an image and have to choose the right of two captions. However because humans can remember their previous responses, we only present one question from each contrastive pair to each human. The scores are then computed across all testers. For humans the two images or the two captions are shuffled - otherwise the correct one would always be in the same spot. The image resolution for the human evaluation is 600 by 600 pixels so that two images fit onto a laptop screen comfortably. (This is lower than the resolution the models receive) The exact instructions and interface are available in Appendix G. Our participants score a mean accuracy of 0.985 with a standard deviation of 0.008. We conclude that RocketScience has an extremely low level of ambiguity.

5 Results

We present the results in Table 1. Table 3 in Appendix E includes additional CLIP-like models. Model names that end with *_cot* have been prompted to do chain-of-thought reasoning on top of their usual system prompt. Gemini 2.5 and o4-mini perform reasoning internally before responding. We find that all open vision-language models, even those trained for spatial understanding perform very poorly and often below random chance. This phenomenon has also been observed in other contrastive vision-language benchmarks, such as Winoground [61] and WhatsUp [31]. Only reasoning models come close to human performance.

| Model Name | Horiz | Vert | Depth | Prox | Order | Abs Pos | Total |
|-----------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Random chance | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 |
| Human | 0.96 | 0.98 | 0.95 | 1.00 | 0.92 | 0.80 | 0.95 |
| ViT-B-32negCLIP [73] | 0.00 | 0.02 | 0.00 | 0.00 | 0.03 | 0.00 | 0.01 |
| CoCa_ViT-L [72] | 0.00 | 0.04 | 0.00 | 0.00 | 0.02 | 0.00 | 0.01 |
| PaliGemma-3b-mix-448 [7] | 0.01 | 0.04 | 0.00 | 0.00 | 0.02 | 0.20 | 0.02 |
| Qwen-2.5-vl-72b-instruct [5] | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Qwen-vl-max [4] | 0.01 | 0.02 | 0.00 | 0.00 | 0.02 | 0.00 | 0.01 |
| Claude-3-7-sonnet-20250219 [2] | 0.17 | 0.38 | 0.11 | 0.52 | 0.18 | 0.00 | 0.24 |
| Llama-4-maverick [41] | 0.17 | 0.23 | 0.05 | 0.52 | 0.15 | 0.40 | 0.20 |
| GPT-4o-2024-08-06 [46] | 0.08 | 0.40 | 0.24 | 0.40 | 0.07 | 0.00 | 0.19 |
| Llama-4-maverick_cot [41] | 0.53 | 0.42 | 0.21 | 0.64 | 0.45 | 0.20 | 0.44 |
| GPT-4o-2024-08-06_cot [46] | 0.44 | 0.68 | 0.39 | 0.56 | 0.52 | 0.60 | 0.51 |
| SpaceOm [11] | 0.01 | 0.02 | 0.03 | 0.04 | 0.00 | 0.00 | 0.01 |
| Glm-4.1v-9b-thinking [60] | 0.77 | 0.68 | 0.42 | 0.4 | 0.68 | 1.00 | 0.64 |
| Gemini-2.5-pro-preview-03-25 [21] | 0.91 | 0.87 | 0.76 | 0.76 | 0.80 | 0.80 | 0.83 |
| o4-mini [45] | 0.97 | 0.91 | 0.89 | 0.68 | 0.88 | 1.00 | 0.89 |

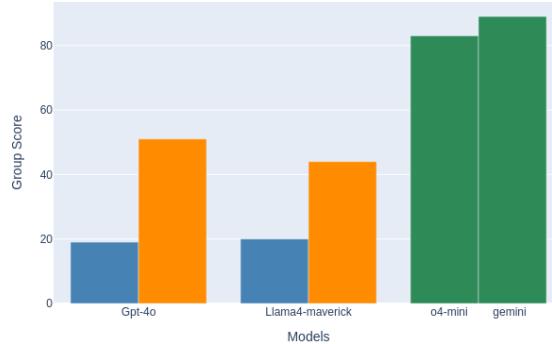
Table 1: Group score on RocketScience by category of the task (Horizontal Position, Vertical Position, Depth, Proximity, Order, Absolute Position, Total Score). Models run with chain-of-thought prompting are marked in orange and reflective models are marked in green. The highest score in each category is bold.

5.1 Why Are Chain-of-Thought Models Better?

We hypothesize that there are two main steps necessary to detect a spatial relation: localization of objects and inference of spatial relation. We examine both stages to determine why reasoning models like o4-mini perform much better than their non-reasoning counterparts like gpt-4o:

| Model | Acc lf | Acc rf |
|---------|------------------|------------------|
| gpt-4o | 96.11 ± 0.96 | 90.55 ± 0.96 |
| o4-mini | 96.66 ± 0.00 | 95.56 ± 1.92 |

(a) Mean accuracy and standard deviation over 3 runs on the localization task (horizontal position subset). The difference in localization performance between non-CoT and CoT models is minimal. A small performance gap is also observed based on object order in the prompt: accuracy is slightly higher when the first-mentioned object appears on the left (Acc lf) compared to when it appears on the right (Acc rf), for both model types.



(b) Group score comparison of models without chain-of-thought (blue), with explicit chain-of-thought prompting (orange), and with implicit chain-of-thought reasoning (green).

Figure 4: Disentanglement experiments of (a) localisation and (b) CoT reasoning

- **Localization of objects:** We test whether o4-mini is better at localizing the objects than gpt-4o. We use the horizontal position subset for this (on which gpt-4o performs very poorly). The two models are prompted to provide bounding boxes for both objects in each image. We then check whether the coordinates of both objects are in the correct spatial configuration. (not exact location) Figure 4a shows the results. We find that gpt-4o is very close to o4-mini’s performance, indicating that reasoning does not help with the localisation stage, but only with concluding the correct spatial relation.
- **Inference of spatial relation:** We use two sets of prompts for non-reflective models: The first prompts each model to output the answer alone immediately and nothing else (non-CoT). The second prompts each model to first reason and then output the results (CoT). We find that the second prompt significantly improves performance over the first one, indicating that chain-of-thought reasoning plays the biggest role in the improved performance. (See Figure 4b)

6 Discussion

6.1 Limitations

First, models accessed via APIs were only evaluated once due to cost constraints. Although we set the sampling temperature to zero where possible to ensure determinism, outputs may still vary slightly between runs. Second, while our dataset aims to reflect real-world complexity, some scenes remain less cluttered with objects than typical real-world environments. Introducing additional clutter while maintaining clear, unambiguous relations remains a significant challenge. Third, we observe notable performance improvements using chain-of-thought prompting; however, this benefit may be specific to top-tier commercial models and might not generalize to smaller or open-source models. Finally, although we strive to minimize changes within each contrastive pair, slight variations in camera angle may occur. This could introduce a potential shortcut where models exploit angle differences to infer spatial relations rather than relying solely on object configurations.

6.2 Ethics

People and personal data are explicitly excluded as subjects within this dataset in an effort to minimize the unnecessary use of human data in experiments. Each sample within the dataset was meticulously reviewed by three of the authors of this paper in an effort to maintain quality standards by minimizing errors and omissions. It is necessary to emphasize that the geographical locations of images are limited to the US and Europe, making the environment and objects specific to these locations. It is therefore crucial to stress that a model that performs well on this benchmark will not necessarily perform well in all geographic locations or with objects specific to them. Additionally, though this benchmark has successfully revealed that most vision-language models fail to effectively model spatial relations, it should not be relied upon alone as a form of evaluation for these relations, as benchmark performance should not act as a replacement for application and location-specific quality

control and testing. We caution that though benchmarks can reveal *some* model shortcomings, they are never exhaustive and we caution against their use alone to rank algorithms in real-world applications/production as this can lead to unexpected societal outcomes.

6.3 Conclusion

We introduce RocketScience, a challenging new benchmark for evaluating spatial relation understanding in vision language models. Built from scratch using real-world, contrastive image-text pairs, RocketScience reveals that most open-source and commercial models perform surprisingly poorly. Our analysis shows that chain-of-thought prompting significantly improves performance. By disentangling the effects of object localization and spatial reasoning, we find that the primary limitation lies in models’ ability to perform structured reasoning about spatial relations, rather than in their visual perception. We hope RocketScience serves as a diagnostic and development tool for future VLMs, encouraging research toward models with more robust spatial understanding.

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A Appendix: Related Work

| Benchmark | contrastive | new data | real data | non-schematic | size |
|-------------------------|-------------|----------|-----------|---------------|-----------|
| MMBench[39] | ✗ | ✗ | ✓ | ✓ | 125 |
| SpatialEval-Real [68] | ✗ | ✗ | ✓ | ✓ | 1000 |
| VSR [38] | ✗ | ✗ | ✓ | ✓ | 2195 |
| CLEVR [30] | ✗ | ✓ | ✗ | ✗ | 15,000 |
| VALSE [48] | ✗ | ✗ | ✓ | ✓ | 535 |
| SugarCrepe [26] | ✗ | ✗ | ✓ | ✓ | 1406 |
| ConMe [27] | ✗ | ✗ | ✓ | ✓ | 6793 |
| SC++ [17] | ✗ | ✗ | ✓ | ✓ | 1406 |
| VGR (ARO) [73] | ✗ | ✗ | ✓ | ✓ | 23,937 |
| RoboSpatial-Home [56] | ✗ | ✓ | ✓ | ✓ | 123 |
| BLINK[19] | ✗ | ✗ | ✓ | ✓ | 286 |
| SpatialBench [10] | ✗ | ✓ | ✓ | ✓ | 35 |
| Space3D-bench [59] | ✗ | ✗ | ✓ | ✓ | 188 |
| Spatial-MM [55] | ✗ | ✗ | ✓ | ✓ | 2,000 |
| EmbSpatial Bench [16] | ✗ | ✗ | ✓ | ✓ | 3,640 |
| NuScenes-SpatialQA [62] | ✗ | ✗ | ✓ | ✓ | 2,500,000 |
| Cosmos1 [44] | ✗ | ✗ | ✓ | ✓ | 292 |
| Spatial457 [69] | ✗ | ✓ | ✗ | ✓ | 9,990 |
| FOREST [50] | ✓ | ✓ | ✗ | ✓ | 4,352 |
| BiVLC [42] | ✓ | ✓ | ✗ | ✓ | 1,400 |
| Rel3D [23] | ✓ | ✓ | ✗ | ✓ | 27,336 |
| VisMin [3] | ✓ | ✓ | ✗ | ✗ | 622 |
| What's Up (A+B) [31] | ✓ | ✓ | ✓ | ✗ | 820 |
| RocketScience | ✓ | ✓ | ✓ | ✓ | 482 |

Table 2: Overview of Spatial Relations benchmarks (or with a subset for that). Contrastive means fully contrastive, new data means entirely new and no recycled parts, real data means not synthetic, non-schematic means different scenes and objects not always in the same positions, size is only the spatial relations subset and measured as number of image-text pairs.

B Appendix: Inputs and Outputs

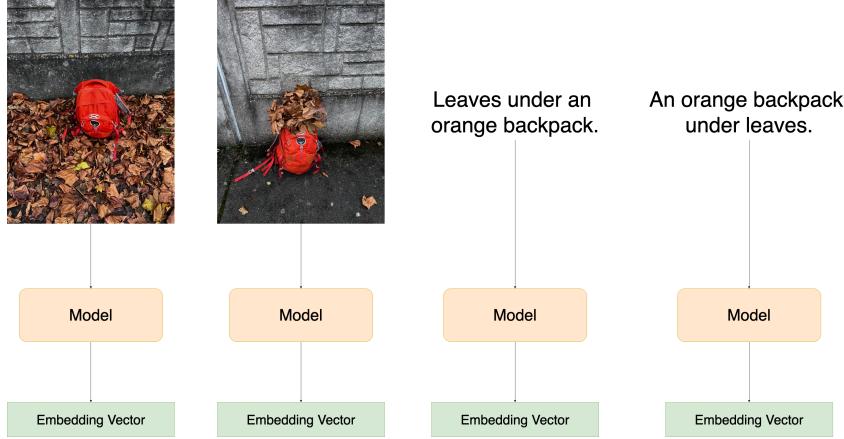


Figure 5: Function of CLIP-like models: they embed each image and text independently without having access to the other inputs at the same time

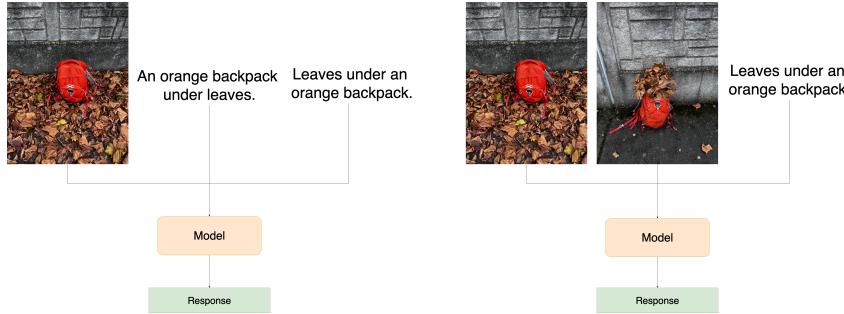


Figure 6: Function of VLMs: they receive either an image and two captions and have to choose a caption or they receive two images and a caption and have to choose an image

The model prompts are as follows: CLIP models simply receive the captions from the dataset without additional prompting. The other VLMs (both normal and reflective) receive two types of prompts:

- "Which caption fits the image best? Reply only with the number 1 or 2, nothing else. 1.) [CAPTION1] 2.) [CAPTION2]"
- "Which image fits the caption best? Reply only with the number 1 or 2, nothing else. Caption: [CAPTION1]"

For our additional experiments we test models' explicit chain-of-thought capabilities. These models are denoted with _cot after their name. They receive different prompts to make them reason:

- "Which caption fits the image best? Reason about it and at the end write RESPONSE and reply only with the number 1 or 2. 1.) [CAPTION1] 2.) [CAPTION2]"
- "Which image fits the caption best? Reason about it and at the end write RESPONSE and reply only with the number 1 or 2. Caption: [CAPTION1]"

Example reasoning trace from gpt-4o for a case with two images and one caption: The caption describes "A grey bin on a white towel." Image 1 shows a grey bin placed directly on a white towel. Image 2 shows a towel covering the grey bin. The best fit for the caption is image 1, as it correctly shows the bin on the towel. RESPONSE 1

C Appendix: Selected examples from the dataset

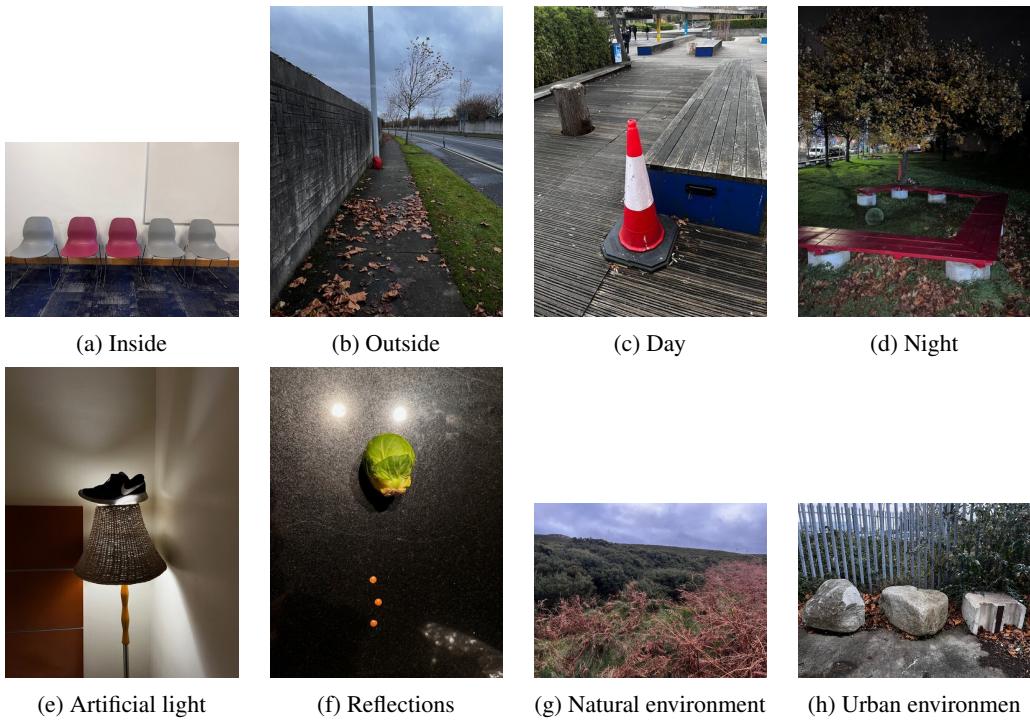


Figure 7: Examples for scene diversity in RocketScience.

D Appendix: Dataset Analysis

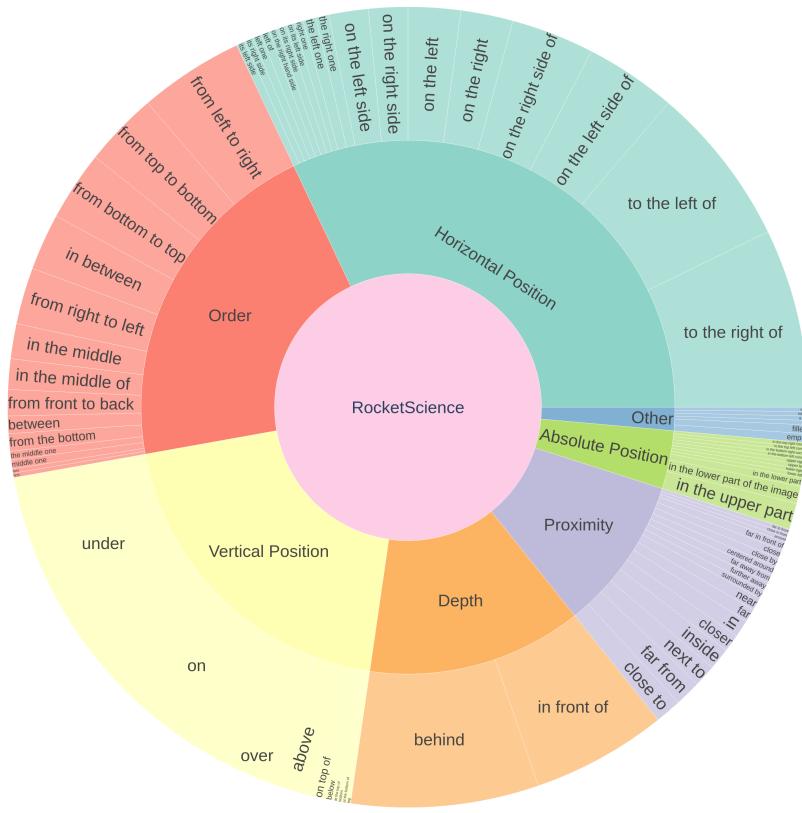


Figure 8: Dataset distribution, relative proportions

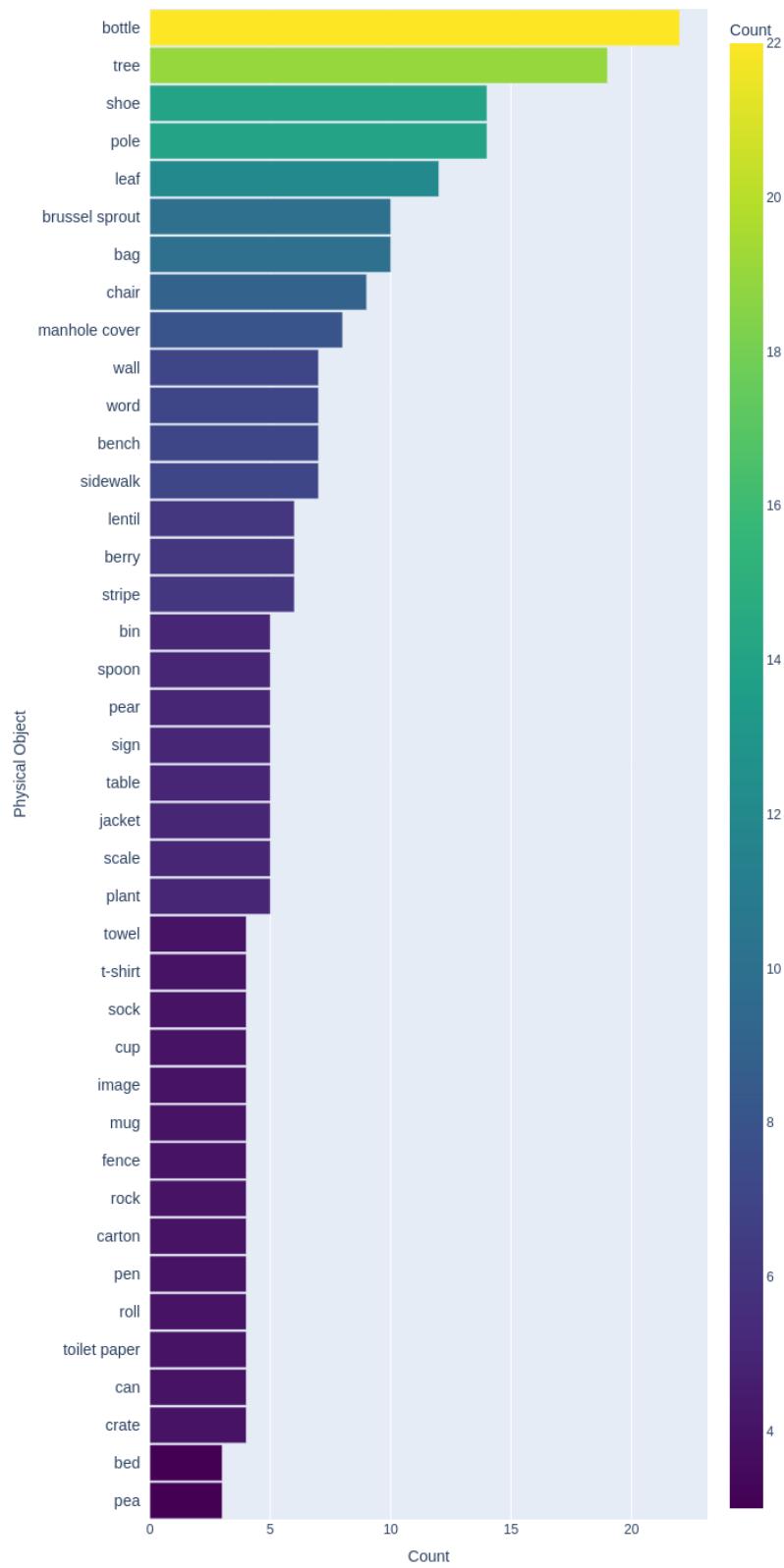


Figure 9: Physical Object Counts

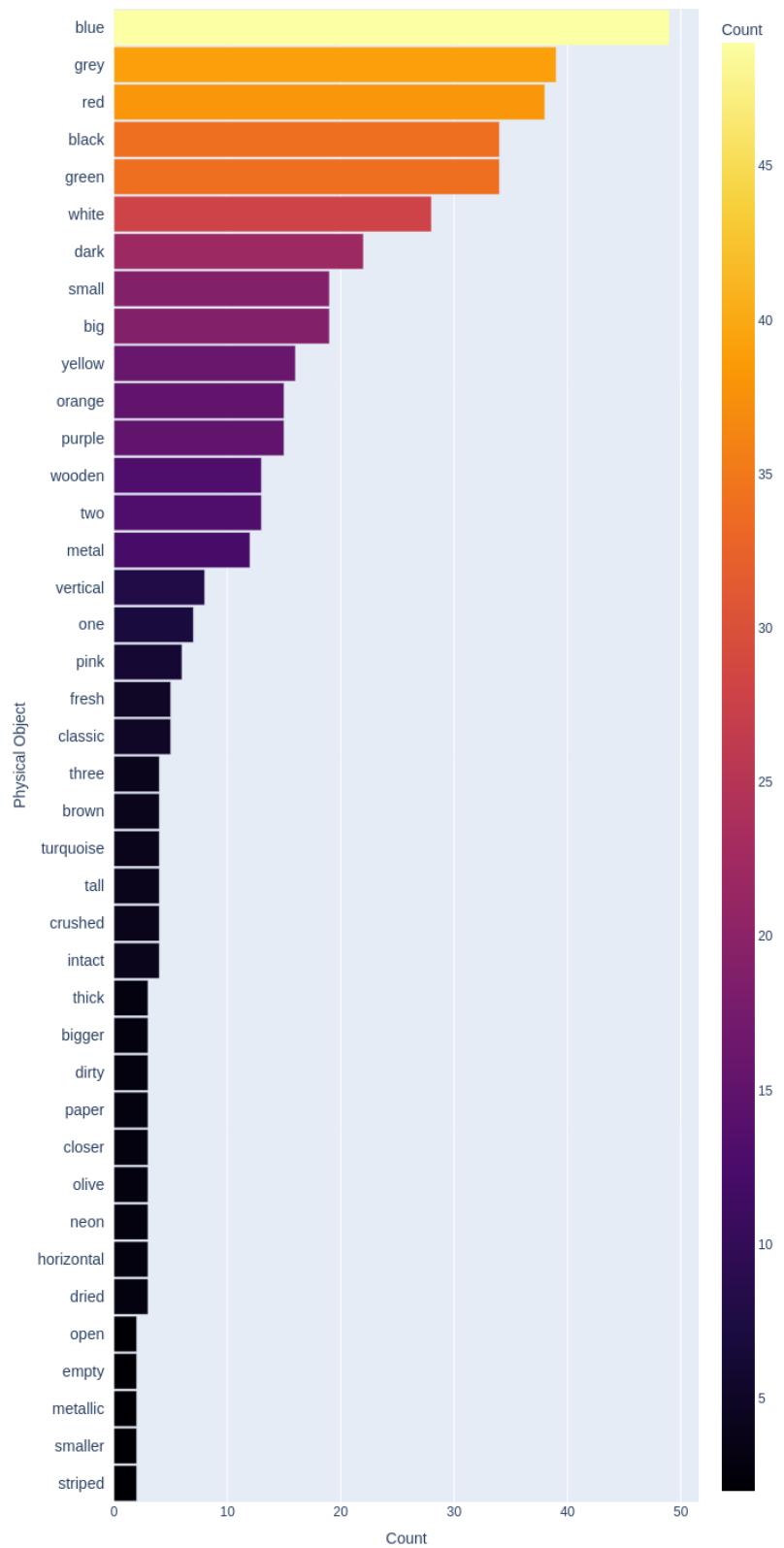


Figure 10: Adjective Counts

E Appendix: Detailed Results

| modelname | textscore | imagescore | groupscore |
|--------------------------------------|-------------|-------------|-------------|
| random | 0.25 | 0.25 | 0.17 |
| human | 0.97 | 0.98 | 0.95 |
| ViT-B-32negCLIP [73] | 0.08 | 0.04 | 0.01 |
| EVA02-B-16merged2b_s8b_b131k [58] | 0.13 | 0.04 | 0.02 |
| EVA02-L-14-336merged2b_s6b_b61k [58] | 0.12 | 0.05 | 0.02 |
| ViT-B-16-SigLIPwebli [75] | 0.13 | 0.04 | 0.02 |
| ViT-L-16-SigLIP-384webli [75] | 0.10 | 0.07 | 0.02 |
| ViT-L-14-CLIPAdatocomp1b [33] | 0.07 | 0.05 | 0.00 |
| ViT-L-16-SigLIP2-512webli [65] | 0.12 | 0.07 | 0.01 |
| coca_ViT-B-32laion2b_s13b_b90k [72] | 0.14 | 0.05 | 0.02 |
| coca_ViT-L-14laion2b_s13b_b90k [72] | 0.10 | 0.04 | 0.01 |
| ViT-B-16-SigLIP2-512webli [65] | 0.10 | 0.05 | 0.02 |
| ViT-B-16openai [51] | 0.11 | 0.05 | 0.02 |
| ViT-B-32openai [51] | 0.11 | 0.02 | 0.01 |
| paligemma-3b-mix-448 [7] | 0.13 | 0.10 | 0.02 |
| qwen-2.5-vl-72b-instruct [5] | 0.47 | 0.01 | 0.00 |
| qwen-vl-max [4] | 0.29 | 0.03 | 0.01 |
| claude-3-7-sonnet-20250219 [2] | 0.53 | 0.37 | 0.24 |
| llama-4-maverick [41] | 0.38 | 0.37 | 0.20 |
| gpt-4o-2024-08-06 [46] | 0.38 | 0.39 | 0.19 |
| llama-4-maverick_cot [41] | 0.59 | 0.66 | 0.44 |
| gpt-4o-2024-08-06_cot [46] | 0.73 | 0.66 | 0.51 |
| SpaceOm [11] | 0.08 | 0.14 | 0.01 |
| glm-4.1v-9b-thinking [60] | 0.84 | 0.72 | 0.64 |
| gemini-2.5-pro-preview-03-25 [21] | 0.94 | 0.89 | 0.83 |
| o4-mini (medium) [45] | 0.91 | 0.94 | 0.89 |

Table 3: Results on the RocketScience benchmark, the second division is CLIP-like models, the third regular VLMs, the fourth regular vlms with explicit chain-of-thought and the last VLMs with implicit chain-of-thought. All CLIP-like models and basic VLMs fail drastically while some reasoning models come very close to human performance.

| Model | Horizontal | | | Vertical | | | Depth | | |
|------------------------------|------------|------|------|----------|------|------|-------|------|------|
| | ts | is | gs | ts | is | gs | ts | is | gs |
| paligemma-3b-mix-448 | 0.08 | 0.13 | 0.01 | 0.21 | 0.11 | 0.04 | 0.16 | 0.13 | 0.00 |
| qwen-2.5-vl-72b-instruct | 0.51 | 0.00 | 0.00 | 0.62 | 0.02 | 0.00 | 0.39 | 0.03 | 0.00 |
| qwen-vl-max | 0.23 | 0.07 | 0.01 | 0.47 | 0.02 | 0.02 | 0.24 | 0.00 | 0.00 |
| claude-3-7-sonnet-20250219 | 0.43 | 0.35 | 0.17 | 0.64 | 0.49 | 0.38 | 0.47 | 0.24 | 0.11 |
| llama-4-maverick | 0.40 | 0.33 | 0.17 | 0.45 | 0.36 | 0.23 | 0.18 | 0.29 | 0.05 |
| gpt-4o | 0.35 | 0.27 | 0.08 | 0.62 | 0.58 | 0.40 | 0.39 | 0.42 | 0.24 |
| llama-4-maverick_cot | 0.67 | 0.72 | 0.53 | 0.55 | 0.66 | 0.42 | 0.37 | 0.50 | 0.21 |
| gpt-4o_cot | 0.72 | 0.63 | 0.44 | 0.83 | 0.77 | 0.68 | 0.74 | 0.55 | 0.39 |
| gemini-2.5-pro-preview-03-25 | 0.99 | 0.92 | 0.91 | 0.96 | 0.91 | 0.87 | 0.89 | 0.84 | 0.76 |
| o4-mini | 0.97 | 0.97 | 0.97 | 0.92 | 0.94 | 0.91 | 0.95 | 0.92 | 0.89 |

Table 4: Text score, image score and group score for each category in the dataset.

| Model | Proximity | | | Order | | | Absolute Position | | |
|------------------------------|------------------|------|------|--------------|------|------|--------------------------|------|------|
| | ts | is | gs | ts | is | gs | ts | is | gs |
| paligemma-3b-mix-448 | 0.04 | 0.00 | 0.00 | 0.13 | 0.07 | 0.02 | 0.40 | 0.60 | 0.20 |
| qwen-2.5-vl-72b-instruct | 0.44 | 0.04 | 0.00 | 0.37 | 0.00 | 0.00 | 0.60 | 0.00 | 0.00 |
| qwen-vl-max | 0.44 | 0.00 | 0.00 | 0.23 | 0.03 | 0.02 | 0.20 | 0.00 | 0.00 |
| claude-3-7-sonnet-20250219 | 0.72 | 0.68 | 0.52 | 0.53 | 0.28 | 0.18 | 0.40 | 0.00 | 0.00 |
| llama-4-maverick | 0.64 | 0.64 | 0.52 | 0.25 | 0.37 | 0.15 | 0.80 | 0.40 | 0.40 |
| gpt-4o | 0.52 | 0.60 | 0.40 | 0.18 | 0.22 | 0.07 | 0.20 | 0.40 | 0.00 |
| llama-4-maverick_cot | 0.68 | 0.88 | 0.64 | 0.68 | 0.57 | 0.45 | 0.40 | 0.80 | 0.20 |
| gpt-4o_cot | 0.68 | 0.76 | 0.56 | 0.72 | 0.60 | 0.52 | 0.60 | 1.00 | 0.60 |
| gemini-2.5-pro-preview-03-25 | 0.88 | 0.88 | 0.76 | 0.92 | 0.87 | 0.80 | 1.00 | 0.80 | 0.80 |
| o4-mini | 0.72 | 0.88 | 0.68 | 0.90 | 0.92 | 0.88 | 1.00 | 1.00 | 1.00 |

Table 5: Textscore, imagescore and groupscore for each category in the dataset

F Appendix: Evaluation Stability

To prove that the size of our benchmark is appropriate, we test the standard deviation of one model with poor performance (gpt4o without chain-of-thought) and one model with good performance (gemini 2.5 pro). We run each model three times and then randomly sample subsets of size 0.5 to 1.0 of the dataset and provide their mean and standard deviation below. RocketScience yields stable evaluation results and would even do so if it were much smaller.

| Share | Gpt-4o (Mean ± Std) | Gemini 2.5 pro (Mean ± Std) |
|--------------|----------------------------|------------------------------------|
| 0.5 | 0.21 ± 0.03 | 0.86 ± 0.01 |
| 0.6 | 0.20 ± 0.03 | 0.85 ± 0.01 |
| 0.7 | 0.20 ± 0.03 | 0.85 ± 0.01 |
| 0.8 | 0.19 ± 0.02 | 0.84 ± 0.01 |
| 0.9 | 0.19 ± 0.02 | 0.85 ± 0.02 |
| 1.0 | 0.18 ± 0.02 | 0.86 ± 0.02 |

Table 6: Performance of Gpt-4o and Gemini 2.5 pro over three runs each on random subsets of RocketScience. The standard deviation stays low at both half the dataset size and the full dataset.

G Appendix: Human Baseline

The full set of instructions given to the participants (apart from the consent form) is: "You will be asked to answer several questions. Each question will consist of two images and a caption, and you will need to click on the image that best matches the caption."

The testing interface can be seen in Figure 11 and Figure 12.

We do not see any significant risks for the study participants and we obtained permission for the human evaluation from University College Dublin's Human Research Ethics Committee.

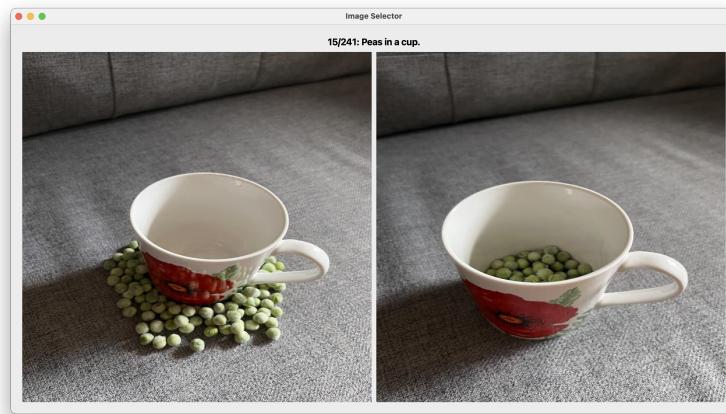


Figure 11: Human baseline interface with two images

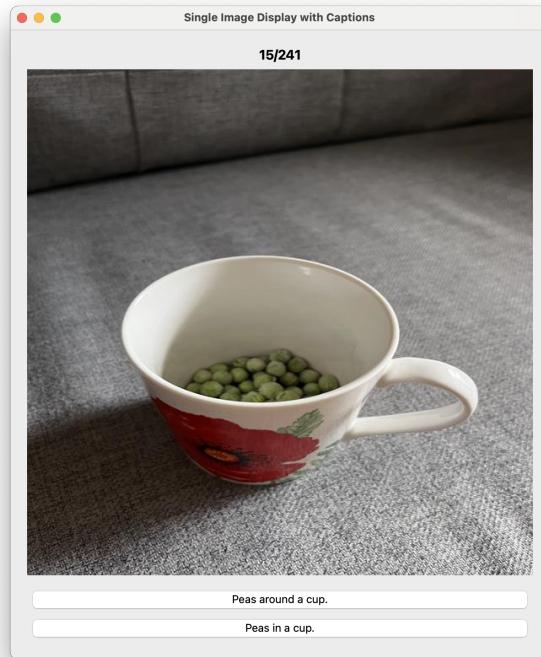


Figure 12: Human baseline interface with two captions

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Justification: The dataset is published on huggingface and the evaluation script is available on github via the link in the abstract, including instructions for how to run it. The model's full names are available in the code, but also stated in the results tables for full reproducibility.

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Justification: The core contribution is a benchmark which was manually created.

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- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.